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Keywords: Stochastic Discount Factors, Performance Measurement, Minimum Discrepancy measures, Nonparametric discounting. JEL Classification: C1,C5,G1

We thank Newedge for sponsoring this research as part of a research chair with EDHEC-Risk Institute. This paper has been presented at EDHEC-Risk Days Europe 2012 in London and EDHEC-Risk Days Asia 2012 in Singapore.

Printed in France, June 2012. Copyright® EDHEC 2012.

The opinions expressed in this study are those of the author and do not necessarily reflect those of EDHEC Business School. The author can be contacted at research@edhec-risk.com.
Abstract

We evaluate the performance of hedge funds through a new nonlinear risk adjustment of returns. The risk adjustment is such that it prices exactly the usual set of risk factors considered in the hedge fund literature. This nonlinear risk adjustment goes beyond the usual linear regression methodology used in many hedge fund performance papers, including nonlinear exposures based on option-like features. The approach proposed in this paper overcomes two important limitations of the linear methodology: it captures the nonlinear exposure of a hedge fund strategy to several risk factors, and it is not limited to nonlinear shapes resembling standard option payoff patterns. We apply this methodology to various hedge fund indices as well as to individual hedge funds, considering a set of risk factors including equities, bonds, credit, currencies and commodities. The main message that emerges from our analysis on the performance of hedge fund strategies is that exposure to higher-moment risks on the various factors matters. Analysing the performance of HFRI indices on primary strategies and sub-classes of primary strategies, we report sizeable differences in performance, between the linear and the nonlinear risk adjustment. Most often the nonlinear risk adjustment reduces the performance but for some sub-classes it enhances their performance. We also show how to conduct a risk analysis and provide an example where a change in a single risk factor can affect the average performance of funds when more robust risk adjustment is applied.
About the Authors

**Caio Almeida** holds a PhD in Electrical Engineering from Catholic University in Rio, and a post-doctorate degree from the Department of Mathematics at Stanford University. From 1997 to 2002, he worked as a quantitative analyst at Banco Pactual, and as a risk manager at JGP Hedge fund, two leading investment companies located in Rio de Janeiro. After teaching for several years at the Business School of IBMEC in Rio, he joined the Graduate School of Economics of the Getulio Vargas Foundation in Rio in 2006 as an assistant professor. His recent work deals with the estimation and evaluation of asset pricing models, as well as the design of dynamic term structure models with applications to forecasting, credit risk, market risk, and integration between underlying and derivative markets. He published in international refereed journals including the *Journal of Econometrics*, the *Journal of Banking and Finance*, *Quantitative Finance*, the *International Journal of Theoretical and Applied Finance*, and the *Journal of Fixed Income*. He is also an associate editor of the *Journal of Banking and Finance*.

**René Garcia** is Professor of Finance at EDHEC Business School and the Academic Director of the EDHEC-Risk Institute PhD in Finance programme. He was previously a professor at the Université de Montréal and the scientific director of the interuniversity research centre CIRANO. His research interests in finance revolve around the valuation of financial assets, portfolio management, and risk management. In econometrics, he is interested in non-linear models, in particular regime-switching models. He has published in leading journals including *Econometrica*, *Journal of Econometrics*, *Journal of Finance*, *Management Science*, and *Review of Financial Studies*. He is a co-founder of the *Journal of Financial Econometrics*. Professor Garcia has received numerous research grants, held the Hydro-Québec chair in integrated risk management and financial mathematics, and was recently awarded a three-year endowment by the AXA Research Fund.
Executive Summary
Robustness is key when assessing the performance of hedge funds. Since investment strategies are very diverse, sources of risk and corresponding exposures are hard to identify. Moreover, pension funds and rich individuals do not exhibit the same risk tolerance and will not assess performance in the same way. Traditional measures cannot offer such robustness to complex risk-factor exposures and investors' risk aversion.

Ratios involving mean returns and volatility (Sharpe, Treynor or Information ratios) or even more sophisticated ratios accounting for downside risk (Sortino, Gain-Loss or Omega ratios) do not control for the wide variety of strategies followed by hedge funds and therefore are not sufficiently informative to rank funds. Peer benchmarking also has its limits: homogeneous peer grouping is difficult given the absence of information regarding the hedge funds' holdings and strategies, and investors cannot assess whether or not the average manager within the peer group generates any value. Measuring performance through alpha after adjusting the returns for the risk exposures to several factors delivers a finer basis for comparing funds. Equity, fixed income, credit, commodity or currency risks are included, together with returns on option strategies built on these primitive factors. A main drawback of the current approaches is to relate hedge fund returns to such risk factors linearly since it has been shown that hedge fund returns exhibit complex nonlinear exposures to traditional asset classes.

In this paper, we propose a new method that captures the complex nonlinear exposures of a hedge fund strategy to several risk factors. It accommodates many nonlinear functions of factor returns, hence the term nonparametric, over and above the usual option payoff patterns. In addition, it produces a risk adjustment function that weights hedge fund returns differently depending on the risk tolerance of an investor. Therefore, the computed alpha performance - the average of the risk-adjusted returns - is robust in both the nonlinear exposure to risk factors and investors' risk aversion.

Alpha performance is measured by the averaged product of a fund's returns by a risk-adjustment function, called stochastic discount factor in asset pricing theory. Intuitively, the methodology is based on seeking to identify a nonlinear function of risk factors that remains positive at all times to avoid arbitrage and that prices perfectly the basis assets selected as factors. In other words, the methodology will assign a zero alpha to any payoff that is trivially related to available factors, so that the measure of abnormal performance for hedge fund returns will only capture the fraction of the hedge fund returns that is due to the managers' active skills. The risk-adjustment function makes clear which risk factors are really important for the performance of hedge funds under analysis.

The main idea is to risk-adjust hedge fund payoffs in a way that accounts for the asymmetry or tail risk exposures.
created by the dynamic strategies pursued by hedge funds. Indeed, the risk-adjusted performance measure will not only be based on means and volatilities of hedge fund returns, which are not sufficient statistics given the strong deviations from normality that hedge fund returns exhibit, but also on higher-order moments of the distribution of hedge fund returns.

To establish the relevance of our approach from an empirical standpoint, we evaluate the performance of various hedge fund indices, considering a set of risk factors including equities, bonds, credit, currencies and commodities, as well as several straddle strategies. We report how the measured alpha varies with the inclusion of option-based factors and with the risk tolerance of the investor. We find that, as we decrease risk tolerance, the alpha decreases significantly for some categories (Emerging Markets), while remaining fairly unchanged for others (Equity Hedge and Macro). In the latter case, we conclude that the performance is robust. Yet in other cases, some funds pay well in bad times (Asian funds or Short Bias), offering insurance value, and their alpha increases as we decrease risk tolerance.

These findings strongly suggest that what was incorrectly measured as hedge fund alpha in previous studies is actually some form of fair reward obtained by hedge fund managers from holding a set of relatively complex linear and nonlinear exposures with respect to various risk factors. Often the reduction in performance comes from a small number of extreme events which are not captured well with the usual linear approach. Our findings also support the view that higher-moment equity risks capture a large part of the nonlinear risk exposure of several hedge fund strategies. However, exposure to higher-moment risks for bond, interest rate or currency is essential for other strategies, in particular Emerging Markets. Finally, we also illustrate with individual funds how a fund manager can measure the sensitivity of his portfolio of funds to shocks affecting risk factors, that is macro shocks, or to idiosyncratic shocks impacting a particular fund.

The approach can be extended to evaluate hedge fund managers’ performance conditionally to specific macroeconomic environments such as high or low interest-rate states, large or limited economic uncertainty, boom or bear markets, liquid or illiquid markets, making the performance measurement more transparent to general economic conditions.
Executive Summary (Full)

A number of institutional investors now include a sizeable portion of hedge funds in their portfolios. This interest in hedge funds can be explained by the poor performance exhibited by traditional asset management. For some years now, numerous studies have shown that the vast majority of active asset managers do not outperform passive investment. Some authors find that the outperformance generated by active management just covers the costs generated by the strategy (Grossman and Stiglitz 1980; Ippolito 1989), while others conclude that the after fee performance of active management is lower than that of passive management (Jensen 1968; Grinblatt and Titman 1992; Hendricks, Patel and Zetchauer 1993; Elton, Gruber, Das and Hlavka 1993; Kahn and Rudd 1995; Malkiel 1995; Elton, Gruber and Blake 1996; Gruber 1996; Carhart 1997, Cuthbertson, Nitzche and O’Sullivan 2008; French 2008; Fama and French 2010, among many others). All of these studies, which were conducted to propose improvement in terms of performance measurement, underline the difficulty of evaluating a portfolio’s true alpha.

Within such a context of disappointing performance, hedge funds were thus seen as a way of improving portfolio performance. Evaluating hedge fund returns requires specific attention, because hedge funds invest in a heterogeneous range of asset classes and cover a wide range of dynamic strategies that have different risk and return profiles. Hedge funds also include options and derivative products, which are not part of traditional management. The widely used performance measures, which were developed based on modern portfolio theory, were specifically designed for traditional investment and particularly for equity investment, even if some authors have included factors to suit other asset classes such as bonds (Sharpe 1992; Elton, Gruber, Das and Hlavka 1993). When risk exposures of traditional asset class returns can be represented with linear models, hedge fund returns present nonlinear exposures to traditional asset classes, mimicking an option pay-off. This aspect has to be taken into account when evaluating their performance.

When it comes to performance measurement, it appears that asset managers are not fully using the techniques proposed by the literature. This was highlighted by Amenc, Goltz and Lioui (2011), who reported the results of a 2008 survey on traditional asset management; respondents of the survey itself were European asset managers. Concerning portfolio performance measurement, it appears from this survey that the vast majority of respondents do not use sophisticated approaches and that there is still a wide gap between practices and academic models. The Sharpe ratio (80% of the respondents) and the information ratio (80% of the respondents) appear to be the most widely used measures to evaluate the performance of asset management. When evaluating the relative performance of a portfolio, 33% of the respondents compare their returns to those of a simple index, though it has been largely demonstrated that such a comparison does not make it possible to take into account the differences in risk exposures between the portfolio and the index, consequently making it impossible to accurately measure the asset manager’s value added. Finally, if many professionals look at their alpha, the methodology used appears to be critical.

for most of them, as about 62% of the respondents evaluate alpha with regard to a peer group, an approach that has been largely criticised (see Myners’ report³), as the risk characteristics of the portfolio do not usually appear to be accurately reflected by the peer group. Only 23% used multi-factor models to evaluate alpha. Measuring the true alpha of a portfolio is the only way to identify skilful managers who may be able to repeat their performance in the future. An accurate measure of alpha can only be obtained after isolating the specific performance (due to manager skill) from the risk premiums that reward the various risk factors to which the portfolio is exposed.

The problem of performance measurement robustness has been well documented for traditional portfolio management. It has been shown that the result of performance measurement may change depending on the index chosen as market factor (see Roll 1977), due to the inefficiency of the proxies and to a poor description of portfolio risk exposures. As a result, the ranking of portfolios may be affected by the choice of the reference index. This is especially true for alpha measured with a single-index model, as well as for ratios referring to a benchmark, such as the information ratio. The use of multifactor models does not completely solve this problem, as these models are not necessarily able to include all risk factors supported by the portfolios. Using a misspecified model can lead to the conclusion that a manager has produced alpha, though this alpha is in fact the return premium rewarding a forgotten risk factor. As a result, investors may be misled in their investment choice. This problem of robustness is exacerbated as soon as hedge funds are concerned.

Defining hedge fund risk exposures can be particularly tricky, due to the large varieties of strategies and the specific nature of hedge fund return profiles (option like pay-offs). A small change in risk can produce a large change in returns in such option-like strategies, as opposed to the linear exposures encountered in traditional investment. The results of hedge fund performance evaluation can then be largely modified if the model used is misspecified.

Robustness is thus key when assessing the performance of hedge funds, and the possibility of using a model that takes it into account is crucial. Traditional ratios involving mean returns and volatility, or even more sophisticated ratios accounting for downside risk, are not sufficient to rank funds. Peer benchmarking also has its limits. Measuring performance through alpha after adjusting the returns for the risk exposures to several factors delivers a finer basis for comparing funds. Given the wide diversity of hedge fund strategies, equity, fixed income, credit, commodity or currency risks are included, together with returns on option strategies built on these primitive factors. A main drawback of the current approaches is linearly relating hedge fund returns to such risk factors. In this paper, we propose a new method that captures the nonlinear exposures of a hedge fund strategy to several risk factors. Our model accommodates many nonlinear functions of returns for the risk factors (hence the term nonparametric), over and above the usual option pay-off patterns. The risk-adjustment nonlinear functions are easily obtained by solving a portfolio problem in which the investors set their own risk tolerance. A hedge fund that exhibits a consistent alpha under all

³ - This report, published in March 2001, was commissioned by the Chancellor of the Exchequer and deals with the investment practices of institutional investors in the UK.
levels of risk tolerance delivers a robust performance.

Below, we elaborate how our approach overcomes the limitations of the existing methods to evaluate the performance of hedge funds. Performance ratios are the simplest measures since they involve statistics that can be computed directly from returns series of any hedge fund. Some involve the first two moments of the return distribution (Sharpe, Treynor or Information ratios) while some others aim to capture the downside risk associated with the fund (Sortino, Gain-Loss or Omega ratios). The main drawback of this approach is that it does not control for the very different strategies used by hedge funds.

A solution involves using peer benchmarks. The idea is to form homogenous groups of managers based on qualitative analysis and/or statistical techniques so as to alleviate the concern over heterogeneity of hedge fund strategies. Managers’ performance is assessed in terms of their ability to outperform the average performance of comparable managers within their peer group. While intuitively attractive, this approach suffers from two major shortcomings. First, it is impossible to form entirely homogenous groups of managers in the absence of information regarding the hedge funds’ holdings and strategies. It is often observed that the best performing managers within a given peer group are those who deviate the most from the average factor exposure in their peer group. Such factor tilts can emanate from active views of the managers, and as such should be regarded as skill, but they can also emanate from a simple misclassification of the manager. A second, arguably more severe, shortcoming is that the investors have no way of knowing whether or not the average manager within the peer group generates any value.

To address the challenge of risk-adjusted performance assessment for hedge funds, a natural approach involves using an asset pricing model, which by construction allows investors to measure what the fair reward should be given the risk exposures of the hedge fund manager. Researchers have used models with a single factor, most often an equity index representing the market, or with multiple factors, adding such risks as international equity, fixed-income, equity volatility, commodities or currencies, and other factors such as book-to-market, size, momentum or default. The alpha of a fund is then obtained from the difference between the fund’s actual performance, and what the normal return should have been on the basis of the estimated factor model.

While representing a clear progress with respect to the previous approaches, traditional multi-factor models only capture linear exposures to the various risk factors, while it has been shown that hedge fund returns exhibit nonlinear exposures to traditional asset classes.

These nonlinearities arise because hedge fund managers can use derivatives and follow dynamic trading strategies, and also because of the explicit sharing of the upside profits. The fee structure of hedge funds is more complex than that of traditional funds. In addition to the usual management fees, which are based on the amount of assets under management, hedge fund managers receive an incentive
remuneration related to the performance of the funds. Hence, post-fee returns exhibit option-like features even if pre-fee returns do not. This phenomenon has significant consequences on performance measurement and requires the development of specific methodologies that take into account the nonlinear structure of hedge fund returns. In addition, some authors (Foster and Young 2008) observe that these incentive schemes do not make it possible to distinguish between skilled managers, who consistently deliver performance, and unskilled managers, who alternate between profit and loss periods. This is an additional argument to carefully consider the choice of the approach to measure hedge fund returns. Therefore, recent literature has added returns on buy-and-hold or dynamic positions in derivatives to the set of traditional risk factors in a linear regression setting. However, even if we could introduce the most complete set of option returns, nothing can guarantee that the chosen underlying assets and levels of moneyness accurately represent the true state-dependent factor exposure of hedge fund managers. A statistical approach exists to estimate the level of moneyness of the options that best characterise the returns of a particular fund, but in practice it is limited by the relatively short samples of hedge fund returns. Studies have therefore focused on identifying positions in put or call options or straddles, one risk factor at a time. It therefore appears impractical to extend the method to several risk factors and to more complex option strategies such as spreads.

This paper proposes to further improve the toolkit for hedge fund risk-adjusted performance evaluation, and aims to overcome the main limitations in previous approaches. Firstly, it allows one to analyse the nonlinear exposure of any hedge fund or hedge fund strategy to several risk factors. Secondly, it is not limited to shapes resembling standard option payoff patterns, and can accommodate more exotic pay-offs. Being nonparametric, it produces a factor model that captures many nonlinear functions of returns for the assets chosen as risk factors, overcoming the aforementioned problem of limited data availability. Moreover, it can add nonlinearities to option risk factors such as the straddle strategies used in Fung and Hsieh (2001). The main idea is to risk-adjust hedge fund pay-offs in a way that accounts for the asymmetry or tail risk exposures created by the dynamic strategies pursued by the hedge funds. Abnormal performance is measured by the expected product of a portfolio’s returns and a risk-adjustment function, called stochastic discount factor in asset pricing theory. The evaluation process can be extended to make risk-adjusted performance assessment conditional upon a set of lagged financial instruments.

Intuitively, the methodology is based on seeking to identify, in a nonparametric way, the proper risk-adjustment function to be used in hedge fund performance assessment by requiring that it prices the basis assets selected as factors as accurately as possible. In other words, the methodology will assign a zero alpha to any pay-off that is trivially related to available factors, so that the measure of abnormal performance for hedge fund returns will only capture the fraction of the hedge fund return that is attributable to the manager’s active skills. Our analysis explicitly accounts for higher moments of returns induced by option-like
strategies and can capture more complex nonlinearities since options portfolios can be included as factors themselves. As a result of this process, the risk-adjusted performance measure will not only be based on means and volatilities of hedge fund returns, which are not sufficient statistics given the strong deviations from normality that hedge fund returns exhibit. As such, the risk-adjusted performance measure takes into account higher-order moments, and in fact the whole distribution of hedge fund returns. One additional advantage of this approach is that it shows how reference assets chosen as risk factors should be weighted within the risk adjustment function that will be used for analysing hedge fund performance. Therefore, it indicates which risk factors are really important for the performance of hedge funds under analysis, and allows one to discard spurious factors that only have a marginal influence in explaining the performance of hedge fund managers. Finally, this approach can be used to evaluate the performance of hedge fund managers conditionally to specific macroeconomic environments such as high or low interest-rate states, large or limited economic uncertainty, boom or bear markets, or liquid or illiquid markets, thus making the performance measurement more transparent to general economic conditions.

Prior studies have used conditioning information to evaluate the performance of managed portfolios, but they limit themselves to conditional measures of performance that only involve conditional means and variances of portfolio returns. We extend the literature on conditional performance measurement by producing conditional measures that take into account all conditional moments of the risk-adjustment functions.

To establish the relevance of our approach from an empirical standpoint, we evaluate the performance of various hedge fund indices, considering a set of risk factors including equities, bonds, credit, currencies and commodities, as well as several straddle strategies. We compare the measured alphas to the more traditional linear or option-based performance measures obtained by the usual simple regression analysis. The first striking empirical finding is that alpha valuations obtained with the implied nonlinear risk-adjustment measures are in general much lower than the performances exhibited when introducing option factors linearly. We also show the robustness of performance to variations in the risk aversion parameter, as illustrated in the exhibit below. Moving from right to left (decreasing risk tolerance), it can be seen that the alpha decreases significantly for some categories (Emerging Markets), while remaining fairly unchanged for others (Equity Hedge and Macro). In the latter case, we will conclude that the performance is robust.

This picture presents the alphas of the seven main hedge fund categories (Emerging Markets (EM), Equity Hedge (EH), Event Driven (EV), Fund of Funds (FoF), Global Index (GI), Macro and Relative Value (RV)) obtained for various values of the risk-aversion parameter. The Bond and Credit risk factors are represented by the 10Y Treasury and Moody’s BAA Bond Indexes, respectively. There are two equity oriented factors represented by the S&P 500 (equity market factor) and the Russell 2000 monthly total return (size spread factor), respectively.
The emerging market factor is represented by the MSCI emerging market index. There are four Primitive Trend-Following Factors (PTFS) represented by lookback straddles on bonds, currency, commodity, short-term rate, and stocks (see Fung and Hsieh 2001).

Performances of Main Hedge Fund Indexes
This picture presents the alphas of the seven main Hedge Fund categories (Emerging Markets (EM), Equity Hedge (EH), Event Driven (EV), Fund of Funds (FoF), Global Index (GI), Macro and Relative Value (RV)) obtained for various values of the risk-aversion coefficient. The Bond and Credit risk factors are represented respectively by the 10Y Treasury and Moody’s BAA Bond Indexes. There are two equity oriented factors represented respectively by the S&P 500 (equity market factor) and the Russell 2000 monthly total return (size spread factor). The emerging Market factor is represented by the MSCI emerging market index. There are five Primitive Trend Following Factors (PTFS) represented by lookback straddles on bonds, currency, commodity, short-term rate, and stocks (see Fung and Hsieh (2001) for details).
I. Introduction
1. Introduction

Performance evaluation of hedge funds has proceeded with two main approaches. One considers only absolute returns, while the other rests on the identification of risk factors behind hedge fund returns. It has been quickly recognised that absolute performance measurement for hedge funds needs to go beyond the traditional Sharpe or Treynor ratios. Indeed, hedge fund return distributions are distinctly abnormal and measures based on the mean and variance are not sufficient to capture the risk associated with hedge fund returns. Other measures have been proposed to account for the negative skewness and positive large kurtosis exhibited by hedge fund return distributions, namely the Sortino ratio, the Stutzer index or the Omega ratio. While these adapted measures are better able to capture the higher-moment risk present in hedge fund returns, they are not sufficient to rank funds. We need additional indicators to know if a given fund is doing well relative to other funds using similar strategies. The relative approach starts with the peer analysis, whereby funds in comparable groups are evaluated based on absolute return measures. Performance relative to peers may be measured during market cycles or over short or long periods. However, the groups may not be homogeneous enough to capture the underlying exposures to different risks. Therefore, measuring performance through alpha after accounting for the beta risks appears to deliver a finer basis for comparison between funds.

The alpha approach necessitates spelling out the risk factors that may affect hedge fund returns. Given the wide diversity of strategies followed by hedge funds the literature has evolved to include exposures to the main sources of risk, such as equity, fixed income, credit, commodity or currency. The main approach is to estimate linear factor models where hedge fund returns are regressed linearly on such risk factors. Such an approach captures only linear exposure to the risk factors, but several studies have shown that a large number of equity-oriented hedge fund strategies exhibit payoffs resembling a short position on a put option on the market index. These approaches to capturing nonlinearities in hedge funds payoffs are targeted towards specific option-like strategies. Fung and Hsieh (2001) analyse trend-following strategies and show that their payoffs are related to those of an investment in a lookback straddle. Mitchell and Pulvino (2001) show that returns to risk arbitrage are similar to those obtained from selling uncovered index put options. Agarwal and Naik (2004) extend these results and show that, in fact, a wide range of equity-oriented hedge fund strategies exhibit this nonlinear payoff structure. Diez de los Rios and Garcia (2011) propose a more general approach to identify the nature of the option that best characterises the payoffs of a hedge fund. It can therefore be used to analyse any strategy. However, one needs to specify the risk factor underlying the option and the number of kinks allowed. Most of their applications have used the market index with one kink, to identify positions in put or call options or straddles. Extending the method to several risk factors and more than one kink runs into the obstacle of limited length time series of hedge fund returns. Therefore, it is empirically impossible
1. Introduction

given the amount of data available to identify spread positions on several risk factors.

The approach proposed in this paper overcomes these limitations. First, it allows one to look at the nonlinear exposure of a hedge fund strategy to several risk factors. Second, it is not limited to shapes resembling standard option payoff patterns. Being nonparametric, it produces a factor model that captures many nonlinear functions of returns for the assets chosen as risk factors, overcoming the above-mentioned problem of limited data availability. Moreover, it can add nonlinearities to option risk factors such as the straddle strategies used in Fung and Hsieh (2001). The main idea is to risk-adjust hedge fund payoffs in a way that accounts for the asymmetry or tail risk exposures created by the dynamic strategies pursued by the hedge funds. Abnormal performance is measured by the expected product of a portfolio’s returns and a risk-adjustment function also called stochastic discount factor. The evaluation can proceed unconditionally or conditionally to a set of lagged instruments.1

The methodology is based on minimising a general convex function to obtain a Minimum Discrepancy (MD) measure (Corcoran 1998) that exactly prices the basis assets selected as factors. A well-known example of such discrepancy measures is the Kullback-Leibler information criterion (KLIC).2 We choose a family of discrepancy functions that admits as particular cases the quadratic criterion of Hansen and Jagannathan (1991), hereafter HJ, and the KLIC, but offers other information criteria that have different implications for assessing performance.

The solutions for these risk-adjustment nonlinear functions are obtained more easily by solving a portfolio problem, with the maximisation of a specific utility function in the Hyperbolic Absolute Risk Aversion (HARA) family.3 The first-order conditions for these HARA optimisation problems provide solutions for the risk-adjustment weights that are nonlinear and positive, directly generalising the linear SDF in HJ (1991) with positivity constraints and guaranteeing no arbitrage when pricing hedge fund payoffs. An additional advantage is that the approach shows how reference assets chosen as risk factors should be weighted within the risk adjustment function, thus indicating which risk factors are really important when analysing hedge fund performance.4

Several studies have used conditioning information to evaluate the performance of managed portfolios.5 Performance can be evaluated conditionally to specific macroeconomic environments such as high or low interest-rate states, large or limited economic uncertainty, boom or bear markets, liquid or illiquid markets, making the performance measurement more transparent to general economic conditions. These studies usually limit themselves to conditional measures of performance that involve only conditional means and variances of portfolio returns. We extend the literature on conditional performance measurement by producing conditional measures that take into account all conditional moments of the risk-adjustment functions.

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1 - See for instance, Ferson and Siegel (2003), Farnsworth et al. (2002), and Bailey, Li and Zhang (2004).
2 - Stutzer (1996) diagnosed asset pricing models with information functions implied by this criterion. Stutzer (1996) used the same information theoretical approach based on the entropy measure to extract canonical probabilities, that is, risk-neutral probabilities that consistently price a set of options using the underlying asset as basis assets or adding to it other traded options. Our methodology naturally generalises his approach to discrepancy measures other than the entropy measure.
3 - This equivalent approach has been stressed in HJ (1991) for a quadratic criterion, where maximising the Sharpe ratio in the space of excess returns corresponds to finding a minimum variance in the space of SDFs. Our approach encompasses the exponential tilting (ET) criterion of Stutzer (1995) and its corresponding optimum portfolio of a CARA investor, as well as the empirical likelihood (EL) criterion and its corresponding log utility maximising portfolio, denominated growth portfolio by Bansal and Lehmann (1997).
4 - In Almeida and Garcia (2010) we provide a detailed econometric methodology to conduct tests for the statistical significance of these risk factors.
5 - A representative example is the study by Farnsworth et al. (2002). They consider several parametric models, both linear and nonlinear, to measure the investment performance of fund managers.
1. Introduction

Conditional approaches have the potential advantage of having thinner-tailed conditional distributions that better control the effect of extreme observations on the moments of asset returns. However, our generalised discrepancy measures, even taken unconditionally, are better able to capture the effect of these extreme observations because they account for higher moments in the unconditional distribution of returns. This is especially important when evaluating the performance of managed portfolios since private information on which fund managers condition their trades is unobservable. In this case only the potentially fatter-tailed unconditional returns are observable. Our unconditional risk-adjustment measures will account for the effect of this unobservable information.

Our implied nonlinear measures are related to a number of previous studies that feature nonlinear risk-adjustment or discounting functions. Bansal and Viswanathan (1993) propose a neural network approach to construct a nonlinear stochastic discount factor that embeds specifications by Kraus and Litzenberger (1976) and Glosten and Jagannathan (1994). Our approach provides a family of different hyperbolic functions of basis factor returns implied by the solution to portfolio problems. In Dittmar (2002), who also analyses nonlinear pricing kernels, preferences restrict the definition of the pricing kernel. Under the assumption of decreasing absolute risk aversion, he finds that a cubic pricing kernel is able to best describe a cross-section of industry portfolios. Our nonparametric approach embeds such cubic nonlinearities implicitly. Boyle et al. (2008) obtain robust prices for derivative securities based on discounting functions that cause minimum perturbations on prices of derivatives payoffs. Our methodology, if used to price derivatives, will provide pricing intervals based on the HARA implied risk-adjustment functions. To establish the relevance of our approach, we evaluate the performance of various hedge fund indices, considering a set of risk factors including equities, bonds, credit, currencies and commodities, as well as several straddle strategies. We compare the measured alphas to option-based performance measures obtained by a linear model. To capture nonlinearities and measure the alpha performance of the funds, Agarwal and Naik (2004) use a linear regression in which they introduce the returns on a portfolio of options along with the other usual risk factors.6

Our analysis accounts explicitly for higher moments of returns induced by option-like strategies. Moreover, an important feature of our discrepancy-based approach is the possibility to capture more complex nonlinearities since options portfolios can be included as factors themselves. Alpha valuations obtained with the implied nonlinear risk-adjustment measures are in general lower than the performances exhibited when introducing option factors linearly. Our study complements the analysis of Agarwal, Bakshi and Huij (2010) who investigate the relationship between the cross-section of hedge fund returns and higher-moment equity risks. We directly relate the performance of hedge funds to higher moments of all risk factors, including straddles on equity, commodity, currency, bond, and

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6 - See also Mitchell and Pulvino (2001) and Fung and Hsieh (2001) for characterising hedge fund returns as returns from option-based trading strategies.
1. Introduction

short interest rate (see Fung and Hsieh, 2001). Our findings support the view that higher-moment equity risks capture a large part of nonlinear risk exposure of several hedge fund strategies. However, exposure to higher-moment risks for bond, interest rate or currency is essential for other strategies, particularly for Emerging Markets.

Our multiplicity of discrepancy measures allows us to conduct a robustness analysis on the performance of hedge funds. In particular, we use an estimator that averages across a range of risk-adjustment functions in order to reflect the assessment of an average investor. We also illustrate how a fund manager can measure the sensitivity of his portfolio of funds to shocks affecting risk factors, that is macro shocks, or to idiosyncratic shocks impacting a particular fund.

The rest of the paper is organised as follows. In section 2, we describe how the minimum discrepancy measures are derived. Section 2.1 details the corresponding dual optimal portfolio problems, while section 2.2 derives the weights on skewness and kurtosis implied by the optimal risk-adjustment measures. In Section 3, we analyse the performance of several HFR hedge fund indices. Section 4 analyses the robustness of the performance findings. Section 5 concludes. Appendix A describes how the optimal SDF is obtained. Appendix B extends the methodology by making the performance assessment conditional to some observed factors. Appendix C describes in detail the strategies associated with the HFRI indices used in the empirical analysis.
1. Introduction
2. Minimum Discrepancy Risk-Adjustment Factors
2. Minimum Discrepancy Risk-Adjustment Factors

Let \( R \) denote the vector of returns of \( K \) basis assets chosen as risk factors whose realizations are given by a time series \( \{ R_{ik} \}_{i=1,...,T; k=1,...,K} \). First, we are looking for admissible risk-adjustment weights, also known as stochastic discount factors (SDFs), that make the average weighted excess returns on the factors equal to zero:

\[
\frac{1}{T} \sum_{i=1}^{T} m_i \left( R_i - \frac{1}{a} 1_K \right) = 0_K. \tag{1}
\]

where \( 0_K \) is a \( K \)-dimensional vector of zeros.

Of course there are many such weighting functions. Therefore, we need to restrict the set of such admissible SDFs. Hansen and Jagannathan (1991) find an admissible linear SDF with minimum variance, obtained by minimising a quadratic function in the space of admissible SDFs. This approach will be similar to the usual regression approach to compute the alpha of hedge funds, except that it imposes a zero pricing error on the factors. Instead, we consider a convex discrepancy function \( \phi \) and we search for a Minimum Discrepancy (MD) SDF that solves the following minimisation problem in the same space of admissible SDFs:

\[
\hat{m}_{MD} = \text{arg min}_{\{m_1, ..., m_T\}} \frac{1}{T} \sum_{i=1}^{T} \phi(m_i),
\]

subject to

\[
\frac{1}{T} \sum_{i=1}^{T} m_i \left( R_i - \frac{1}{a} 1_K \right) = 0_K,
\]

\[
\frac{1}{T} \sum_{i=1}^{T} m_i = a, m_i > 0 \ \forall i. \tag{2}
\]

In this optimisation problem, restrictions to the space of admissible SDFs come directly from the general discrepancy function \( \phi \). The conditions \( \sum_{i=1}^{T} m_i \left( R_i - \frac{1}{a} 1_K \right) = 0_K \) and \( \frac{1}{T} \sum_{i=1}^{T} m_i = a \) must be obeyed by any admissible SDF \( m \) with mean \( a \).

In addition, we explicitly impose a positivity constraint to guarantee that the implied MD SDF is compatible with absence of arbitrage in an extended economy containing derivatives of basis assets (Chen and Knez 1996). This minimisation problem is based on the space of discrete SDFs with dimension \( T \) (the dimension of the sample of data), which can become impractical. According to Borwein and Lewis (1991), the minimisation problem can be solved in a generally much smaller dimensional space by using the following dual problem:

\[
\hat{\lambda} = \text{arg sup}_{\alpha \in \mathbb{R}, \lambda \in \Lambda} \alpha * \alpha - \sum_{i=1}^{T} \frac{1}{T} \phi^* \left( \alpha + \lambda' \left( R_i - \frac{1}{a} 1_K \right) \right), \tag{3}
\]

where \( \Lambda \subseteq \mathbb{R}^K \) and \( \phi^* \) denotes the convex conjugate of \( \phi \) restricted to the positive real line:

\[
\phi^*(z) = \text{sup}_{w > 0} zw - \phi(w). \tag{4}
\]

Note that any convex discrepancy function can be chosen to arrive at empirical estimates of these minimum discrepancy SDFs. We choose the Cressie-Read (1984) family of discrepancies defined as:

\[
\phi^\gamma(m) = \frac{(m - a)^{\gamma+1} - a^{\gamma+1}}{\gamma(\gamma+1)}, \ \gamma \in \mathbb{R}, \tag{5}
\]

where each fixed value of \( \gamma \) implies one specific discrepancy function. This family embeds as particular cases the SDFs derived by HJ (1991), Snow (1991), Stutzer (1995), Bansal and Lehmann (1997), and Cerny (2003). In addition, it offers a nice economic motivation to our information theoretic minimisation problems since they are equivalent to dual HARA utility.
maximisation problems (see Almeida and Garcia 2010).

We show in Appendix A how to solve the dual problem and recover the restricted admissible SDF.

For each choice of $\gamma$ we obtain a distinct set of estimates for $\lambda$ ($\hat{\lambda}_n$) that will lead to a different MD stochastic discount factor ($\hat{m}^\gamma_{MD}$). The MD SDF $\hat{m}^\gamma_{MD}$ is recovered by solving the first-order conditions of the problem (see Appendix A):

$$\hat{m}^\gamma_{MD} = \frac{(a^\gamma + \gamma \hat{\lambda}_n' (R_i - \frac{1}{a} 1_K))^\frac{1}{\gamma}}{\frac{1}{T} \sum_{i=1}^{T} (a^\gamma + \gamma \hat{\lambda}_n' (R_i - \frac{1}{a} 1_K))^\frac{1}{\gamma}}, \ i = 1, ..., T.$$  (6)

Note that the population form for the SDF solving the MD problem will be a hyperbolic function of the original returns $R$:

$$\hat{m}_{MD}(R) = \frac{a^\gamma + \gamma \hat{\lambda}_n' (R - \frac{1}{a} 1_K)^\frac{1}{\gamma}}{E \left[ (a^\gamma + \gamma \hat{\lambda}_n' (R - \frac{1}{a} 1_K))^\frac{1}{\gamma} \right]}.$$  (7)

Specific values of $\gamma$ will specialise the optimal portfolio problems to widely adopted utility functions. A value of $-1$ will correspond to a logarithmic utility function, 0 to the exponential, and 1 to quadratic utility. For $\gamma = 1$, similarly to HJ, the optimal SDF will be a linear function of excess returns.

2.1 Equivalent Optimal Portfolio Problems

The maximisation problem in equation (3) specialised to the Cressie Read family (see equation 24 in Appendix A) has an interesting economic interpretation as an optimal portfolio problem. The solution for the MD problem for each Cressie Read estimator will correspond to an optimal portfolio problem based on the following HARA-type utility function

$$u(W) = \frac{1}{\gamma + 1} (a^\gamma - \gamma W)^\frac{\gamma+1}{\gamma},$$  (11)

with $a > 0$ and $W$ such that $a^\gamma - \gamma W > 0$, which guarantees that function $u$ is well defined for an arbitrary $\gamma$, is concave and strictly increasing.

Specific values of $\gamma$ will specialise the optimal portfolio problems to widely adopted utility functions. A value of $-1$ will correspond to a logarithmic utility function, 0 to the exponential, and 1 to quadratic utility. The corresponding SDFs appear above in Equations (8), (9) and (10). Stutzer (1995) proposed an interpretation for the exponential case based on a standard two-period model of optimal portfolio choices (see Huang and Litzenberger 1988). We extend this interpretation to the whole Cressie-Read family. Suppose an investor

$\hat{m}_{(\gamma=-1)}(R) = \mu * \frac{1}{(a^\gamma + \hat{\lambda} (R - \frac{1}{a} 1_K))}.$  (8)

$\hat{m}_{(\gamma=0)}(R) = \mu * e^\hat{\lambda} (R - \frac{1}{a} 1_K).$  (9)

$\hat{m}_{(\gamma=1)}(R) = \mu * \left( a + \hat{\lambda} (R - \frac{1}{a} 1_K) \right).$  (10)

where, in each case, $\mu$ is such that the SDF mean equals $a$. As we will see in the next section, the corresponding dual problems can be interpreted as optimal portfolio problems to widely adopted utility functions. A value of $-1$ will correspond to a logarithmic utility function, 0 to the exponential, and 1 to quadratic utility. For $\gamma = 1$, similarly to HJ, the optimal SDF will be a linear function of excess returns.
2. Minimum Discrepancy Risk-Adjustment Factors

distributes his/her initial wealth $W_0$, putting $\lambda_j$ units of wealth on the risky asset $R_j$ and the remaining $W_0 - \sum_{j=1}^K \lambda_j$ in a risk-free asset paying $r_f$. Terminal wealth is then $W = W_0 \ast r_f + \sum_{j=1}^K \lambda_j \ast (R_j - r_f)$. Assume in addition that this investor maximises the HARA utility function provided above in equation (11), solving the following optimal portfolio problem:

$$\Omega = \sup_{\lambda \in \Lambda} E(u(W)),$$

where $\Lambda = \{ \lambda : 1 - \gamma W(\lambda) > 0 \}$. Note that by scaling the original vector $\lambda$ to be

$$\tilde{\lambda} = \left( \frac{\lambda}{1 - \gamma W(\lambda)} \right),$$

we can approximately decompose the utility function in

$$u(W) \approx u(W_0 \ast r_f) \ast \left( a^2 + \gamma \tilde{\lambda} (R - \frac{1}{a} \tilde{\lambda}) \right)^{\frac{\gamma+1}{\gamma}}.$$

This decomposition essentially shows that solving the optimality problem in (24) will measure the gain achieved when switching from a total allocation of wealth to the risk-free asset paying $r_f$ to an optimal (in the utility $u$ sense) diversified allocation that includes both risky assets and the risk-free asset.

2.2 How Much Weight on Skewness and Kurtosis?

In this section we provide a Taylor expansion of the HARA utility function implied by the Cressie Read estimators. According to the optimal portfolio interpretation section (subsection 2.1), the utility function that is maximised to obtain the solution of the MD Cressie Read problems is given by:

$$u(W) = -\frac{1}{\gamma + 1} (1 - \gamma W)^{\frac{\gamma+1}{\gamma}}$$

where $W = W_0 \ast r_f + \lambda' \ast (R - r_f)$ with $r_f$ representing the risk-free rate (the inverse of the SDF mean $r_f = \frac{1}{a}$. The solution of the HARA portfolio problem gives the optimal lambdas $\lambda_{opt}$ that correspond to the following optimal wealth $W_\ast = W_0 \ast r_f + \lambda_{opt} \ast (R - r_f)$.

Note that as

$$W_\ast - E(W_\ast) = \lambda'_{opt} \ast (R - E[R]),$$

we can approximately decompose the utility function in

$E[u(W_\ast)] \approx u(E(W_\ast))$

$$+ \frac{1}{2} u_2(E(W_\ast)) \ast E(W_\ast - E(W_\ast))^2$$

$$+ \frac{1}{3} u_3(E(W_\ast)) \ast E(W_\ast - E(W_\ast))^3$$

$$+ \frac{1}{24} u_4(E(W_\ast)) \ast E(W_\ast - E(W_\ast))^4 (14)$$

Those derivatives are respectively given by:

$$u_2(v) = -(1 - \gamma v)^{-1+\frac{1}{\gamma}}$$

$$u_3(v) = (1 - \gamma)(1 - \gamma v)^{-2+\frac{1}{\gamma}}$$

$$u_4(v) = -(1 - \gamma)(1 - 2\gamma)(1 - \gamma v)^{-3+\frac{1}{\gamma}}$$

Looking at the third derivative of $u$ we see that skewness could be weighted negatively for Cressie Read estimators with $\gamma > 1$. However, according to the Taylor expansion, the optimal lambda gives an extra degree of flexibility for the sign of the third moment. For instance, a negative lambda
2. Minimum Discrepancy Risk-Adjustment Factors

for estimators with $\gamma > 1$ will provide a positive weight to skewness. This flexibility guarantees that for the whole range of $\gamma$s our utility function can potentially satisfy the concept of decreasing absolute risk aversion from Arditti (1967) ($\lambda_{\text{opt}}^3 u_3(t0) > 0$).

Figure 1 illustrates the sensitivity of our estimators to skewness and kurtosis. Skewness weights are always positive and increase when $\gamma$ goes away from the quadratic case ($\gamma = 1$). For $\gamma = -3$ the weight is about three times larger than the weight obtained with the exponential tilting ($\gamma = 0$). The linear SDF CR($\gamma = 1$) gives zero weight to skewness. Regarding the fourth derivative, except for the region of $0.5 < \gamma < 1$, kurtosis is a nonpositive and concave function of $\gamma$ indicating that all CR estimators outside that region satisfy the concept of decreasing absolute prudence proposed by Kimball (1993) ($\lambda_{\text{opt}}^4 u_4 < 0$). Limiting cases including the quadratic utility (CUE, $\gamma = 1$) and the cubic utility (CR $\gamma = 0.5$) put zero weight to kurtosis. Note that Cressie Read estimators decline monotonically with $\gamma$. 
2. Minimum Discrepancy Risk-Adjustment Factors
3. SDF Approach to Performance Measurement
3 SDF Approach to Performance Measurement

To evaluate the performance of hedge funds, we need to properly discount returns that exhibit non-normalities and nonlinearities. Chen and Knez (1996) have rationalised a stochastic discount factor (SDF) approach to assess the performance of mutual funds. Performance is assessed by either an SDF based on parametric asset pricing models such as CAPM, APT, and consumption-based models or by a family of SDFs satisfying mild economic conditions such as the law of one price or no-arbitrage. Nevertheless, as remarked by Cochrane and Saa-Requejo (2000), making use of the whole family of admissible SDFs to price a derivative asset (or a fund return as in this paper) generates intervals of prices that are too large. In contrast, our proposed Cressie-Read family restricts performance analysis to a specific subset of admissible SDFs that is particularly well suited to capture nonlinear patterns embedded in returns, since they compensate risk through hyperbolic functions of the primitive risk-factors returns.

To detect the presence of nonlinearities in hedge fund returns, most papers have used option-like functions in an otherwise linear regression on several risk factors. Extending earlier work by Fung and Hsieh (2001) and Mitchell and Pulvino (2001), Agarwal and Naik (2004) show that a wide range of equity-oriented hedge fund strategies exhibit a relationship with option-based risk factors that consist of returns obtained by buying, and selling one month later, liquid put and call options on the Standard & Poor’s (S&P) 500 index. An important improvement with the discrepancy-based SDF approach is to include more elaborate nonlinearities. First, the approach entails nonlinear exposures to all included factors while the former option-based approach is limited to a few factors. Second, in the discrepancy-based approach, one can include options portfolios as reference portfolios, adding nonlinearities on these option-like exposures.

The SDF approach has the distinct advantage of valuing these complex nonlinearities without relying on a particular asset pricing model. Indeed, the performance of a hedge fund, that we will designate by $\alpha_{HF}$, will be given by:

$$\alpha_{HF} = E[m_{CR}R_{HF} - 1], \quad (18)$$

where $R_{HF}$ refers to the returns on a particular hedge fund and $m_{CR}$ to the SDF series implied by a particular Cressie-Read discrepancy measure. We should emphasise that the expected discounted returns are evaluated unconditionally. In other words, we evaluate an average performance over a certain period. In mutual fund performance evaluation a conditional evaluation is most often performed to verify that a positive performance is not simply the reflection of some publicly available information and is really attributable to the ability or superior information of the manager. In Appendix B, we show how to extend our methodology to incorporate conditioning information in the evaluation of performance.

In our empirical assessment of hedge fund performance we consider only an unconditional measure. This will illustrate the usefulness of our discrepancy-based SDF for evaluating the performance of portfolios exhibiting returns with potentially high skewness and kurtosis. Moreover, the model-free and nonparametric nature of performance.
our approach makes it less necessary to condition. When an asset pricing model is at the centre of the performance evaluation it may be justified to account for economic or financial factors deemed important but left out of the model. In our approach we choose the number of risk factors that appear to affect hedge fund returns and include them in our reference portfolios. Our discrepancy function explores linear and nonlinear exposure to these factors. Another reason may be that the conditioning information is always public since the true private information, which is in fact used to actually manage the portfolios, is unobservable. Therefore, with respect to this private information, we observe the portfolio returns always unconditionally. It means in particular that this absence of conditioning will generate fatter tails (see Garcia, Renault and Tsafack 2007). Our unconditional SDFs are incorporating higher moments, which helps to better capture the effect of this unobservable private information.

### 3.1 Risk-Adjustment or Stochastic Discount Factors Implied by Risk Factors

Previous studies that have characterised hedge fund returns have typically used a number of linear and nonlinear (option return portfolios) factors. We follow Fung and Hsieh (2001) and select the factors that they use to describe hedge fund returns.\(^{13}\) Their linear model contains nonlinear exposures through Primitive trend following where \(r_{ex,t}\) denotes the excess returns of the hedge fund or index to be explained, \(SNP_{exc}\) is the monthly return on the S&P 500 minus the 1-month T-bill, SML is the Russell 2000 index total monthly return minus the S&P 500 total monthly return, \(MSCI_{em}\) is the monthly total return on the MSCI Emerging Markets index, \(RBD10\) is the change in constant maturity yield 10-year Treasury bond, \(BAAMBD10\) is the change in the spread between Moody's BAA and the 10-year Treasury, and finally 5 PTSFs for bonds (BD), currency (FX), commodities (COM), interest rate (IR) and stocks (STK).

Table 1 provides descriptive statistics about these ten risk factors. The statistics about primary equity, bond and emerging market risk factors are without surprise — a mean close to 9% for the S&P 500 index and close to 10% for the Russell and the MSCI indexes, with standard deviations of around 15, 20 and 25% respectively. The bond and the credit factors exhibit much lower means (between 1 and 2%) but also much smaller volatilities (close to 8%). Most indexes exhibit little skewness and excess kurtosis, except the credit factor for the latter. This is important to remember to interpret the results of our analysis when we consider only these risk factors to build the stochastic discount factors. The picture is radically different for the trend following factors constructed by Fung and Hsieh (2001). Means are sizeable and alternate in sign, while the volatilities are two to five times the volatilities of an equity index. The PTSFIR has a volatility close to 100%. Most exhibit positive skewness and excess kurtosis, except the credit factor for the latter. This is important to remember to interpret the results of our analysis when we consider only these risk factors to build the stochastic discount factors. The picture is radically different for the trend following factors constructed by Fung and Hsieh (2001). Means are sizeable and alternate in sign, while the volatilities are two to five times the volatilities of an equity index. The PTSFIR has a volatility close to 100%. Most exhibit positive skewness and excess kurtosis, with PTSFIR again showing the highest numbers (4 and 26% respectively). These descriptive statistics will be important to understand our SDF results below.
The first step in our performance evaluation experiment is to compute the stochastic discount factor. In order to obtain the implied SDF for different values of \( \gamma \) in our CR discrepancy function, we must solve an optimal portfolio problem under the particular utility function defined by a particular value of \( \gamma \) on the dual space. We choose to estimate SDFs for \( \gamma \in \{-3, -2, -1, -0.5, 0, 0.5, 1\} \), a set that includes the HJ linear SDF with positivity constraint (\( \gamma = 1 \)), a pair of SDFs that give mild weights to skewness and kurtosis (\( \gamma = -1, 0 \)), and two SDFs that give larger absolute weights to skewness and kurtosis (\( \gamma = -2 \) and \( -3 \)). In Figure 1, we plot the implied weights put on skewness and kurtosis by the various values of \( \gamma \). First, both weights are zero at the value of 1 (HJ) since the discrepancy function is quadratic. The weights are monotonically increasing and positive for skewness and monotonically decreasing and negative for kurtosis. For the 0.5 value of \( \gamma \) the weights are not function of optimal wealth and equal to 0.5 and 0 for skewness and kurtosis respectively. To isolate the role of the risk factors associated with the straddles introduced by the PTFS, we repeat the dual optimisation without these factors. The weights follow the same patterns as before but they are larger in absolute value. This is consistent with the fact that the weights on the skewness and kurtosis of the primary assets’ returns need to be larger when no derivatives are included in the set of risk factors. When the straddles are included they capture part of skewness and kurtosis and therefore confer directly these properties to optimal wealth.

The portfolio weights resulting from the optimisation of the dual HARA problem are provided in Table 4 and in Table 5, with or without lookback options included in the SDF. Let us start with the primary assets not including options. All positions are long except for the credit factor that is strongly sold short. The larger weights are put on the equity indexes and the bond. The MSCI weight is the lowest. The weights vary with \( \gamma \) especially for the bond and the credit factors. We observe that for the values of -2 and -3 for \( \gamma \) the weights are lower in absolute values than for the other values. This is explained by the fact that these two values put the highest weight on kurtosis and that these two factors exhibit the highest kurtosis among the risk factors.

When we include the lookback straddles, the patterns are not so clear-cut but several facts emerge. The position on the credit factor is still negative and sizeable but not as much as before. The bond factor exhibits an interesting pattern. First, the weight is larger than before, without the options, but the weight also increases from the negative to the positive \( \gamma \)s, although not monotonically. The position on the S&P is mostly positive and sizeable, except for \( \gamma = -3 \). For the Russell index, the pattern is inverted, positive for the most negative values of \( \gamma \), negative thereafter. Among the lookback straddles, two sets of weights stand out, the PTFS with respect to the interest rate, the PTFS relative to stocks. The position with respect to the latter is uniformly negative and large in absolute value, while the position for the interest rate straddle is positive and also sizeable. The stock straddle negative position accentuates the long position in the S&P while positive
position in the interest rate straddle hedges the long exposure taken with the bond.

The implied SDFs for three values of $\gamma (1, 0$ and $-3)$ are plotted in Figure 2. A first obvious remark is that the SDFs without options are much less volatile than the ones with options for all values of $\gamma$, even though the volatility increases when $\gamma$ decreases. They all look well behaved, although some periods seem to receive a larger weight, which increases with lower values of $\gamma$. Apart from a much higher volatility, the SDFs with options exhibit distinctively large peaks associated with events that had a large impact on wealth. They considerably amplify the events that were already visible in the SDFs without options. The same peaks appear for the three values of in 1998, 2002 and 2006. We will analyse the sensitivity of the performance results to these extreme events in section 4 on robustness.

A fundamental tenet of the methodology is the exact pricing of the risk factors. We report in Table 6 and Table 7 the pricing errors on each of the factors for the different values of $\gamma$, without and with options respectively. When pricing the primary risk factors without the PTFS all factors are almost perfectly priced for all values of $\gamma$. With the options, for the non-positive values the pricing errors are almost always practically zero. In the positive they increase, especially for the pricing errors of PTIR when $\gamma$ is equal to one. It is intuitive since as above-mentioned the weights on kurtosis are both zero for $\gamma = 0.5$ and $\gamma = 1$ and they are fixed at 0.5 and 0 for skewness for these last two values. Therefore, the SDF will have a hard time to price factors that exhibit significant skewness and kurtosis. We also report the pricing errors on the average of all CR values. It is an alternative SDF that we will consider when evaluating performance.

3.2 Computing the Alphas of Hedge Fund Indices for Primary Strategies

We now use these SDFs to assess the performance of the set of HFRI indices from January 1990 till December 2010. The HFRI monthly indices are a series of equally-weighted indices of constituent funds, as reported by the hedge fund managers listed with HFR database. The HFR hedge fund database is currently comprised of 6,700 funds and funds of funds worldwide. To be included in the HFRI database, fund managers must submit a complete set of information, including, most importantly, net of all fees monthly performance and assets under management in US dollars. Constituent funds must have either $50 million under management or a track record greater than 12 months.

An equally-weighted global index provides an overall measure of the performance of the hedge fund industry, while the primary strategies are Equity Hedge, Event Driven, Relative Value, Macro, and Emerging Markets. Mixtures of these strategies are captured by the Funds of Funds index. These strategies are described in Appendix C.

To obtain the $\alpha_{HF}$ performance measure defined in Equation (18) we use the respective implied SDFs and the returns on the hedge fund indices. Performance results are reported in Table 9 and Figure 3. In the upper panel of the figure, we draw the performance of the main indices when no options are included in the stochastic
3. SDF Approach to Performance Measurement

discount factor. The main finding is that the performance appears almost independent of $\gamma$. As we remarked when commenting on the descriptive statistics of the indices, most risk factors do not exhibit significant skewness or kurtosis. Therefore, the different weights implied by the different values of $\gamma$ do not affect overall the performance of the various hedge fund indices. The performance remains uniform across all values of $\gamma$, and even identical for some strategies such as Equity Hedge or Macro.

When we introduce the PTFS factors, the picture changes radically. We now see large differences between the performances associated with the different values of $\gamma$.

Let us consider Emerging Markets. The performance with a linear SDF ($\gamma = 1$) is 5.4%, while it falls to 1.0% for $\gamma = -3$. For all indices the performance decreases as we put more weight on skewness and kurtosis by decreasing $\gamma$. An interesting alternative SDF to be considered is the average SDF across different gammas. Note that as long as each individual SDF is admissible (in the sense that it prices well the basis assets returns) their average will also price the basis assets returns and will generate a performance for each fund index equal to the average of the performances across $\gamma$’s. The average performance is one possible robust measure of performance since it averages investors’ overall risk tolerance, represented by the value of gamma. Therefore it could be interpreted as the performance assessment of an average investor. At the bottom of Table 9, we can see that there is a difference of around one percentage point between the performance obtained with a linear model ($\gamma = 1$) and this average investor for most indices, except for emerging markets with a difference of 2.5 percentage points.

3.3 Computing the Performance of Sub-Classes of Primary Strategies

In this section we want to explore the performance variation within each strategy class. In Appendix C, we provide a description of the sub-classes of strategies within each primary strategy. The performances of these sub-classes are plotted in Figure 4 for the SDFs without options and Figure 5 for the SDFs with options.

Let us look at the performance when the SDFs do not include options. Similarly to the primary classes, the performance appears rather flat when we vary $\gamma$, emphasising the similar discounting obtained when the underlying risk factors exhibit little skewness or excess kurtosis. For the global indices and the funds of funds the performance remains modest compared to the categories such as Emerging Markets or Equity Hedge. The star performers with an average alpha of more than 10% are Russia and Eastern Europe in Emerging Markets and Energy in Equity Hedge. This reflects the very high mean exhibited by these two categories in Table 3.

For the performances of most sub-classes for the SDFs with options in Figure 5 a clear pattern emerges. The performance decreases when $\gamma$ becomes more negative, sometimes drastically. A case in point is the sub-class Russia-Eastern Europe in the Emerging Markets primary strategy. It starts with a stellar 14% for a linear discounting ($\gamma = 1$) to a performance close to 4% for $\gamma = -3$ that puts larger weights on skewness and kurtosis. The global sub-class in the

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16 - The linear model differs from a linear regression since we impose as a restriction that the stochastic discount factor is strictly positive as it should be under the absence of arbitrage. The average performance obtained from an OLS regression will be between 30 and 50 basis points on an annualised basis higher than the performance for $\gamma = 1$.

17 - Not all indices for the sub-classes extend over the full 1990-2010 period. For example, in Emerging Markets, the sub-class Russia-Eastern Europe starts only in 1994. Therefore the average performance may be affected for reasons associated with the sampling period since we evaluate the performance unconditionally.
3. SDF Approach to Performance Measurement

same primary strategy is also showing a marked decrease to end up in the negatives for negative values of $\gamma$. This latter category has a kurtosis of 16.1.

There are a few exceptions to this general pattern. The Asia sub-class in the same Emerging Markets category remains rather flat across the various values of $\gamma$. Interestingly, its average is higher than with the SDFs without options, showing that in this case introducing options adds value to the strategy uniformly. Looking at Table 3 we see that this category has less extreme observations than its companion regions and values for skewness and kurtosis are close to normal. Three other sub-classes exhibit a decreasing performance when $\gamma$ increases. In the Event Driven set of strategies, the Private Issue sub-class loses about two percentage points based on average performance between -3 and 1. It seems to be due to an extreme value since the maximum value is very high compared to the other event driven categories, pushing the mean return to 10.1 %. The same declining pattern is present in the Europe sub-class of Global indices and in the Short Bias sub-class of the Equity Hedge. Kurtosis appears to be higher for this region.

Equity Hedge stills exhibits the star performer with a performance of close to 16% for $\gamma = -3$ in the Energy sub-class. It is in fact higher than the average performance of this sub-class for the SDF without options. Again, kurtosis does not appear to be very high for this subcomponent.

3.4 Performance of Individual Hedge Funds in the Emerging Markets Category

In the two previous sections, we have seen that the performance of a global index may hide an important variability among the sub-components of the index. It is therefore important to assess the variability of performance at the highest level of detail, that is at the level of individual funds within a particular class of strategies. We will look at the Emerging Markets strategy, which showed important differences between the global index and the sub-components. We select individual funds of this category in the data of the Center for International Securities and Derivatives Markets (CISDM). Among the 569 available funds we retained the funds that had at least 36 months of continuous returns, which brought the number to 341 funds.

To compute the individual performance, we proceed as before. Using equation (18) for each fund, we multiply the observed returns of the fund by the implied stochastic discount factors corresponding to the various values of $\gamma$. In Table 10 we report descriptive statistics of the cross-sectional distribution of individual alphas (341 in total). Even though we biased the mean of our estimates upwards by including only the funds that were long enough in existence, we can see that the high variances together with the very high kurtosis, especially for the negative values of $\gamma$ reflecting more risk aversion, make individual hedge-fund picking a treacherous exercise. The cross-sectional distribution of alphas is very far from a normal distribution for negative values of $\gamma$ and close to it for $\gamma = 1$. In the latter case, we ignore the higher moments and get a Sharpe ratio.
just a bit lower to the one found for the index in Table 2.

As stressed in section 2.2, the implied SDFs for different values of $\gamma$ put different weights on the skewness and kurtosis of the portfolio returns. In Table 11, we report a set of regression results for the various values of $\gamma$ we selected. In each column, we find the coefficients of a simple regression of the mean performance of the individual funds on a constant plus the mean, standard deviation, skewness and kurtosis of each fund. This cross-sectional regression aims at capturing the percentage of performance explained by these first four moments. Remember that for all non-positive $\gamma$s the SDF that discounts the returns puts weights on all the moments of the return distribution. The signs of the coefficients correspond to intuition. Investors like mean and positive skewness, hence the positive sign of these coefficients, and dislike variance and kurtosis, which accordingly appear with a negative sign. All moments have high t-statistics, except for skewness that is only marginally significant for some values of $\gamma$. The $R^2$s are increasing monotonically between 34%, for $\gamma = -3$, and 70% for $\gamma = 1$. These regressions can be used to quickly assess the performance of a particular hedge fund in the emerging markets universe not part of the sample given the moments of its return distribution.
4. Robustness
4. Robustness

We have shown how different values of $\gamma$ could affect the conclusions of our analysis. In this section we want to focus on the robustness concepts that can be invoked to address this question. First we want to gauge the sensitivity of the performance to key parameters and to key events in the sample. Second, we will show how to build a robust measure of performance with a SDF that results from averaging across a range of values of $\gamma$ before solving the portfolio optimisation problem.

4.1 Performance Sensitivity to the Average Interest Rate

In deriving the discounting factor in section 2 it is clear that its mean value, set according to the average of the short interest rate over the sample period considered, is essential for ultimately assessing the performance of hedge fund indices. Of course a lower short interest rate will in general increase the average performance but it will not be a direct translation of the difference in the average level of interest rates. We expect it to vary across the values of $\gamma$ and across strategies. To investigate the impact across categories of such a lower short rate we report in Table 12 the differences in performance between a high short rate average (3.6% in our base case) and a low average (1.2%), which reflects more the interest rate level of the last few years. We report the differences for the sets of $\gamma$ values and primary strategies that we selected before for the benchmark case. We also include the results for the sub-classes of Emerging Markets and Equity Hedge primary strategies.

First, looking at the main categories, we can see that in general the differential performance is pretty uniform across values of $\gamma$. The average increase in performance when we lower the interest rate is between 1.5 and 1.9%. The values are lower and more variable for Emerging Markets and Equity Hedge. For the first category, the added performance goes from 0.85% for $\gamma = -3$ to 1.24% for $\gamma = 1$. For the Equity Hedge, it varies from 1.25% to 1.43%.

To better understand the additional performance in these two categories we also report in Table 12 the difference in performance in the sub-classes of these two primary strategies. For Emerging Markets, the patterns are quite varied. Russia-Eastern Europe is less sensitive to an increase in the mean of the SDF with less than 1% difference but the impact varies across the values of $\gamma$. On the contrary, Latin America increases by roughly 1.2% for all values of $\gamma$. Global increases from 0.45% for $\gamma = -3$ to 1.36% for $\gamma = 1$. A reverse pattern is observed for Asia, from 1.57% for $\gamma = -3$ to 1.31% for $\gamma = 1$. These patterns can be rationalised by the stronger kurtosis and larger extremes in the Global and Russia-Eastern Europe subcomponents. In the Equity Hedge strategies, Short Bias stands as a very interesting case since it exhibits a difference in performance of around 4%. A lower interest rate will magnify the returns on the short selling strategy since leverage is cheaper.

4.2 Performance Sensitivity to Extreme Events

Looking at the optimal SDFs in Figure 2 it is easy to see that large peaks appear, especially for the value of $-3$ for $\gamma$ which weights kurtosis or extreme events more heavily. When we say that the SDFs have to
price all the risk factors well, it means that they have to capture the extreme events considered as factors that affected the various financial markets. To illustrate the performance sensitivity to extreme events we selected the three highest values of the SDF for $\gamma = -3$. The three dates that came out were August 1998, July 2002, and January 2006. The first two dates are in fact visible in all SDFs and correspond to the LTCM collapse and the bursting of the internet bubble. These events triggered major declines in the equity markets, the Russell index falling by close to 20% in August 1998 and by 15% in July 2002. The third event is not related to equity markets, but has to do with the fall in the dollar after a rise of 200 basis points of the US Federal Funds rate in 2005. This caused major losses in the bond, interest rate and currency primitive trend following strategies (-24, -30 and -8% respectively). It is important to assess the influence of these extreme events on the average performance of the various hedge fund strategies. Table 13 reports the average performance when such events are discounted at the average discount rate (0.997) instead of the optimal weight computed before. The results are striking. The impact is huge for Emerging Markets. The average performance jumps from 1 to 10.8% for $\gamma = -3$. The performance increase is very important in all the other strategies, with the smallest increase in Macro (1 to 2 percentage points). This sensitivity analysis illustrates how important such extreme events have on performance. Without properly discounting the returns in these events we grossly overestimate the average performance.

4. Robustness

4.3 Performance Sensitivity to Systematic and Idiosyncratic Shocks

In the previous sections, we have linked the performance of indices or individual funds to a set of risk factors. Given this relationship, a manager of a portfolio of funds will naturally want to know how the performance of the portfolio will be affected by anticipated changes to the risk factors. These changes may be based on economic or financial fundamentals or on scenarios chosen by management as part of a stress test. These shocks may affect the whole time series of some risk factors or just a few observations related to specific periods. One can also focus on a particular fund and relate its average performance to idiosyncratic shocks either through its time series of returns or through a change in moments of its distribution of returns. In the subsections below, we clarify how to conduct these sensitivity analyses for both types of shocks.

4.3.1 Alpha changes following shocks to risk factors

Suppose that the return matrix of risk factors $R$ is affected by a vector of shocks $R + \varepsilon$, that is the returns of one or more of the risk factors are impacted by shocks of potentially different magnitudes. How do we measure the effect of these shocks on the alpha of a particular hedge fund or portfolio of hedge funds? Let us start with the definition of the alpha of a particular hedge fund:

$$\alpha_{HF} = E[m_{CR} R_{HF} - 1],$$

where $R_{HF}$ refers to the returns on a particular hedge fund and $m_{CR}$ to the SDF series implied by a particular Cressie-Read discrepancy measure. Therefore, the change in the alpha HF will be given by:
4. Robustness

\[
\Delta \alpha_{HF} = \Delta E[m_{CR}R_{HF} - 1] \\
= E[m_{CR}(R + \varepsilon)R_{HF} - 1] - E[m_{CR}(R)R_{HF} - 1] \\
= E\{m_{CR}(R + \varepsilon) - m_{CR}(R)\}R_{HF}
\]

(20)

Given the expression for the SDF:

\[
\tilde{m}_{MD}(R) = a \left( \alpha \gamma + \gamma \lambda' (R - \frac{1}{a} 1_K) \right)^{\frac{1}{\gamma}} \\
\quad \quad \text{for } E\left[ (\alpha \gamma + \gamma \lambda' (R - \frac{1}{a} 1_K) )^{\frac{1}{\gamma}} \right]
\]

(21)

the change in expected alpha performance is easily computed. The empirical implementation of such a sensitivity analysis is conducted by replacing the expectation by the sample average. We provide in Table 14 the results of a small experiment regarding the change in average performance of the subcomponents of the Emerging Markets primary strategy. To recall, we showed in Figure 5 the average performance of the subcomponents of the various primary strategies for the set of selected gamma values. In Table 14, we report these values for the emerging markets subcomponents along with the change in performance brought about by a lower mean of 20 basis points per month (2.4% annually) in the MSCI emerging market index returns.

Results are quite instructive. While the impact is negligible for values of \( \gamma \) greater than \( \gamma - 1 \), the effect is quite sizeable for the two more negative values of \( \gamma \) –2 and –3. There we can see that it deepens quite a lot the negative performance of the Global subcomponent and sends in negative alpha territory all emerging markets indices except Asia for \( \gamma = -3 \). The conclusion is that a moderate change in a risk factor may trigger a big change in performance when evaluation rests on a more robust discounting. It shows that the nonlinear discounting model does a better job at capturing the dependencies of hedge fund returns with respect to factor returns; using a linear model may in fact lead to the wrong conclusions regarding the effect of even a sizeable decrease in mean factor returns. This suggests that changes in higher moments of the risk factors may impact even more strongly hedge fund returns.

4.3.2 Alpha changes following shocks to hedge fund returns

To analyse the effect of idiosyncratic shocks to a particular fund, one can perturb the returns themselves for some specific scenarios and use equation (19) to assess the change in the average performance of the fund:

\[
\Delta \alpha_{HF} = E[m_{CR}\varepsilon_{HF}],
\]

(22)

where \( \varepsilon_{HF} \) is a time series of shocks with values different from zero in the periods affected by the scenarios.

Another way of assessing the effect of idiosyncratic shocks to a particular fund is to measure the impact of changes through changes in the moments of the hedge fund return distribution. We have reported in Table 11 regression results linking average performance of a set of individual hedge funds to the mean, standard deviation, skewness and kurtosis of these funds. Given the coefficients of regression, one can also assess the impact of a change in one of the statistics of a particular fund belonging to the same category (in section 3.4 we had estimated this regression for emerging markets funds). These regressions
4. Robustness

of individual average performance on the corresponding statistics can be run for any grouping of the individual funds and therefore provide flexibility in conducting sensitivity analyses for various scenarios.

4.4 Performance Sensitivity to Equity Risk

We have chosen to include the most comprehensive and diversified set of option factors provided by Fung and Hsieh (2001). Other authors have focused mainly on equity risk options. Agarwal and Naik (2004) include a set of equity options (puts and calls) to capture nonlinear strategies based on the equity market. We conducted our analysis with the main primary factors as before but including the set of equity options instead of the set of PTFS. Results are reported in Table 15. The pricing errors are also very small for all values of \( \gamma \) (see Table 8). In terms of average performance, we find a higher alpha overall for the various main strategies. This is to be expected since the options are related only to equity risk. However, the over performance is small for most strategies, and smallest for Equity Hedge. The category where the difference is the largest is Emerging Markets where we have a 3 to 4 percentage points higher alpha for the most negative values of \( \gamma \). Equity risk is certainly not enough to capture the risk in this category.

4.5 A Robust Measure of Performance

As a possible robust measure of performance, we suggest the use of an estimator that averages across a range of HARA functions, and solves the portfolio optimisation problem of this averaging function. This should imply a SDF that takes into account different gamma curvatures (or degrees of risk aversion in our interpretation). In addition, it emphasises the fact that our methodology is not limited to the Cressie Read family, since a linear combination of HARA functions is not a HARA function. We solve this problem for an average of all HARA functions with say \( K \) values of \( \gamma \), and for a fixed SDF mean equal to \( a \):

\[
\sup_{\lambda \in \Lambda_{\text{HARA}}} \frac{1}{K} \sum_{j=1}^{K} E \left[ -\frac{1}{\gamma_j + 1} \left( a_j^\gamma \gamma_j \lambda_j (R - r_f) \right)^{\gamma_j + 1} \right]
\]

where

\[
\Lambda_{\text{HARA}} = \{ \lambda \in R^K, \text{ s.t. for } i = 1, ..., \}
\]

\[
T^j: \min_j \left( a_j^\gamma \gamma_j \lambda_j (R_t - r_f) \right) > 0\}.
\]

The implied SDF for this robust estimator should be less volatile than the individual implied Cressie Read SDFs in both good and bad states since it is solving an averaging problem. It is important to clarify that this robust SDF is not an average of the previously obtained SDFs which we computed in section 3.2, but a new SDF implied from a completely different portfolio problem. Making use of the average estimator can be especially useful for hedge funds whose performance exhibits too much variation across different CR estimators. Like this average estimator we can produce other functions than aggregate Cressie-Read discrepancies under a unified metric, as long as the final discrepancy function is convex.
4. Robustness
5. Conclusion
5. Conclusion

Robust performance evaluation is particularly important for hedge funds. It rests on the identification of the underlying risk factors and their relationship with hedge fund returns. We proposed a methodology that accommodates the nonlinear exposures of hedge fund returns to the primary sources of risk, such as equities, bonds, term and default spreads, and emerging markets, as well as to straddles on these primary factors. The approach captures the exposure to higher-moment risks on the various factors and allows for different weights on skewness and kurtosis in particular, depending on the risk tolerance of the investor. Once the risk adjustment functions are computed the evaluation of the average performance amounts to a simple weighted average, where the weights discount the returns. In general exposure to higher-moment risk reduces the performance of the HFRI indices for the primary strategies. Emerging Markets stands as a case in point. The reduction of performance between a linear exposure to risk factors and a nonlinear one with low risk tolerance is in the order of four percentage points on an annualised basis. This is further illustrated in the analysis of the sub-classes within each main strategy, with some average performance going into the negative when larger weights are put on higher moments. Often the reduction in performance comes from a small number of extreme events which are not well-captured with the usual regression approach. However, some sub-classes, such as Asia in Emerging Markets or Short Bias in Equity Hedge, exhibit average performance patterns that decrease with risk tolerance since they provide insurance in bad times. For our analysis of individual funds in the Emerging Markets category, we clearly see that the cross-sectional distributions of average alpha performance exhibit lower means, larger variances and higher skewness and kurtosis when the risk adjustment becomes more stringent. Finally a risk analysis shows that a more robust risk discounting may be necessary to see the effect of variations in risk factors.
Appendices & Tables
Appendices & Tables

Appendix A - Finding the Optimal Admissible Minimum-Discrepancy (MD) SDF
In the following theorem, we provide the solution method to obtain an admissible SDF that obeys the restrictions imposed by the discrepancy function. After solving the dual problem, we recover the MD SDF by using the first-order conditions of this maximisation problem.

**Theorem 1:** Let the discrepancy function belong to the class of Cressie Read functions:

\[ \phi(m) = \frac{m^{\gamma+1} - a^{\gamma+1}}{\gamma(\gamma+1)} \quad \text{with} \quad \gamma \in \mathbb{R}. \]

In this case, the optimisation problem in equation (3) specialises to:

\[
X_{\gamma} = \arg \sup_{\lambda \in \Lambda_{CR}} \frac{1}{T} \sum_{i=1}^{T} \left( \frac{a^{\gamma+1}}{\gamma + 1} - \frac{1}{\gamma + 1} \left( a^{\gamma} + \gamma \lambda' \left( R_i - \frac{1}{a} 1_K \right) \right)^{\frac{\gamma+1}{\gamma}} \right), \tag{24}
\]

where

\[ \Lambda_{CR} = \{ \lambda \in R^K, \ s.t. \ for \ i = 1, ..., T : (a^{\gamma} + \gamma \lambda' \left( R_i - \frac{1}{a} 1_K \right)) > 0 \}. \]

**Proof of Theorem 1:** Under the Cressie Read family, the convex conjugate of \( \phi \) is given by:

\[ \phi^*(z) = \frac{(\gamma z)^{\gamma+1}}{\gamma + 1} + \frac{a^{\gamma+1}}{\gamma(\gamma + 1)} \tag{25} \]

The optimisation problem becomes:

\[
\hat{\lambda} = \arg \sup_{\alpha \in \mathbb{R}, \lambda \in \Lambda} \alpha - \sum_{i=1}^{T} \frac{1}{T} \left( \gamma \left( \frac{a^{\gamma}}{a} + \lambda' \left( R_i - \frac{1}{a} 1_K \right) \right)^{\frac{\gamma+1}{\gamma}} \right) - \frac{a^{\gamma+1}}{\gamma(\gamma + 1)}. \tag{26}
\]

In order to concentrate \( \alpha \) out of the optimisation problem in equation (26)

let \( \Gamma(\alpha) = \alpha - \frac{(\gamma \alpha)^{\gamma+1}}{\gamma+1} \)

Then the optimal concentrated should solve:

\[
\frac{d\Gamma(\alpha)}{d\alpha} = 0 \Rightarrow \hat{\alpha} = \frac{a^{\gamma+1}}{\gamma} \tag{27}
\]

Substituting \( \hat{\alpha} \) on Equation (26) gives the desired result.

For each choice of \( \gamma \) we obtain a distinct set of estimates for \( \lambda(\hat{\lambda}_\gamma) \) that will lead to a different MD stochastic discount factor \((\hat{m}^\gamma_{MD})\). The MD SDF \( \hat{m}^\gamma_{MD} \) is recovered via the first-order conditions of Equation (24) with respect to \( \lambda \), evaluated at the optimal Lagrange Multipliers \( \hat{\lambda} \) that solve (24):

\[
\frac{1}{T} \sum_{i=1}^{T} \left( a^{\gamma} + \gamma \hat{\lambda}_\gamma' \left( R_i - \frac{1}{a} 1_K \right) \right)^{\frac{1}{\gamma}} \left( R_i - \frac{1}{a} 1_K \right) = 0_K \tag{28}
\]
By comparing Equation (28) to Equation (2) we obtain the MD SDF:

\[ m^i_{MD} = a \frac{\left( a^\gamma + \gamma \hat{\lambda}^i \left( R_t - \frac{1}{a}1_K \right) \right)^{\frac{1}{\gamma}}}{\frac{1}{T} \sum_{t=1}^{T} \left( a^\gamma + \gamma \hat{\lambda}^i \left( R_t - \frac{1}{a}1_K \right) \right)^{\frac{1}{\gamma}}}, \quad i = 1, ..., T. \]  

(29)

Note that the population form for the SDF solving the MD problem will be a hyperbolic function of the original returns \( R_t \):

\[ \hat{m}_{MD}(R) = a \frac{\left( a^\gamma + \gamma \hat{\lambda} \left( R - \frac{1}{a}1_K \right) \right)^{\frac{1}{\gamma}}}{E \left[ \left( a^\gamma + \gamma \hat{\lambda} \left( R - \frac{1}{a}1_K \right) \right)^{\frac{1}{\gamma}} \right]}. \]

(30)

**Appendix B - Conditioning Information**

An important extension of our methodology considers conditioning information when obtaining the SDFs. This can be naturally implemented by introducing conditional expectations on Equation (18)

\[ E(m_{t+1}R_{t+1}|I_t) = 1_K, \]  

(31)

where \( I_t \) is the information set at time \( t \).

Building on the work of Bekaert and Liu (BL, 2004), we make use of the concept of a scaled return \( \tilde{R}_{t+1} = z_tR_{t+1} \) (see Cochrane (2000)), where the scale is given by an \( I_t \)-measurable \( K \)-dimensional random variable \( z_t \), with \( K \) being the dimension of the basis assets return vector. The idea is to assume that the conditional expectation in (31) could be substituted by an infinity of unconditional expectations of the type:

\[ E(m_{t+1}z_tR_{t+1}) = 1_K z_t. \]

(32)

Let the vector \( y_t \) represent the set of (Markovian) conditioning variables of the economy such that \( I_t = \sigma(y_t) \), where \( \sigma(\cdot) \) represents the \( \sigma \)-algebra generated by \( \cdot \). Given an instrument \( z_t \), consider the one-dimensional scaled payoff space \( P_{z_t} = \{ \alpha z_tR_{t+1}, \alpha \in \mathbb{R} \} \). It should be clear that the infinitely many \( I_t \)-measurable instruments \( z_t \) define a family of scaled payoff spaces indexed by \( z_t \). Note that for each member in the Cressie Read family \( \gamma \), there is a MD bound associated with each scaling vector \( z_t \), which only depends on the unconditional moments of the scaled return \( z_tR_{t+1} \). A small but important difference from the approach in Section 2 is that scaled returns \( z_tR_{t+1} \) have prices \( 1^{\infty}_{z_t} \) instead of 1. To deal with this case, we have to solve a slightly more general version of Equation (3) that deals with prices different from unity (see Borwein and Lewis (1991)):

\[ \hat{\lambda} = \arg \sup_{\alpha \in \mathbb{R}, \lambda \in \Lambda} \frac{1}{T} \sum_{t=1}^{T} \lambda \left[ 1_K z_{t-1} - \frac{1}{T} \phi_{\ast +} \left( \frac{\alpha}{a} + \lambda \left( z_{t-1}R_t - \frac{1}{a} \right) \right) \right], \]

(33)
where $\Lambda \subseteq R^K$. Note that this is a one-dimensional problem in the Lagrange Multiplier since the scaled return is a transformation from $R^K$ to $R$. Applying this equation to a member of the Cressie Read family $\phi(m) = \frac{m^{\gamma+1} - a^{\gamma+1}}{\gamma(\gamma+1)}$ we obtain:

$$\hat{\lambda}_{\gamma}(z) = \arg \sup_{\lambda \in \Lambda_{CR}} \frac{1}{T} \sum_{t=1}^{T} \left( \frac{a^{\gamma+1}}{\gamma + 1} + \lambda^{1/\gamma} z_{i-1} - \frac{1}{\gamma + 1} \left( a^{\gamma} + \gamma \lambda \left( z_{i-1} - \frac{1}{a} \right) \right)^{\gamma+1} \right),$$

(34)

where $\Lambda_{CR} = \{ \lambda \in R, \text{s.t. for } i = 1, ..., T : (a^\gamma + \gamma \lambda \left( z_{i-1} - \frac{1}{a} \right) > 0 \}.$

The first-order conditions of this problem with respect to $\lambda$ indicate that the MD SDF for a fixed instrument $z_i$ is:

$$\hat{m}_{MD}^t(z) = a \left( \frac{a^{\gamma} + \gamma \hat{\lambda}_{\gamma}(z) \left( z_{i-1}R_t - \frac{1}{a} \right)}{\frac{1}{T} \sum_{t=1}^{T} \left( a^{\gamma} + \gamma \hat{\lambda}_{\gamma}(z) \left( z_{i-1}R_t - \frac{1}{a} \right) \right)^{\gamma}} \right)^{1/\gamma}, t = 1, ..., T.$$

(35)

**Appendix C – Description of HFRI Indices**

These descriptions are based on the Appendix 1 of the 2011 HFRI Hedge Fund Indices methodology document.

**Primary Strategy Descriptions**

**Equity Hedge:** Equity Hedge strategies maintain long and short positions in primary equity and equity derivatives securities. Strategies can be broadly diversified or narrowly focused on specific sectors.

**Event-Driven:** Investment Managers maintain positions in securities of companies that are or may be involved in varied corporate transactions such that mergers, restructuring, financial distress, tender offers, shareholder buybacks, debt exchanges, security issuance or other capital structure adjustments. ED exposure contains a combination of sensitivities to equity markets, credit markets, and idiosyncratic, company specific developments.

**Macro:** Investment Managers execute a broad range of strategies in which the investment process is based on current or anticipated movements in economic variables and their potential impact on equity, fixed income, currency and commodity markets. Managers may employ discretionary and systematic analysis or quantitative and fundamental approaches.

**Relative Value:** Investment Managers predicate their strategy on the realization of a valuation discrepancy in the relationship between multiple securities such as equity, fixed income, derivatives or other types.

**Fund of Funds:** Invest in a diversified portfolio of managers through funds or managed accounts. The goal is to reduce the risk of investing with an individual manager. A manager of such a fund may allocate funds to numerous managers within a single strategy or with numerous managers in multiple strategies.

**Emerging Markets:** The constituents of the Emerging Markets indices are selected according to their regional investment focus only. There is no investment strategy criteria. The geographic areas are Asia ex-Japan, Russia/Eastern Europe, Latin America, Africa or the Middle East.
Sub-Strategy Descriptions

**Equity Hedge**
1. **Equity Market Neutral** strategies include factor-based or statistical arbitrage/trading techniques to construct portfolios that are neutral to one or several variables, such as broader equity markets in dollar or beta terms. Leverage is often used to enhance the return of the identified positions. Equity Market Neutral strategies typically maintain characteristic net equity market exposure no greater than 10% long or short.
2. **Quantitative Directional** strategies also employ factor-based or statistical arbitrage trading techniques in order to exploit pricing anomalies or an informational advantage but they typically maintain varying levels of net long or short equity market exposure over various market cycles.
3. **Sector - Energy/Basic Materials** strategies use investment processes designed to identify opportunities in specific niche areas of the market. They identify companies engaged in the production and procurement of inputs to industrial processes. They typically maintain a primary focus in this area and expect to maintain in excess of 50% of portfolio exposure to these sectors over various market cycles.
4. **Sector - Technology/Healthcare** strategies use investment processes designed to identify opportunities in specific niche areas of the market. They identify companies engaged in all development, production and application of technology, biotechnology and related to production of pharmaceuticals and healthcare industry. They typically maintain a primary focus in this area and expect to maintain in excess of 50% of portfolio exposure to these sectors over various market cycles.
5. **Short-Biased** strategies employ analytical techniques to identify overvalued companies. The primary characteristic is that the manager maintains consistent short exposure and expects to outperform traditional equity managers in declining equity markets.

**Event-Driven**
1. **Distressed/Restructuring** strategies focus primarily on corporate credit instruments trading at significant discounts to their value at issuance or par value at maturity due to either formal bankruptcy proceedings or market perception of near term proceedings.
2. **Merger Arbitrage** strategies focus primarily on opportunities in equity and equity related instruments of companies which are currently engaged in a corporate transaction. Merger arbitrage strategies typically have over 75% of positions in announced transactions over a given market cycle.
3. **Private Issue** strategies focus primarily on opportunities in equity and equity related instruments of companies which are primarily private and illiquid in nature. Funds are expected over a given market cycle to maintain greater than 50% of the portfolio in private securities.

**Relative Value**
1. **Fixed Income - Asset Backed** includes strategies that seek to isolate attractive opportunities between a variety of fixed-income instruments specifically securitized by collateral commitments such as loans, pools and portfolios of loans, receivable, real estate, mortgage,
machinery or other tangible financial commitments. Investment managers hedge, limit or offset interest rate exposure in view of limiting the risk of the position to strictly the yield disparity of the instrument relative to the lower risk instruments.

2. **Fixed Income - Convertible Arbitrage** includes strategies that seek to isolate attractive opportunities between the price of a convertible security and the price of a nonconvertible security, typically of the same issuer. Positions are sensitive to the credit quality of 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 conditions.

3. **Fixed Income - Corporate** includes strategies that seek to isolate attractive opportunities between a variety of fixed income instruments, typically realizing an attractive spread between multiple corporate bonds or between a corporate bond and a government bond.

4. **Multi-Strategies** are typically quantitatively driven and seek to identify attractive positions that exploit spreads involving combinations of fixed income, derivative, equity, real estate and other instruments. These strategies are expected to maintain more than 30% of portfolio exposure in two or more distinct strategies.

5. **Yield Alternatives** strategies aim at exploiting yield differentials between related instruments in Energy Infrastructure (through investment in Master Limited partnerships, utilities or power generation) or Real Estate (directly in commercial or residential or indirectly through REITs). Strategies typically contain greater than 50% of portfolio exposure in one of the two sectors.

---

**Fund of Funds**

1. **Conservative**: This index includes funds that seek consistent returns by primarily investing in more conservative strategies such equity market neutral, fixed income arbitrage and convertible arbitrage.

2. **Diversified**: This index includes funds that invest in a variety of strategies among multiple managers. Such funds show typically minimal loss in down markets while achieving superior returns in up markets.

3. **Market Defensive**: This index includes funds that generally engage in short-biased strategies such as short selling and managed futures. A fund in the FOF Market Defensive Index exhibits higher returns during down markets than during up markets.

4. **Strategic**: This index includes funds that generally engage in more opportunistic strategies such as Emerging Markets, Sector specific, and Equity Hedge. A fund in the FOF Strategic index tends to outperform the FOF composite index in up markets and underperform the index in down markets.

**Emerging markets**

1. **Asia ex-Japan**: Primary focus on Asia, typically with less than 10% exposure in Japan.

2. **Global**: No greater than 50% exposure in any specific geographic region.

3. **Latin America**: Primary focus in region, with greater than 50% exposure in these areas.

4. **Russia/Eastern Europe**: Primary focus in region, with greater than 50% exposure in these areas.
### Table 1: Risk Factors Descriptive Statistics.
This table presents the means, standard deviations (STD), skewness, kurtosis, maximum (max), and minimum (min) of the risk factors analyzed in this paper, for returns observed during the period Jan 1994 to December 2010 (204 observations). The Bond and Credit risk factors are represented respectively by the 10Y Treasury and Moody’s BAA Bond Indexes. There are two equity oriented factors represented respectively by the S&P 500 (equity market factor) and the Russell 2000 monthly total return (size spread factor). The Emerging Market factor is represented by the MSCI Emerging Market index. There are five Primitive Trend Following Factors (PTFS) represented by lookback straddles on bonds, currency, commodity, short-term rate, and stocks (see Fung and Hsieh (2001) for details). Cressie Read estimators solve HARA utility maximization problems whose portfolios are linear combinations of the listed risk factors. Means and standard deviations are annualized, not min and max statistics, which are kept monthly.

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<th>Stat.</th>
<th>PTBD</th>
<th>PTFX</th>
<th>PTCOM</th>
<th>PTIR</th>
<th>PTSTK</th>
<th>S&amp;P</th>
<th>RU2000</th>
<th>MSCI</th>
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<td>17.14</td>
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<td>8.11</td>
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</table>

### Table 2: Hedge Funds Descriptive Statistics.
This table presents the means, standard deviations (STD), skewness, kurtosis, maximum (max), and minimum (min) of returns of the Hedge fund indexes analyzed in this paper, for returns observed during the period Jan 1994 to December 2010 (204 observations). Means and standard deviations are annualized, not min and max statistics, which are kept monthly.

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Table 3: Hedge Funds Sub-categories Descriptive Statistics.
This table presents the means, standard deviations (STD), skewness, kurtosis, maximum (max), and minimum (min) of returns of the Hedge fund sub-categories of the indexes analyzed in this paper, for returns observed during the period Jan 1994 to December 2010 (204 observations). Means and standard deviations are annualized, not min and max statistics, which are kept monthly.

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<th>STD</th>
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</table>
Appendices & Tables

Table 4: Optimal Portfolio Weights for CR Estimators without Options.

Risk factors are composed by monthly returns over the period 1994:1 to 2010:12. The Bond and Credit risk factors are represented respectively by the 10Y Treasury and Moody’s BAA Bond Indexes. There are two equity oriented factors represented respectively by the S&P 500 (equity market factor) and the Russell 2000 monthly total return (size spread factor). The Emerging Market factor is represented by the MSCI Emerging Market index. Cressie Read estimators solve HARA utility maximization problems whose portfolios are linear combinations of the listed risk factors. A fixed SDF mean equal to 0.997 is adopted. The SDF mean is obtained with the average of the 3 month Treasury bill over the period Jan 1994 - Dec 2010 that is equal to 30 basis points on a monthly basis.

<table>
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<tr>
<th>γ</th>
<th>S&amp;P</th>
<th>RU2000</th>
<th>MSCI</th>
<th>10yTr</th>
<th>BAA</th>
<th>r_f</th>
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<td>-6.03</td>
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Table 5: Optimal Portfolio Weights for CR Estimators.

Risk factors are composed by monthly returns over the period 1994:1 to 2010:12. The Bond and Credit risk factors are represented respectively by the 10Y Treasury and Moody’s BAA Bond Indexes. There are two equity oriented factors represented respectively by the S&P 500 (equity market factor) and the Russell 2000 monthly total return (size spread factor). The Emerging Market factor is represented by the MSCI Emerging Market index. There are five Primitive Trend Following Factors (PTFS) represented by lookback straddles on bonds, currency, commodity, short-term rate, and stocks (see Fung and Hsieh (2001) for details). Cressie Read estimators solve HARA utility maximization problems whose portfolios are linear combinations of the listed risk factors. A fixed SDF mean equal to 0.997 is adopted. The SDF mean is obtained with the average of the 3 month Treasury bill over the period Jan 1994 - Dec 2010 that is equal to 30 basis points on a monthly basis.

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<th>PTR</th>
<th>PTSTK</th>
<th>S&amp;P</th>
<th>RU2000</th>
<th>MSCI</th>
<th>10yTr</th>
<th>BAA</th>
<th>r_f</th>
</tr>
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<tbody>
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<td>-3</td>
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<td>0.62</td>
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<td>2.93</td>
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<td>4.52</td>
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</table>

Table 6: Pricing Errors (in basis points) on the primitive risk assets under the CR implied SDFs without Options.

This table presents pricing errors (in basis points) achieved by implied SDFs when pricing ten risk factors adopted as basis assets. Risk factors are composed by monthly returns over the period 1994:1 to 2010:12. The Bond and Credit risk factors are represented respectively by the 10Y Treasury and Moody’s BAA Bond Indexes. There are two equity oriented factors represented respectively by the S&P 500 (equity market factor) and the Russell 2000 monthly total return (size spread factor). The Emerging Market factor is represented by the MSCI Emerging Market index. There are five Primitive Trend Following Factors (PTFS) represented by lookback straddles on bonds, currency, commodity, short-term rate, and stocks (see Fung and Hsieh (2001) for details). Cressie Read estimators solve HARA utility maximization problems whose portfolios are linear combinations of the listed risk factors. A fixed SDF mean equal to 0.997 is adopted. The SDF mean is obtained with the average of the 3 month Treasury bill over the period Jan 1994 - Dec 2010 that is equal to 30 basis points on a monthly basis. The average CR SDF is an SDF that is given by the average of all CR SDFs across different parameters γ.

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<td>Average CR SDF</td>
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Table 7: Pricing Errors (in basis points) on the primitive risk assets under the CR implied SDFs.

This table presents pricing errors (in basis points) achieved by implied SDFs when pricing ten risk factors adopted as basis assets. Risk factors are composed by monthly returns over the period 1994:1 to 2010:12. The Bond and Credit risk factors are represented respectively by the 10Y Treasury and Moody’s BAA Bond indexes. There are two equity oriented factors represented respectively by the S&P 500 (equity market factor) and the Russell 2000 monthly total return (size spread factor). The Emerging Market factor is represented by the MSCI Emerging Market index. There are five Primitive Trend Following Factors (PTFS) represented by lookback straddles on bonds, currency, commodity, short-term rate, and stocks (see Fung and Hsieh (2001) for details). Cressie Read estimators solve HARA utility maximization problems whose portfolios are linear combinations of the listed risk factors. A fixed SDF mean equal to 0.997 is adopted. The SDF mean is obtained with the average of the 3 month Treasury bill over the period Jan 1994 - Dec 2010 that is equal to 30 basis points on a monthly basis. The average CR SDF is an SDF that is given by the average of all CR SDFs across different parameters $\gamma$.

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<th>PTTSTK</th>
<th>S&amp;P</th>
<th>RU2000</th>
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</table>

Table 8: Pricing Errors (in basis points) for CR implied SDFs Using Alternative Equity Option Factors.

This table presents pricing errors (in basis points) achieved by implied SDFs when pricing nine risk factors adopted as basis assets. Risk factors are composed by monthly returns over the period 1994:1 to 2009:08. The Bond and Credit risk factors are represented respectively by the 10Y Treasury and Moody’s BAA Bond indexes. There are two equity oriented factors represented respectively by the S&P 500 (equity market factor) and the Russell 2000 monthly total return (size spread factor). The Emerging Market factor is represented by the MSCI Emerging Market index. Four Equity Option factors adopted by Agarwal and Naik (2004) are included: At the money and out of the money S&P 500 put and call returns. A fixed SDF mean equal to 0.997 is adopted. The SDF mean is obtained with the average of the 3 month Treasury bill over the period Jan 1994 - Dec 2010 that is equal to 30 basis points on a monthly basis.

<table>
<thead>
<tr>
<th>$CR(\gamma)$</th>
<th>S&amp;P</th>
<th>RU2000</th>
<th>MSCI</th>
<th>10yTr</th>
<th>Mo.BAA</th>
<th>ATM Call</th>
<th>OTM Call</th>
<th>ATM PUT</th>
<th>OTM PUT</th>
</tr>
</thead>
<tbody>
<tr>
<td>-3</td>
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<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>-2</td>
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<td>0.0</td>
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<td>-0.2</td>
<td>-0.2</td>
<td>0.0</td>
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<td>-0.2</td>
<td>-0.2</td>
<td>-0.2</td>
</tr>
<tr>
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<td>0.0</td>
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<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
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<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
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<td>-3.4</td>
<td>-3.4</td>
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<tr>
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<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
</tbody>
</table>
Table 9: Hedge Funds Performance Evaluation under Different Estimators.
This table contains the alphas of different Hedge Fund main categories (Emerging Markets (EM), Equity Hedge (EH), Event Driven (EV), Fund of Funds (FoF), Global Index (GI), Macro, and Relative Value (RV)) obtained with implied SDFs from different Cressie Read estimators. Risk factors are composed by monthly returns over the period 1994:1 to 2010:12. The Bond and Credit risk factors are represented respectively by the 10Y Treasury and Moody’s BAA Bond Indexes. There are two equity oriented factors represented respectively by the S&P 500 (equity market factor) and the Russell 2000 monthly total return (size spread factor). The Emerging Market factor is represented by the MSCI Emerging Market Index. There are five Primitive Trend Following Factors (PTFs) represented by lookback straddles on bonds, currency, commodity, short-term rate, and stocks (see Fung and Hsieh (2001) for details).
Cressie Read estimators solve HARA utility maximization problems whose portfolios are linear combinations of the listed risk factors. A fixed SDF mean equal to 0.997 is adopted. The average CR SDF is an SDF that is given by the average of all CR SDFs across different parameters γ.

<table>
<thead>
<tr>
<th>CR(γ) SDFs without options</th>
<th>EM</th>
<th>EH</th>
<th>ED</th>
<th>FoF</th>
<th>GI</th>
<th>Macro</th>
<th>RV</th>
</tr>
</thead>
<tbody>
<tr>
<td>-3</td>
<td>3.4</td>
<td>3.2</td>
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<td>1.2</td>
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<td>1.3</td>
<td>4.2</td>
<td>4.8</td>
<td>4.6</td>
</tr>
<tr>
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<td>3.8</td>
<td>3.2</td>
<td>5.7</td>
<td>1.3</td>
<td>4.2</td>
<td>4.8</td>
<td>4.6</td>
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<tr>
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<td>3.2</td>
<td>5.7</td>
<td>1.3</td>
<td>4.2</td>
<td>4.8</td>
<td>4.6</td>
</tr>
<tr>
<td>0.5</td>
<td>3.9</td>
<td>3.2</td>
<td>5.7</td>
<td>1.3</td>
<td>4.2</td>
<td>4.8</td>
<td>4.6</td>
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<tr>
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<td>3.9</td>
<td>3.2</td>
<td>5.8</td>
<td>1.4</td>
<td>4.2</td>
<td>4.8</td>
<td>4.6</td>
</tr>
<tr>
<td>Average CR SDF</td>
<td>3.8</td>
<td>3.2</td>
<td>5.7</td>
<td>1.3</td>
<td>4.2</td>
<td>4.8</td>
<td>4.6</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>CR(γ) SDFs with options</th>
<th>EM</th>
<th>EH</th>
<th>ED</th>
<th>FoF</th>
<th>GI</th>
<th>Macro</th>
<th>RV</th>
</tr>
</thead>
<tbody>
<tr>
<td>-3</td>
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<td>6.1</td>
<td>4.3</td>
<td>1.2</td>
<td>3.9</td>
<td>5.8</td>
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<td>1.3</td>
<td>4.0</td>
<td>6.0</td>
<td>3.4</td>
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<td>4.9</td>
<td>1.6</td>
<td>4.3</td>
<td>6.4</td>
<td>3.7</td>
</tr>
<tr>
<td>-0.5</td>
<td>2.7</td>
<td>6.6</td>
<td>5.2</td>
<td>1.8</td>
<td>4.6</td>
<td>6.6</td>
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<td>4.9</td>
<td>6.9</td>
<td>4.3</td>
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<tr>
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<td>7.3</td>
<td>4.7</td>
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<td>5.4</td>
<td>7.0</td>
<td>6.4</td>
<td>2.6</td>
<td>5.5</td>
<td>7.5</td>
<td>4.8</td>
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<tr>
<td>Average CR SDF</td>
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<td>6.6</td>
<td>5.3</td>
<td>1.9</td>
<td>4.6</td>
<td>6.6</td>
<td>4.0</td>
</tr>
</tbody>
</table>

Table 10: Individual Emerging Markets Funds Performance Statistics.
This table presents the means, standard deviations (STD), skewness, kurtosis, maximum (max), and minimum (min) of performance (discounted returns) of the individual hedge funds in the Emerging Markets Category. Means and standard deviations are annualized, not Max and Min statistics, which are kept monthly.

<table>
<thead>
<tr>
<th>Stat.</th>
<th>Emerging Markets</th>
</tr>
</thead>
<tbody>
<tr>
<td>γ = -3</td>
<td>5.90</td>
</tr>
<tr>
<td>γ = -2</td>
<td>27.53</td>
</tr>
<tr>
<td>γ = -1</td>
<td>-2.09</td>
</tr>
<tr>
<td>γ = -0.5</td>
<td>13.26</td>
</tr>
<tr>
<td>γ = 0</td>
<td>5.94</td>
</tr>
<tr>
<td>γ = 0.5</td>
<td>-16.55</td>
</tr>
<tr>
<td>γ = 1</td>
<td>-5.94</td>
</tr>
</tbody>
</table>
### Table 11: Regression of Individual Emerging Markets Funds Performance on Moments of Individual Funds Returns

This table presents the regression coefficients and the R² of the performance of individual funds in the Emerging Markets category on the means, standard deviations (STD), skewness, and kurtosis of their respective returns. Student-t statistics are between parentheses. The performance is computed for several values of γ.

<table>
<thead>
<tr>
<th>γ = -3</th>
<th>γ = -2</th>
<th>γ = -1</th>
<th>γ = -0.5</th>
<th>γ = 0</th>
<th>γ = 0.5</th>
<th>γ = 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.0012</td>
<td>0.0011</td>
<td>0.0008</td>
<td>0.0005</td>
<td>0.0002</td>
<td>-0.0002</td>
</tr>
<tr>
<td>Mean</td>
<td>1.1768</td>
<td>1.1284</td>
<td>1.0510</td>
<td>1.01239</td>
<td>0.9717</td>
<td>0.9455</td>
</tr>
<tr>
<td>Var</td>
<td>-0.6603</td>
<td>-0.6083</td>
<td>-0.4887</td>
<td>-0.4094</td>
<td>-0.3052</td>
<td>-0.2123</td>
</tr>
<tr>
<td>Skew</td>
<td>0.0011</td>
<td>0.0012</td>
<td>0.0011</td>
<td>0.0010</td>
<td>0.0008</td>
<td>0.0006</td>
</tr>
<tr>
<td>Kurt</td>
<td>1.5017</td>
<td>1.6376</td>
<td>1.8306</td>
<td>1.8448</td>
<td>1.6876</td>
<td>1.5134</td>
</tr>
</tbody>
</table>

### Table 12: Sensitivity of Performance to Variations in the Short Interest Rate.

This table contains the differences in annualized alphas (in basis points) of main Hedge Fund categories (Emerging Markets (EM), Equity Hedge (EH), Event Driven (EV), Fund of Funds (FoF), Global Index (GI), Macro, and Relative Value (RV)) considering the performance under a low interest rate (1.2 per cent per year) minus the performance under a high interest rate (3.6 per cent per year). Risk factors are composed by monthly returns over the period 1994:1 to 2010:12.

<table>
<thead>
<tr>
<th>CR(γ)</th>
<th>Hedge Funds Main Categories</th>
<th>Emerging Markets Categories</th>
<th>Equity Hedge Categories</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EM</td>
<td>EH</td>
<td>ED</td>
</tr>
<tr>
<td>-3</td>
<td>157.2</td>
<td>44.6</td>
<td>129.2</td>
</tr>
<tr>
<td>-2</td>
<td>147.4</td>
<td>49.5</td>
<td>125.5</td>
</tr>
<tr>
<td>-1</td>
<td>133.5</td>
<td>67.1</td>
<td>114.2</td>
</tr>
<tr>
<td>-0.5</td>
<td>138.7</td>
<td>85.7</td>
<td>125.6</td>
</tr>
<tr>
<td>0</td>
<td>135.7</td>
<td>103.3</td>
<td>124.0</td>
</tr>
<tr>
<td>0.5</td>
<td>113.7</td>
<td>114.7</td>
<td>107.2</td>
</tr>
<tr>
<td>1</td>
<td>109.9</td>
<td>135.5</td>
<td>122.7</td>
</tr>
<tr>
<td>CR(γ)</td>
<td>Emerging Markets Categories</td>
<td>Equity Hedge Categories</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Asia</td>
<td>Global</td>
<td>Latin Amer.</td>
</tr>
<tr>
<td></td>
<td>124.0</td>
<td>134.7</td>
<td>146.7</td>
</tr>
</tbody>
</table>

Appendices & Tables
Table 13: Hedge Funds Performance Evaluation When Extreme Events are Neglected.
This table contains the alphas of different Hedge Fund main categories (Emerging Markets (EM), Equity Hedge (EH), Event Driven (EV), Fund of Funds (FoF), Global Index (GI), Macro, and Relative Value (RV)) obtained with implied SDFs from different Cressie Read estimators when the SDFs values on the three states of nature with the most extreme events (Aug 1998, Jul 2002 and Jan 2006) are substituted by the SDF mean (0.997) and the SDFs are renormalized to keep a mean equal to 0.997. Risk factors are composed by monthly returns over the period 1994:1 to 2010:12. The Bond and Credit risk factors are represented respectively by the 10Y Treasury and Moody’s BAA Bond Indexes. There are two equity oriented factors represented respectively by the S&P 500 (equity market factor) and the Russell 2000 monthly total return (size spread factor). The Emerging Market factor is represented by the MSCI Emerging Market index. There are five Primitive Trend Following Factors (PTFS) represented by lookback straddles on bonds, currency, commodity, short-term rate, and stocks (see Fung and Hsieh (2001) for details). The average CR SDF is an SDF that is given by the average of all CR SDFs across different parameters $\gamma$.

<table>
<thead>
<tr>
<th>CR($\gamma$) SDFs with options</th>
<th>EM</th>
<th>EH</th>
<th>ED</th>
<th>FoF</th>
<th>GI</th>
<th>Macro</th>
<th>RV</th>
</tr>
</thead>
<tbody>
<tr>
<td>-3</td>
<td>10.8</td>
<td>10.1</td>
<td>9.2</td>
<td>4.4</td>
<td>8.2</td>
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<td>6.1</td>
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<td>-2</td>
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<td>4.7</td>
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<td>7.9</td>
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<td>10.8</td>
<td>9.8</td>
<td>5.1</td>
<td>8.8</td>
<td>8.4</td>
<td>6.5</td>
</tr>
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<td>9.5</td>
<td>5.0</td>
<td>8.6</td>
<td>8.5</td>
<td>6.4</td>
</tr>
<tr>
<td>0</td>
<td>10.6</td>
<td>9.9</td>
<td>9.1</td>
<td>4.7</td>
<td>8.1</td>
<td>8.4</td>
<td>6.3</td>
</tr>
<tr>
<td>0.5</td>
<td>9.6</td>
<td>9.4</td>
<td>8.7</td>
<td>4.4</td>
<td>7.6</td>
<td>8.4</td>
<td>6.1</td>
</tr>
<tr>
<td>1</td>
<td>8.9</td>
<td>8.6</td>
<td>8.1</td>
<td>3.8</td>
<td>7.1</td>
<td>8.2</td>
<td>5.7</td>
</tr>
<tr>
<td>Average CR SDF</td>
<td>10.7</td>
<td>10.0</td>
<td>9.2</td>
<td>4.6</td>
<td>8.1</td>
<td>8.2</td>
<td>6.2</td>
</tr>
</tbody>
</table>

Table 14: Performance Sensitivity to Shocks in Risk Factors - Emerging Markets
This table presents the change in the average performance of Emerging Markets indices when the MSCI Emerging Market index returns fall by an average 2.4 per cent annually, for different values of the Cressie–Read parameter $\gamma$.

<table>
<thead>
<tr>
<th>Average Performance</th>
<th>$\gamma = -3$</th>
<th>$\gamma = -2$</th>
<th>$\gamma = -1$</th>
<th>$\gamma = -0.5$</th>
<th>$\gamma = 0$</th>
<th>$\gamma = 0.5$</th>
<th>$\gamma = 1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Emerging Markets - Total</td>
<td>1.0</td>
<td>1.3</td>
<td>2.1</td>
<td>2.7</td>
<td>3.5</td>
<td>4.4</td>
<td>5.4</td>
</tr>
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<td>5.0</td>
<td>4.7</td>
<td>4.2</td>
<td>3.9</td>
<td>4.0</td>
</tr>
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<td>Emerging Markets - Global</td>
<td>-2.7</td>
<td>-2.3</td>
<td>-1.1</td>
<td>0.0</td>
<td>1.6</td>
<td>3.2</td>
<td>4.8</td>
</tr>
<tr>
<td>Emerging Markets - Latin America</td>
<td>2.0</td>
<td>2.5</td>
<td>3.4</td>
<td>3.7</td>
<td>4.0</td>
<td>4.4</td>
<td>5.2</td>
</tr>
<tr>
<td>Emerging Markets - Russia</td>
<td>4.5</td>
<td>4.6</td>
<td>6.2</td>
<td>7.6</td>
<td>9.9</td>
<td>12.0</td>
<td>13.9</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Emerging Markets - Total</td>
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<td>-0.1</td>
<td>0.0</td>
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<td>-0.05</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Emerging Markets - Global</td>
<td>-4.3</td>
<td>-1.4</td>
<td>-0.2</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Emerging Markets - Latin America</td>
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<td>-0.9</td>
<td>-0.1</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Emerging Markets - Russia</td>
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<td>-2.0</td>
<td>-0.3</td>
<td>0.0</td>
<td>0.0</td>
</tr>
</tbody>
</table>
Table 15: Hedge Funds Performance Evaluation with Alternative Equity Option Factors.
This table contains the alphas of different Hedge Fund main categories (Emerging Markets (EM), Equity Hedge (EH), Event Driven (EV), Fund of Funds (FoF), Global Index (GI), Macro, and Relative Value (RV)) obtained with implied SDFs from different Cressie Read estimators. Risk factors are composed by monthly returns over the period 1994:1 to 2009:08. The Bond and Credit risk factors are represented respectively by the 10Y Treasury and Moody’s BAA Bond Indexes. There are two equity oriented factors represented respectively by the S&P 500 (equity market factor) and the Russell 2000 monthly total return (size spread factor). The Emerging Market factor is represented by the MSCI Emerging Market index. Four Equity Option factors adopted by Agarwal and Naik (2004) are included: At the money and out of the money S&P 500 put and call returns. Cressie Read estimators solve HARA utility maximization problems whose portfolios are linear combinations of the listed risk factors. A fixed SDF mean equal to 0.997 is adopted. The average CR SDF is an SDF that is given by the average of all CR SDFs across different parameters γ.

<table>
<thead>
<tr>
<th>CR(γ) SDFs without options</th>
<th>Hedge Funds Categories</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EM</td>
</tr>
<tr>
<td>-3</td>
<td>3.8</td>
</tr>
<tr>
<td>-2</td>
<td>4.0</td>
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<tr>
<td>-1</td>
<td>4.1</td>
</tr>
<tr>
<td>-0.5</td>
<td>4.1</td>
</tr>
<tr>
<td>0</td>
<td>4.2</td>
</tr>
<tr>
<td>0.5</td>
<td>4.2</td>
</tr>
<tr>
<td>1</td>
<td>4.2</td>
</tr>
<tr>
<td>Average CR SDF</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>CR(γ) SDFs with options</th>
<th>Hedge Funds Categories</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EM</td>
</tr>
<tr>
<td>-3</td>
<td>4.0</td>
</tr>
<tr>
<td>-2</td>
<td>4.4</td>
</tr>
<tr>
<td>-1</td>
<td>4.2</td>
</tr>
<tr>
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<td>4.1</td>
</tr>
<tr>
<td>0</td>
<td>4.3</td>
</tr>
<tr>
<td>0.5</td>
<td>4.5</td>
</tr>
<tr>
<td>1</td>
<td>4.6</td>
</tr>
<tr>
<td>Average CR SDF</td>
<td>4.4</td>
</tr>
</tbody>
</table>

Figure 1: Skewness and Kurtosis Weights on Cressie Read Estimators
This picture presents the third and fourth derivatives of the HARA function \(-\frac{1}{\gamma+1} (1 - \gamma W)^{\gamma+1}\) evaluated at the expected optimal wealth W, obtained on HARA portfolio problems. The portfolio problems are based on the Fung and Hsieh (2001) set of risk factors. The Bond and Credit risk factors are represented respectively by the 10Y Treasury and Moody’s BAA Bond Indexes. There are two equity oriented factors represented respectively by the S&P 500 (equity market factor) and the Russell 2000 monthly total return (size spread factor). The Emerging Market factor is represented by the MSCI Emerging Market index. There are five Primitive Trend Following Factors (PTFs) represented by lookback straddles on bonds, currency, commodity, short-term rate, and stocks (see Fung and Hsieh (2001) for details). We report two sets of weights on skewness and kurtosis: the first with the portfolio problems adopting only five risk factors not including the five straddles (blue line) and the second adopting ten risk factors including the five straddles (red line). A fixed SDF mean equal to 0.9977 is adopted.
Figure 2: CR Stochastic Discount Factors Extracted from Risk Factors

This picture presents CR stochastic discount factors based on monthly returns on a set of 10 risk factors over the period 1994:12 to 2010:12. The Cressie Read SDFs are obtained via utility maximization problems based on HARA functions parameterized by $\gamma$. The Bond and Credit risk factors are represented respectively by the 10Y Treasury and Moody’s BAA Bond Indexes. There are two equity oriented factors represented respectively by the S&P 500 (equity market factor) and the Russell 2000 monthly total return (size spread factor). The Emerging Market factor is represented by the MSCI Emerging Market Index. There are five Primitive Trend Following Factors (PTFS) represented by lookback straddles on bonds, currency, commodity, short-term rate, and stocks (see Fung and Hsieh (2001) for details). We report two SDFs for each Cressie Read parameter ($\gamma$): the first adopting five risk factors not including the five option straddles (blue line) and the second adopting ten risk factors including the five option straddles (red line). A fixed SDF mean equal to 0.9977 is adopted.
Figure 3: Performances of Main Hedge Fund Indexes
This picture presents the alphas of the seven main Hedge Fund categories (Emerging Markets (EM), Equity Hedge (EH), Event Driven (EV), Fund of Funds (FoF), Global Index (GI), Macro and Relative Value (RV)) obtained with implied SDFs from different Cressie Read estimators. The Cressie Read SDFs are obtained via utility maximization problems based on HARA functions parameterized by \( \gamma \).

The Bond and Credit risk factors are represented respectively by the 10Y Treasury and Moody’s BAA Bond Indexes. There are two equity oriented factors represented respectively by the S&P 500 (equity market factor) and the Russell 2000 monthly total return (size spread factor). The Emerging Market factor is represented by the MSCI Emerging Market index. There are five Primitive Trend Following Factors (PTFs) represented by lookback straddles on bonds, currency, commodity, short-term rate, and stocks (see Fung and Hsieh (2001) for details). A fixed SDF mean equal to 0.9977 is adopted.
Appendices & Tables

Figure 4: Performances for Subclasses of Hedge Fund Strategies Based on SDFs Without Options

This picture presents the alphas of different subclasses of Hedge Fund categories based on (Emerging Markets (EM), Equity Hedge (EH), Event Driven (EV), Fund of Funds (FoF), Global Index (GI), and Relative Value (RV)) obtained with implied SDFs from different Cressie Read estimators. The Cressie Read SDFs are obtained via utility maximization problems based on HARA functions parameterized by $\gamma$. The Bond and Credit risk factors are represented respectively by the 10Y Treasury and Moody’s BAA Bond indexes. There are two equity oriented factors represented respectively by the S&P 500 (equity market factor) and the Russell 2000 monthly total return (size spread factor). The Emerging Market factor is represented by the MSCI Emerging Market index. There are five Primitive Trend Following Factors (PTFS) represented by lookback straddles on bonds, currency, commodity, short-term rate, and stocks (see Fung and Hsieh (2001) for details). A fixed SDF mean equal to 0.9972 is adopted.
Figure 5: Performances for Subclasses of Hedge Fund Strategies Based on SDFs With Options
This picture presents the alphas of different subclasses of Hedge Fund categories based on (Emerging Markets (EM), Equity Hedge (EH), Event Driven (EV), Fund of Funds (FoF), Global Index (GI), and Relative Value (RV)) obtained with implied SDFs from different Cressie Read estimators. The Cressie Read SDFs are obtained via utility maximization problems based on HARA functions parameterized by $\gamma$. The Bond and Credit risk factors are represented respectively by the 10Y Treasury and Moody’s BAA Bond indexes. There are two equity oriented factors represented respectively by the S&P 500 (equity market factor) and the Russell 2000 monthly total return (size spread factor). The Emerging Market factor is represented by the MSCI Emerging Market index. There are five Primitive Trend Following Factors (PTFs) represented by lookback straddles on bonds, currency, commodity, short-term rate, and stocks (see Fung and Hsieh (2001) for details). A fixed SDF mean equal to 0.9972 is adopted.
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Newedge AIS offers financing and reporting options that are specifically tailored to client requirements, and to the different assets and instruments traded. The firm focuses on analysing and understanding customers’ requirements, legal structure and business, before providing a personalised risk management solution.

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The Choice of Asset Allocation and Risk Management
EDHEC-Risk structures all of its research work around asset allocation and risk management. This issue corresponds to a genuine expectation from the market. On the one hand, the prevailing stock market situation in recent years has shown the limitations of diversification alone as a risk management technique and the usefulness of approaches based on dynamic portfolio allocation. On the other, the appearance of new asset classes (hedge funds, private equity, real assets), with risk profiles that are very different from those of the traditional investment universe, constitutes a new opportunity and challenge for the implementation of allocation in an asset management or asset-liability management context.

This strategic choice is applied to all of the Institute's research programmes, whether they involve proposing new methods of strategic allocation, which integrate the alternative class; taking extreme risks into account in portfolio construction; studying the usefulness of derivatives in implementing asset-liability management approaches; or orienting the concept of dynamic "core-satellite" investment management in the framework of absolute return or target-date funds.

Academic Excellence and Industry Relevance
In an attempt to ensure that the research it carries out is truly applicable, EDHEC has implemented a dual validation system for the work of EDHEC-Risk. All research work must be part of a research programme, the relevance and goals of which have been validated from both an academic and a business viewpoint by the Institute's advisory board. This board is made up of internationally recognised researchers, the Institute's business partners, and representatives of major international institutional investors. Management of the research programmes respects a rigorous validation process, which guarantees the scientific quality and the operational usefulness of the programmes.

Six research programmes have been conducted by the centre to date:
- Asset allocation and alternative diversification
- Style and performance analysis
- Indices and benchmarking
- Operational risks and performance
- Asset allocation and derivative instruments
- ALM and asset management

These programmes receive the support of a large number of financial companies. The results of the research programmes are disseminated through the EDHEC-Risk locations in Singapore, which was established at the invitation of the Monetary Authority of Singapore (MAS), the City of London in the United Kingdom, and Nice, France. In addition, it has a research team located in the United States.

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- Regulation and Institutional Investment, in partnership with AXA Investment Managers
The philosophy of the Institute is to validate its work by publication in international academic journals, as well as to make it available to the sector through its position papers, published studies, and conferences.

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For more information, please contact:
Carolyn Essid on +33 493 187 824
or by e-mail to: carolyn.essid@edhec-risk.com

EDHEC-Risk Institute
393 promenade des Anglais
BP 3116
06202 Nice Cedex 3 — France
Tel: +33 (0)4 93 18 78 24

EDHEC Risk Institute—Europe
10 Fleet Place - Ludgate
London EC4M 7RB - United Kingdom
Tel: +44 207 871 6740

EDHEC Risk Institute—Asia
1 George Street - #07-02
Singapore 049145
Tel.: +65 6438 0030

www.edhec-risk.com