Directional and Non-Directional Risk Exposures in Hedge Fund Returns

G. Hübner[a], M. Lambert[b] and N. Papageorgiou[c]

This paper re-examines the ability of the factor model approach to evaluate the performance of the Equity Hedge, Event Driven, Macro, Relative Value, and Funds of Hedge Funds styles. As Hedge Fund returns are not normally distributed, we assign a premium to higher-order comoments of Hedge Fund returns with the US market aggregate. In addition to traditional asset- (conditioned by the levels of some information variables) and option-based factors, our analysis incorporates two sets of distributional premiums that have not yet been exploited in Hedge Fund asset pricing. We show that US higher-moment equity risk premiums constructed through hedge portfolios on covariance, coskewness, and cokurtosis risks are significant for Equity Hedge, Event Driven, and Macro Hedge Fund styles. Furthermore, we provide evidence that there is still much information embedded in option prices, particularly in the implied higher-moments of Bakshi *et al.* (2003). These premiums increase the explanatory power of the models across all the Hedge Fund strategies but the Macro and Relative Value categories.

Keywords: Hedge Funds, Nonlinear Risk Premiums, Comoments, Implied Higher-Moments
Jel Codes: G10, G12

---

[a] HEC Management School, University of Liège, Belgium Faculty of Economics and Business Administration, Maastricht University, the Netherlands; Gambit Financial Solutions, Belgium. Mailing address: G.Hubner@ulg.ac.be, HEC Management School - University of Liège, rue Louvrex, 14, B 4000 Liège (Belgium). Phone: (+32) 42327428.
[b] Postdoctoral Researcher, School of Business and Economics, Maastricht University, the Netherlands, and Solvay Brussels School of Economics and Management, Free University of Brussels, Belgium. Mailing address: m.lambert@maastrichtuniversity.nl. School of Business and Economics, Maastricht University, Tongersestraat 53, Room B 1.05A, 6211 LM Maastricht, The Netherlands. Phone: +31 43 388 39 49. Corresponding author.
[c] Associate professor of finance, HEC Montreal and Director of Research, Desjardins Global Asset Management. E-mail: nicolas.papageorgiou@hec.ca

1. Introduction

Over the last ten years, a significant amount of research has focused on analyzing the performance of Hedge Funds.

Early research (i.e. Ackermann *et al.*, 1999; Leland, 1999; Agarwal and Naik, 2000a) clearly demonstrated that the market model of Sharpe (1964), Lintner (1965), and Mossin (1966) and its related performance measures offer a poor benchmark for evaluating Hedge Fund returns. The model major failing is that it only rewards linear exposure to one source of risk, whereas it is well known that Hedge Funds trade in a variety of different securities and markets. Besides, the dynamic trading and arbitrage strategies implemented by Hedge Funds generate payoff profiles that often are nonlinear functions of the returns of the underlying assets (Fung and Hsieh, 1997a; Agarwal and Naik, 2001).

Numerous contributions have been made for capturing these non-normalities in Hedge Fund returns with option-contract time-series (e.g., Mitchell and Pulvino, 2001; Agarwal and Naik, 2001; Fung and Hsieh, 2001, 2002a,b; 2004a,b). A recent trend, which has not yet been sufficiently explored, is to capture these non-normalities through the exposures of Hedge Funds to higher-order moments of various markets. Indeed, many authors, notably Arditti (1967, 1969), Levy (1969), Jean (1971), Rubinstein (1973), and Scott and Horvath (1980), have demonstrated that, if returns are not normally distributed, higher-order moments play an important role in maximising the investor's expected utility. Therefore, in accordance with the Four-Moment Asset Pricing Model of Dittmar (2002), Hedge Fund performance should assign a premium to their higher-order comoments with the aggregate market portfolio.

Our paper contributes to the literature about the use of higher-moment market models for explaining Hedge Fund returns in two ways. One is through the inclusion of robust empirical premiums related to backward-looking estimates of higher-moment risks. The other contribution is the inclusion of forward-looking estimates of higher-moments embedded in option prices. These two particular sets of premiums have never been applied to Hedge Funds data, neither simultaneously nor even in isolation.

On the one hand, our paper is (to our knowledge) one of the first to use robust estimates for the US equity returns attached to a unitary covariance, a unitary coskewness and a unitary cokurtosis with the US stock market portfolio in order to evaluate Hedge Funds returns. We rely on the methodology of Lambert and Hübner (2010) to derive the equity higher-order comoment risk premiums that reward the excess return from historical (backward-looking) exposures to high over small covariance, historical exposures to high over low cokurtosis, and historical exposures to small over high coskewness. This analysis allows us to relate Hedge Fund returns to those of a portfolio that spans covariance, coskewness, and cokurtosis risks. The loadings of the Hedge Fund returns on these portfolios should be interpreted as the exposure to the covariance, coskewness, and cokurtosis risk premiums rather than simple comovements with higher-order market moments.

On the other hand, our paper is the first one to evaluate the impact on Hedge Fund returns of a change in the US expected market prices (for a risk-neutral investor) for variance, skewness, and kurtosis (see also Bondarenko, 2006 for an analysis of the volatility price; and Agarwal *et al.*, 2008a,b, for an indirect use of implied moments for Hedge Fund pricing). These prices correspond to the costs of replicating (through option contracts) the second, third, and fourth moments of the market return distribution. The theoretical framework for this risk-neutral valuation is described in Bakshi *et al.* (2003) and is valid for all levels of investors' risk aversion. Hedge Funds frequently trade in contracts that have direct implications on their levels of volatility, skewness, and kurtosis. Since investors dislike variance and kurtosis but positively value skewness, a portofolio performance could be enhanced in mean-variance terms by buying kurtosis and variance and by selling skewness, i.e. by taking kurtosis, variance, and (negative) skewness risk (Leland, 1999). Therefore, the portfolio returns are expected to be influenced by the evolution of these risk prices. The loadings on these factors should be interpreted as the allocation of Hedge Fund returns to forward-looking higher-moment risks: a positive (negative) loading on the volatility and kurtosis (skewness) premiums of Bakshi *et al.* (2003) should be interpreted as a purchase of risk, while a negative (positive) value, should be interpreted as a sale of risk.

We attempt to improve models traditionally used for evaluating Hedge Fund returns. The objective is to dissociate the returns that are due to exposures to systematic risk factors (beta returns) from those that are due to manager skills (alpha returns). We borrow a set of factors from the existing literature in order to complement a regression-based analysis made of the two new types of distributional factors.

First, we extend our linear model by incorporating multiple bond- and equity-like factors. These premiums are referred to either as asset-based factors since they mimic traditional asset classes, or as directional factors, since when Hedge Funds invest in a market, they take a bet on the direction of its asset values. Second, the exposures to directional factors are conditioned onto publicly available information to make them time-varying.

Finally, we consider a set of option-contract time-series (referred hereafter either as optional factors, or option-based factors) which have been largely used to replicate the option-like strategies carried out by Hedge Funds. These factors are not risk premiums, but rather returns generated from rules-based (or mechanical) trading strategies. They are nonetheless closely linked to our moment-related factors. The augmentation of the linear multifactor model with option-based factors[1] (which have skewed payoffs) is indeed

[1] Option-based factors replicate higher orders of the market returns: See Chapter 2 for more information about the links between the higher-moment factors.

similar to Harvey and Siddique (2000) augmentation of Fama and French (1993) three-factor model by a nonlinear factor delivered from skewness (e.g., Agarwal and Naik, 2004).

Our paper provides evidence that there is significant information embedded in distributional factors which has not previously been exploited. We follow the strategy classification of the *Hedge Fund Research, Inc.* (*HFR*) and show that higher-order equity risk premiums and the innovations in the market prices for volatility, skewness and kurtosis increase the explanatory power of traditional models across all the Hedge Fund strategies.

The rest of the paper is structured as follows. In Section 2, we present the Hedge Fund data used in this study and form the dependent dataset. Given the opportunistic behavior of most of the Hedge Funds, we expect to find different sensitivities to the different sets of factors exposed above. Section 3 provides technical details regarding the factors that are selected for our analysis. To employ all of them in a performance evaluation would however lead to a fuzzy picture of the significant exposures of the different strategies. Therefore, in Section 4., we derive the best combination of risk factors for each Hedge Fund category and discuss the performance of the different strategies based on these models. Section 5 concludes.

2. Hedge Fund Data

Hedge Fund returns are extracted from the *Hedge Fund Research* (*HFR*) database. Monthly returns of individual Hedge Funds are obtained from January 1994 to December 2006, i.e. a maximum of 156 observations per fund. This sample includes the technology bubble of the late nineties, the severe market deflation of the early 2000s, and the major market crises that tumbled on financial markets (Peso Crisis, Russian Crisis, LTCM collapse, Asian Crisis, Terrorist Attacks).

In order to limit any reporting biases, we removed from the database all the funds that reported results for less than 12 consecutive months. (1,511 out of 7,533 funds were excluded due to this restriction). The monthly mean return of each strategy is then obtained by computing the equally-weighted average return of all funds belonging to that category during the given month. All observations with a monthly return superior to 100% or equal to 0 around the date of observation (lead and lag of one month), indicating possible reporting errors, were excluded from the final dataset.

Our research relies on the hypothesis that Hedge Fund returns present a return profile very different from the traditional assets. The quality of any model can also differ strongly among Hedge Fund strategies (Jaeger and Wagner, 2005). Therefore, it is important to form portfolios of Hedge Funds according to their return payoff similarities.

2.1. Hedge Funds Sorting Portfolios

The classification that has been referenced for a long time is the breakdown of the Hedge Fund universe into two main categories, i.e. on the one hand, non-directional or "market neutral" strategies defined as the ones presenting low levels of correlation with the market, and on the other hand, directional strategies which at the contrary can display quite higher levels of correlation. The problem intrinsic with such a breakdown is that risk-neutrality has been proved to be valid only for the first moment, i.e. with regard to the expected return (see Agarwal and Naik, 2000b). Non-directional strategies can thus not be referred to as risk-neutral regarding the second, the third or the fourth moments, since in volatile period, liquidity squeeze increases correlations across assets.

For this reason, this paper follows the new strategy classification system developed by *Hedge Fund Research, Inc*. Five categories are identified and are intended to reflect the strategic investments that are undertaken in the Hedge Fund universe. First, Equity Hedge (EH) strategy gathers "*investment managers that maintain positions both long and short in primarily equity and equity derivative securities*". Second, the Event Driven (ED) category describes the strategy of "*investment managers that maintain positions in securities of companies currently or prospectively involved in corporate transactions of a wide variety, including but not limited to: mergers, restructurings, financial distress, tender offers, shareholder buybacks, debt exchanges, security issuance or other capital structure adjustments*". Third, the Macro (M) strategy concern "*investment managers which execute a broad range of strategies in which the investment process is predicated on movements in underlying economic variables and the impact these have on equity, fixed income, currency, and commodity markets*". Fourth, the Relative Value (RV) class concerns all "*investment managers who maintain positions in which the investment thesis is predicated on realization of a valuation discrepancy in the relationship between multiple securities*". Finally, Funds of Funds (FF) invest in numerous managers' funds within a strategy or across different strategies. The goal is to diversify the risk of investing in one individual fund[2].

This classification is informative about each strategy payoff. The definition of the different categories evolves over time as each strategy is likely to persist even if investment opportunities change within the category.

2.2. Descriptive Analysis of the Sample

Table 1 reports the descriptive statistics from the Hedge Fund sample over January 1994-December 2006.

[2] See the *Hedge Fund Research Inc*. Strategy Classification System

Table 1

Descriptive statistics of Hedge Fund strategies with regard to the stock market portfolio

Category	Symbol	Nr of Fds	% of the category	% of the total	Living Funds	Dead Funds	Mean (%)	Median (%)	Max. (%)	Min. (%)	S.D. (%)	Skew.	Kurt.	J-B	Sharpe ratio
HFR Classification															
Equity Hedge	EH	1322	51.97	31.25	1104	218	1.344	1.420	9.156	-9.155	2.354	-0.156	2.736	49.30***	0.435
Event driven	ED	286	11.24	6.76	255	31	1.133	1.265	4.433	-6.962	1.432	-1.349	5.717	259.78***	0.568
Macro	M	422	16.59	9.98	331	91	1.272	1.495	1.032	-12.498	2.583	-0.735	4.952	173.48***	0.369
Relative Value	RV	514	20.20	12.15	461	53	0.971	1.030	3.152	-3.811	0.878	-1.237	5.980	272.27***	0.742
Fund of Funds	FF	1686	100	39.86	1291	395	0.768	0.788	5.694	-5.486	1.421	-0.148	2.901	55.26***	0.316
Total		4230	100	100	3442	788									
S&P 500	SP						0.800	1.214	9.672	-14.58	4.110	-0.614	0.843	14.41***	0.117

Table 1 reports the mean, median, maximum, minimum, standard deviation (S.D.), skewness, kurtosis, and the Jarque-Bera (J-B) statistics for the 5 *Hedge Fund Research* Hedge Fund styles, and for the S&P 500, taken as benchmark. The database composition is also described.

*, ** and *** stand for significant at 10%, 5%, and 1%, respectively.

Table 1 provides a framework against which we can evaluate Hedge Fund nonlinear risk exposures. Each category represents the equally-weighted portfolio of the funds that make up the category. These return series provide a complete representation of each style and would not have been obtained through the use of synthetic indexes available from database providers.

Over the 13 years considered in our sample period, the best performing portfolio of Hedge Funds has been the Equity Hedge portfolio with an averaged monthly return of 1.34%. The other Hedge Funds portfolios also present very attractive returns: with the exception of the portfolio of Funds of Hedge Funds, all of them outperform the S&P 500. While the dispersion in volatility levels between the different Hedge Fund portfolios is very high (underlining the heterogeneity in Hedge Fund strategies), the volatility risk of all strategies is lower than that of the S&P 500. However, as there is no free lunch, the return distributions of all portfolios of Hedge Funds display significantly fatter tails over the period than the S&P 500 does. Compounded by negative skewness, fat tails imply that more severe losses are expected during severe downturns. Besides, the Event Driven, Macro, and Relative Value strategies display lower levels of negative skewness than the S&P 500. The decrease in volatility, in skewness and the increase in kurtosis imply that potential upside is traded off against downside protection in normal market conditions (and catastrophe risk in highly volatile markets).

This nonlinear profile is more or less pronounced across the strategies. The most alternative risks are to be found in Event Driven and Relative Value Hedge Funds, while the highest levels of volatility are expected in Equity Hedge and Macro styles.

3. Variable Selection and Construction

This section reviews the different risk factors that were selected for pricing the Hedge Fund returns. We employ a large variety of factors as Hedge Funds do not limit their risk exposures to equity risk (Jaeger and Wagner, 2005). The first sub-section presents the directional factors. The second sub-section presents two different types of distribution-based factors as well as the option-based factors, which together comprise the set of non-directional factors.

3.1. Directional Factors

We identify a number of asset-based and conditioning factors that aim at capturing the exposures of Hedge Funds to the risks of a broad set of asset classes.

3.1.1. *Asset-Based Factors*

The return on the Russell 3000 index (RUS) is taken as proxy for the market portfolio. This choice is similar to the ones in recent studies such as Agarwal and Naik (2001, 2004), Capocci and Hübner (2004). We have also selected the additional risk premiums used by Carhart (1997) in his four-factor model, namely the SMB, the factor-mimicking portfolio for size ('*small minus big*'), HML, the factor-mimicking portfolio for book-to-market equity ('*high minus low*') and UMD, the factor-mimicking portfolio for the momentum effect ('*up minus down*')[3].

We adopt three style factors that have been shown to add a significant explanatory power in previous studies. Two factors are introduced by Agarwal and Naik (2000a): one factor for non-US equities investing funds, the MSCI World excluding US (WEX), and

[3] The SMB, HML, and UMD factors are downloaded from K. French's website.

one factor to account for the fact that Hedge Funds invest in foreign bond indices, the Citigroup World Government Bond Index excluding US (WGBI). The significance of the third factor, namely the JP Morgan Emerging Market Bond Index (EMB), is documented by Capocci and Hübner (2004).

Finally, we attempt to bring a proxy for the predictability of stock returns, evidenced by Ferson and Schadt (1996), into the unconditional linear model. We have selected the US NBER Business Cycle (RCI for Recession Index), a Boolean index capturing either economic recession (1) or expansion (0).

The summary statistics for all the 8 directional premiums with the exception of the Boolean one (the recession index or RCI) are given in Table 2.

Table 2
Descriptive statistics of asset-based factors

Type	Symbol	Mean (%)	Med. (%)	Max. (%)	Min. (%)	S.D. (%)	Skew.	Kurt.	J-B	ADF
Russell 3000	RUS	0.484	1.111	7.930	-15.867	4.123	-0.7315	1.099	21.774***	-7.092***
Size	SMB	0.249	-0.140	14.62	-11.60	3.518	0.427	1.716	23.89***	-7.727***
Value/Growth	HML	0.262	0.295	14.92	-20.79	4.122	-0.840	6.708	310.80***	-6.467***
Momentum	UMD	0.740	0.770	18.39	-25.06	5.120	-0.636	5.362	197.40***	-7.515***
World market	WEX	0. 681	0.984	9.094	-13.688	4.027	-0.840	1.0137	25.0177***	-6.446***
World Gov.	WGBI	0.108	0.141	2.578	-2.258	0.782	-0.163	0.257	1.122	-5.748***
Emerging Bond	EMB	0.644	1.244	9.680	-27.771	4.272	-2.230	12.485	1142.46***	-8.646***

Table 2 reports some descriptive statistics for the asset-based or directional factors. An Augmented (with more than one lag) Dickey-Fuller test for the rejection of a unit root is performed. The ADF statistics are reported. *S.D. = Standard Deviation, J-B = Jarque-Bera statistics.*

If we order these premiums by increasing risk, the first factor to be considered is the World Government Bond Index (WGBI). This time-series records, as expected, low levels in all the risk dimensions. Besides, the Jarque-Bera test does not reject its normality. Second, shorting big caps (SMB) seems to result in a sale of negative skewness. As found in Dennis and Mayhew (2002), large firms tend to present more negative skewness than do small firms. Third, investing in a momentum strategy, or in the Emerging bond markets are among the most risky and rewarding strategies. Although similar levels of risk characterize the value/growth investment, the strategy does not offer the same return. Fama, French and Carhart factors as well as the Emerging Market Bond Index are proxying for alternative sources of risk given the values taken by their skewness and kurtosis statistics. Using regression-based analyses, previous papers have indeed examined whether the Fama and French (1993) and Carhart (1997) empirical factors are not just proxies for higher-order asset covariations (e.g., Barone-Adesi *et al.*, 2004; Chung *et al.*, 2006; and Hung, 2007). Finally, investing in the US stock market or the worldwide stock market seems to provide similar risk. Note that all these regressors are stationary as shown by the values of the Dickey Fuller statistics. They are thus acceptable candidates to be used as explanatory variables in the Hedge Funds return specification.

3.1.2. *Conditioning Factors*

Modeling dynamic trading strategies via static positions in asset-based risk factors is dealt with as an "errors-in-variables" problem. Hedge Fund return expectations are conditioned onto predetermined variables (information variables) for which the empirical predictability has been tested. In this way, it is possible to reflect the importance of the timing of publicly available information (Brealey and Kaplanis, 2001). Such a conditional performance analysis has been advocated by Chen and Knez (1996), Ferson and Schadt (1996), Christopherson *et al.* (1998), and Christopherson *et al.* (1999). These models have been shown to explain a significant portion of portfolio returns, but have mostly been applied to Mutual Funds.

Some recent studies have applied this methodology to Hedge Funds. Kat and Miffre (2002) consider conditional performance measures consistent with the semi-strong form of efficiency. They find that the inclusion of conditioning factors significantly alters the measurement of performance. However, neither Kazemi and Schneeweis (2003) nor Chen and Liang (2007) provide evidence to support this conclusion.

Similarly to Kazemi and Schneeweis (2003), we employ four information variables (Z) to construct our premiums[4]: the corporate bond spread (the difference between the BBB and AAA ten-year corporate bond yields), the term yield spread (ten-year minus one-year treasury bills), the 3-month T-Bill rate, and the value of the VIX index. The choice of the VIX index is motivated by the importance of volatility trading in the optional investment strategies carried by Hedge Funds (Busse, 1999). For our application, this variable is likely to provide a greater explanatory power than the dividend yield on the S&P index originally proposed by Ferson and Schadt (1996).

The inclusion of L information variables in the K-factor linear pricing model results in the creation of $L*K$ conditioning risk premiums $\mathbf{Z}'_{t-1}\mathbf{X}_{\mathbf{t}}$, where $Z'_{t-1} = Z_{t-1} - \overline{Z}$. The number of conditioning factors should therefore be restricted. We limit ourselves to the set of factors in the original Carhart (1997) model, using the excess return on the Russell 3000 as the market proxy, and the Emerging Market Bond Index. This leaves us with L = 4 and K = 5. Furthermore, to avoid multicollinearity problems, we choose at most one instrument per factor. Thus, there are no more than five information variables in a regression.

For each instrument, we denote the corresponding variable Z followed by the initial of the instrument ('C' for Credit, 'R' for T-Bill Rate, 'S' for Slope, and 'V' for VIX) and the name of the variable. Thus, for the product of the lagged credit spread with the momentum risk premium, the corresponding variable is ZCUMD. (*See the list of acronyms at the end of the Chapter*)

[4] Several papers on conditional performance evaluation have employed similar instruments, see Ferson and Schadt (1996), Christopherson *et al.* (1998,1999), Busse (1999), Amenc *et al.* (2003), and Chen and Liang (2007).

3.2. Non-Directional Factors

We select regressors that capture nonlinear exposures to market risk factors in the Hedge Fund explanatory model. Distribution- and option-based factors are considered. Since both sets of premiums are intended to capture return nonlinearities, they are referred to as non-directional factors by opposition to the asset-based and conditioning factors.

3.2.1. *Distribution-Based Factors*

Provided that investors attribute a certain importance to higher-order moments, a set of factors must provide the asset pricing model with the necessary corrections to capture the skewness and kurtosis exposures of Hedge Funds. Therefore, in addition to a comprehensive set of directional factors, we discuss two types of moment-related factors. Both fill an important gap in utility theory by relating higher-moment equity risks and risk aversion.

i. The Ex-Post Comoment Equity Premiums

In this section, we evaluate the market rewards for increasing the volatility or the kurtosis and decreasing the skewness of the US stock market.

We follow the methodology developed in Lambert and Hübner (2010) to estimate these risk premiums. The comoment equity risk premiums are retrieved from the replication of three portfolios that display respectively a unitary covariance, coskewness, and cokurtosis with the US market aggregate. Each month, a conditional three-stage ranking procedure is used to split NASDAQ, AMEX, and NYSE US stocks into 27 value-weighted portfolios. Three sorts "within a sort" are performed: the first two sorts are conducted on the control risks, the last sort being the risk dimension to be priced. For instance, in order to price cokurtosis risk, the stocks are first ranked into 3 portfolios according to their covariance (resp. coskewness) estimates. Each of the three portfolios is sorted into 3 portfolios according to their coskewness (resp. covariance) estimates. The 9 portfolios are then sorted according to their stock cokurtosis estimates.

The estimates of stock higher-comoment risk exposures rely on a cubic extension of the traditional market model of Sharpe (1964) into a nonlinear return-generating process including the square and the cube of the market returns. Proxies for beta, coskewness, and cokurtosis correspond to the respective loadings on the market premium, on the square of the market excess returns and on their cube. For each risk factor, we then consider the 18 portfolios that score high and low on the risk dimension to be priced. The premium is finally defined as the simple average of the 9 differences in returns between the 9 portfolios that score high (resp. low for the skewness factor) on the 9 that score low (resp. high).

Using this methodology, we construct the series of the covariance (C), the coskewness (SK), and the cokurtosis (KU). As they are based on a historic valuation of moment risk exposures, these are referenced as ex-post estimates of higher-comoment equity risk premiums.

The ability of these time-series to capture the nonlinear structure of payoffs has already been suggested in Harvey and Siddique (2000), Ajili (2005), Kat and Miffre (2006a), Kole and Verbeek (2006), Agarwal *et al.* (2008a,b), and Moreno and Rodriguez (2009). Namely, Kat and Miffre (2006a), Kole and Verbeek (2006), Agarwal *et al.* (2008a,b), or Moreno and Rodriguez (2009) among others have already formed portfolios mimicking the returns attached to US equity coskewness and cokurtosis exposures. Agarwal *et al.* (2008a,b) create however their portfolios directly on the Hedge Fund market. The methodology proposed in our paper, focusing on premiums derived from the equity market, delivers more reliable premiums. Besides, contrary to Kat and Miffre (2006a), Kole and Verbeek (2006) and Agarwal *et al.* (2008a,b), our skewness and kurtosis premiums obey to the hypothesis that higher systematic risks should be associated with higher returns (Fama and Mac Beth, 1973). Indeed, our premiums display significant positive average returns, while the kurtosis premium of Agarwal *et al.* (2008a,b) is significantly negative over the sample period 1994-2004. Kat and Miffre (2006a) replicate the Fama and French methodology on coskewness and cokurtosis in the US stock market. Their skewness premium is however significantly negative over the period January 1985-August 2004, while our premium is positive over the same period.

ii. The Risk-Neutral Implied Volatility Index

There is ample evidence regarding the volatility timing ability of Hedge Fund managers (see Ang *et al.*, 2007; and Chen and Liang, 2007). The following sections will consider the derivation of moment premiums (including the variance) along with the Bakshi *et al.* (2003) method. Agarwal *et al.* (2008a) show that the implied volatility of Bakshi *et al.* (2003) mimics the VIX index (collected on the CBOE website). In order to remain consistent with the existing literature, we use the first difference in the VIX index (DNVIX) as a proxy for the change in market implied volatility.

iii. The Risk-Neutral Implied Skewness and Kurtosis

In this section, we retrieve useful information regarding the moments of the distribution of market indices from the option markets. Since the seminal work of Latané and Rendleman (1976), the derivatives literature has put great emphasis on the notion of implied volatility. The structure of standard deviations of index returns retrieved from option prices provides information that is not captured by historical volatilities. In the same spirit, information about market skewness and kurtosis can be retrieved from option markets (see Dennis and Mayhew, 2002 and Bakshi *et al.*, 2003) and used in Hedge Funds pricing (as in Agarwal *et al.*, 2008a,b).

The paper of Bakshi *et al.* (2003) introduces a method to retrieve the intrinsic values of the risk-neutral variance, skewness and kurtosis payoffs from option prices. Their evaluations express risk-neutral skewness and kurtosis as functions of volatility, cubic, or quartic contracts whose payoffs are defined by stocks' continuously compounded return taken to the 2nd, 3rd, and 4th power respectively. And as any payoff function can be spanned by a continuum of OTM calls and puts (Bakshi and Madan, 2000), they build a model-free connection between the prices of OTM and higher-moment equity risk prices.

Bakshi *et al.* (2003), Dennis and Mayhew (2002) have demonstrated that risk-neutral higher-moments provide additional information on the equity market beyond what has been attributed to implied volatilities.

These encouraging findings call for further investigation regarding the information embedded in risk-neutral implied moments, and the ability of the higher-moments to explain Hedge Fund returns. In particular, we construct two variables accounting for the risk-neutral skewness and kurtosis[5] embedded in the time series of index option returns.

The theoretical values of the risk-neutral skewness (*NSK*) and kurtosis (*NKU*) for options with time-to-maturity τ are defined as follows (Bakshi *et al.*, 2003, Theorem 1):

$$NSK(\tau) = \frac{e^{r\tau}W(\tau) - 3\mu(\tau)e^{r\tau}V(\tau) + 2\mu(\tau)^3}{\left[e^{r\tau}V(\tau) - \mu(\tau)^2\right]^{3/2}} \tag{1}$$

$$NKU(\tau) = \frac{e^{r\tau}X(\tau) - 4\mu(\tau)e^{r\tau}W(\tau) + 6e^{r\tau}\mu(\tau)^2V(\tau) - 3\mu(\tau)^4}{\left[e^{r\tau}V(\tau) - \mu(\tau)^2\right]^2} \tag{2}$$

[5] We test this variable as well, unlike Dennis and Mayhew (2002) who restrict themselves to the estimation of the risk-neutral skewness.

where $V(\tau)$, $W(\tau)$ and $X(\tau)$ are the prices of the volatility, the cubic, and the quartic contracts, respectively, and are given by the following expressions:

$$V(\tau)=\int_{S(0)}^{\infty}\frac{2\left(1-\ln\left[\frac{K}{S(0)}\right]\right)}{K^2}C(\tau;K)dK+\int_{0}^{S(0)}\frac{2\left(1+\ln\left[\frac{K}{S(0)}\right]\right)}{K^2}P(\tau;K)dK \tag{3}$$

$$W(\tau)=\int_{S(0)}^{\infty}\frac{6\ln\left[\frac{K}{S(0)}\right]-3\left(\ln\left[\frac{K}{S(0)}\right]\right)^2}{K^2}C(\tau;K)dK-\int_{0}^{S(0)}\frac{6\ln\left[\frac{S(0)}{K}\right]+3\left(\ln\left[\frac{S(0)}{K}\right]\right)^2}{K^2}P(\tau;K)dK \tag{4}$$

$$X(\tau)=\int_{S(0)}^{\infty}\frac{12\ln\left[\frac{K}{S(0)}\right]^2-4\left(\ln\left[\frac{K}{S(0)}\right]\right)^3}{K^2}C(\tau;K)dK+\int_{0}^{S(0)}\frac{12\ln\left[\frac{S(0)}{K}\right]^2+4\left(\ln\left[\frac{S(0)}{K}\right]\right)^3}{K^2}P(\tau;K)dK \tag{5}$$

while $\mu(\tau)$ is given by:

$$\mu(\tau)=e^{r\tau}-1-\frac{e^{r\tau}}{2}V(\tau)-\frac{e^{r\tau}}{6}W(\tau)-\frac{e^{r\tau}}{24}X(\tau) \tag{6}$$

Similarly to the procedure adopted by Dennis and Mayhew (2002), we discretize the integrals of equations (3) to (5) through piecewise trapezoidal approximation.

For the estimation, we use a sample of daily prices of put and call options written on the S&P500 index option. The sample period ranges from January 1994 to January 2007. For each first trading day of the month (corresponding to the estimation date), we record the prices of the out-of-the-money (OTM) puts and calls for the option series maturing during the following month. This choice of option maturities yields a very high degree of liquidity for most options as well as a high range of strike prices for the OTM puts and calls. Every day, we record the prices for up to eleven different series of OTM calls and puts. The intervals between adjacent strike prices range from $5 in 1994 to $15 in 2006.[6] In case of missing values in the option time-series, the unavailable data are replaced by

[6] Most of the time, options with closer strike prices do not display sufficient liquidity to yield usable prices. Our choices of strike intervals aim at tracking the market tendency to consider only a subset of options that are actively traded at each date.

values from up to 3 days later. If the data are still not available, the observation is simply excluded from the analysis.

For each month, we estimate the implied risk-neutral skewness and kurtosis for the first three trading days of the month, and then take a simple average of the daily values. This procedure allows us to limit the microstructure issues (thin trading, limited number of options, and estimation error due to the trapezoidal approximation) as well as to diversify away a part of the measurement risk due to the very nonlinear structure of the skewness and kurtosis functions.

Note that to parameterize the trapezoidal estimation of the integrals in equations (3) to (5), we need two unobservable inputs: the option premium corresponding to an exactly at-the-money (ATM) option, and the strike price corresponding to an option premium that is not distinguishable from zero. This strike price is taken as the bound for the support of the integral.

The ATM option premium is simply obtained by taking a linear interpolation between the prices of the closest OTM (out-of-the-money) and ITM (in-the-money) options with respect to their implied volatilities. The most extreme strike price is obtained by a linear extrapolation between the current index price and the strike price of the deepest OTM option taken in the sample. Given the very low value taken by the deepest OTM option price, the numerical error incurred by this approximation is very low.

Risk-neutral volatility, skewness, and kurtosis correspond to the actual value of the payoffs of one contract over respectively the US market volatility, skewness, and kurtosis. Finally, we use the innovations in risk-neutral implied skewness and kurtosis, i.e. the first difference between monthly values of the measures given in equations (1) and (2), as candidate variables in our regression-based analysis. We call these variables the "risk-neutral moments" DNSK and DNKU, respectively.

See infra for a comparative descriptive analysis of the aforementioned factors with optional factors.

3.2.2. *Option-Based Factors*

The previous subsection demonstrates how distribution-based strategies can be employed to better understand the nonlinearities in Hedge Fund returns. In our analysis, we will also include more traditional option-based factors that have been traditionally used in the Hedge Fund literature to account for the nonlinear returns (for example Fung and Hsieh, 2001, 2002a,b; Mitchell and Pulvino, 2001; Agarwal and Naik, 2004; and Huber and Kaiser, 2004). We construct artificial option-based investment strategies.

i. The Returns on Artificial Index Options

In order to compute the returns on analytical option values, we implement a procedure that refines the one used by Glosten and Jagannathan (1994) and Agarwal and Naik (2001). At the beginning of each month, we identify the level of the S&P500 index. We then construct four sets of synthetic options with one-month to maturity: an at-the money put, an at-the-money call, an out-of-the-money put and an out-of-the-money call. The initial price of these options is calculated by the Black-Scholes formula using the continuously compounded 1-month T-bill rate (risk-free rate), the historical volatility on the S&P500 for the previous 12 months (volatility), and the contemporaneous value of the S&P500 index multiplied by 0.95 (for the OTM puts), by 1 (for the ATM options), and by 1.05 (for OTM calls) as the strike prices. We call AAMC, AAMP, AOMC and AOMP the series of realized returns on these artificial strategies.

ii. Stale Pricing Factor

Much concern about stale pricing in Hedge Fund returns has been expressed in the literature (Asness *et al.*, 2001; Conner, 2003). Indeed, as a part of their strategy, Hedge Fund managers can choose to invest in highly illiquid securities, or have the incentive (in order to increase their published performance) to smooth prices such that the effective volatility is reduced over time (Weisman and Abernathy, 2000). This has however serious consequences when determining the Hedge Fund return generating process since significant relationships can be understated by non-synchronicity between dependent and independent variables (Asness *et al.*, 2001) or strong serial correlation in Hedge Funds returns (Lo, 2002; Getmansky *et al.*, 2004)

As suggested in the very early literature on the issue, we could introduce in our model lagged version of the market returns (Fama, 1965; Fisher, 1966; Ibbotson, 1975; and Schwert, 1977; Scholes and Williams, 1977; Dimson, 1979). Asness *et al.* (2001) were the first to apply a correction of this type on Hedge Funds market betas. However, the US market premium is only appropriate for a category of funds pursuing long-only US equity strategy. In our case, extending this argument, synthetic option-based variables will account for the stale pricing effect. Therefore, we also store the lagged returns of artificial option indexes. We call LAMC, LAMP, LOMC, LOMP, the series of the lagged at-the-money call and put, and out-of-the-money call and put.

3.2.3. *Descriptive Analyses of Risk Factors*

The optional and distributional factors are intended to capture nonlinearities in returns. The two sets of factors provide very different yet equally valuable insights into the nature of these nonlinearities. The interesting feature that distribution-based factors provide is that they discriminate between the effects of skewness and kurtosis. The regression coefficients for the distributional factors capture the specific Hedge Fund loadings on forward-looking and backward-looking estimates of the volatility, skewness, and kurtosis US equity premiums. The option payoffs, however, do not dissociate the higher-moments, but provide an intuitive picture of the nature of the nonlinearity. The regression-based coefficients on the option contract time-series describes the trading strategy, by displaying a payoff profile that is similar to a short or long position (or combination of both) in these instruments.

We consider them together in a descriptive statistical analysis, shown in Table 3.

Table 3
Descriptive statistics of optional and distributional factors

Type	Symbol	Mean (%)	Med. (%)	Max (%)	Min (%)	S.D. (%)	Skew.	Kurt	J-B	ADF
Artificial ATM Calls	AAMC	0.918	0.354	50.723	-36.511	9.832	0.663	5.029	175.85***	-6.53***
Artificial ATM Puts	AAMP	1.076	-0.717	74.481	-45.488	13.207	1.3126	9.1098	584.22***	-6.53***
Artificial OTM Calls	AOMC	25.406	-0.436	2531.4	-97.730	208.492	11.365	136.933	125238***	-7.24***
Artificial OTM Puts	AOMP	63.312	-0.815	7947.7	-99 .801	638.560	12.302	152.81	155715.5***	-7.14***
Risk-Neutral Volatility	DVIX	-0.000	-0.030	19.480	-12.900	3.697	0.770	5.610	219.93***	-9.87***
Risk-Neutral Skewness	DNSK	-0.648	-3.271	213.474	-168.829	69.100	0.023	0.116	0.101	-10.91***
Risk-Neutral Kurtosis	DNKU	3.555	3.031	1127.765	-1414.86	35.674	-0.212	2.618	45.41***	-10.75***
Ex-Post Covariance	C	-0.098	0.333	16.739	-22.416	4.264	-1.445	11.266	498.45***	-4.25***
Ex-post Skewness	SK	0.140	0.076	5.170	-4.707	1.931	-0.021	2.606	1.020	-4.95***
Ex-post Kurtosis	KU	0.257	0.276	13.410	-11.668	3.427	0.164	6.406	76.120***	-5.59***

Table 3 reports some descriptive statistics for the non-directional factors. An Augmented (with more than one lag) Dickey-Fuller test for the rejection of a unit root is performed. The ADF statistics are reported. *S.D. = Standard Deviation, J-B = Jarque-Bera statistics.*

First, regarding the artificial option-contract time-series, out-of-the-money options present significantly higher returns over the period than at-the-money ones. Both the standard deviation and the kurtosis statistics are larger for out-of-the-money than for at-the-money options. Our results are consistent with Theorem II of Bakshi *et al.* (2003), which shows that more risk-neutral left-tail risk is associated with more empirical kurtosis risk. The proportion of risk-neutral left-tail risks has indeed been shown to be superior for out-of-the-money options. Second, risk-neutral indexes follow the investors' market sentiment about the expected prices of the second, third and fourth moments of the US stock market distribution. The innovations in the VIX index translate the expected change in the price of the market volatility. As investors dislike volatility risk, the mean of the VIX should be negative. The average change in the volatility contract was very close to zero over the period. As investors like positive skewness, the price of the risk-neutral skewness should be positive. The time-series of the innovations in risk-neutral skewness displays a negative value over the period. To earn return, Hedge Funds should thus be sellers of positive skewness, or buyers of negative skewness. The average change in risk-neutral kurtosis prices is positive, meaning that positive returns should be associated with a long exposure in kurtosis. Both the skewness and kurtosis contracts time-series are highly volatile.

The last part of the table focuses on the rewards related to the physical joint density of the US stocks with the market portfolio. We record a slightly negative average reward (the median value is however positive) related to a unitary comovement with the market, when the effects of coskewness and cokurtosis have been eliminated. The average equity coskewness risk premium is positive over the period. Finally, a strategy buying high cokurtosis and selling low ones was rewarded by a positive return. Note that all variables are stationary. They can thus be introduced into a return generating process intended to price Hedge Funds.

Moreover, given the complexities of this set of optional and distributional factors, it is relevant to identify the possible anteriority or causal-relationship between these factors. Therefore, we conduct Fisher tests with the null hypothesis of the absence of Granger causality among these factors. Each factor series is regressed on all one-month lagged optional and distributional premiums, including itself. The significance of all one-month lagged variables but itself is displayed in Table 4.

Table 4

Pairwise Granger causality tests on optional and distributional variables

Causal	LAMC	LAMP	LOMC	LOMP	AAMC	AAMP	AOMC	AOMP	DNVIX	DNSK	DNKU	C	SK	KU
AAMC	0.0133	0.2394	-0.0570	0.0169		-0.0144	0.1156***	-0.0341***	0.3610	-0.0212	-0.0070	0.4033*	-0.08299*	0.0988
AAMP	0.2627	0.1507	-0.1050	0.0324	0.1213		0.1756***	-0.0501***	0.3156	-0.0322	-0.0117	0.3344	-1.1785**	-0.0399
AOMC	4.2180	0.1574	-1.8484**	0.5752**	0.2063	-7.6865*		-1.0154***	-6.7985	0.2345	0.0185	-2.2117	-2.8171	-5.5937
AOMP	15.0820	-3.4649	-5.1479*	1.620*	6.3284	-24.6978	9.3769***		-25.9370	0.9089	0.1195	-9.9872	-2.8262	-20.0195
DNVIX	-0.0140	0.0508	-0.0295**	0.0091**	-0.2746***	-0.0083	0.0616***	-0.0184***		-0.0071	-0.0016	0.0172	-0.2639	0.0294
DNSK	0.7424	0.6508	-0.5513**	0.1635**	0.3670	-2.0843	0.4285*	0.4285*	4.4137**		-0.0434	-1.1635	-1.6749	1.3181
DNKU	0.3705	-5.3745	2.3735*	-0.6923*	-2.9777	11.0733*	-1.8984*	0.4819	-16.4630*	0.8126		1.8285	6.1823	-6.4558
C	-0.0102	0.0136	0.0019	-0.0010	0.2908**	-0.1535	-0.0256	0.0085	-0.0573	0.0089	0.007		-0.1405	0.1478
SK	0.0424	-0.0382	0.0047	-0.0015	0.0165	0.0192	-0.0139*	0.0041*	-0.0111	-0.0107	-0.0013	0.0020		0.1136
KU	-0.0616	0.0516	0.0100	-0.0034	0.1895**	0.0135	-0.0421***	0.0125***	0.1806*	-0.0331***	-0.0046*	0.0032	-0.0671	

Table 4 reports the Fisher t-stats for Granger causality tests on the non-directional variables. The first column designates the dependent variables. The variables on the line coordinates are the independent or causal variables. Each line reports the results of a regression of the dependent variables on the one-month lagged independent variables (including itself). * denotes a 10% significance level, ** denotes a 5% significance level, *** denotes a 1% significance level.

AAMC, AAMP, AOMC, AOMP = At-the-money call and put, and out-of-the-money call and put

LAMC, LAMP, LOMC, LOMP = Lagged option-based factors

DNVIX, DNSK, DNKU = Risk-neutral volatility, skewness, and kurtosis index

C, SK, KU = Ex-post covariance, coskewness, and cokurtosis premiums

The first note of interest is the strong significance of the artificial options for explaining both types of distributional factors. Among the distributional factors, the prices for risk-neutral moments are not determined by the US equity higher-moment factors. On the other side, the volatility, the skewness, and the kurtosis contracts have a strong impact on the returns attached to the historical US cokurtosis risk premium. This implies that the historical higher-moment risk premiums and the implied moments of Bakshi *et al.* (2003) are not capturing contemporaneous risk premiums. Risk-neutral moments provide information about future historical moments of the portfolio. For this reason, the empirical higher-moment risk premiums can be qualified as backward-looking, while the implied moment premiums are referred to as forward-looking factors. Bakshi *et al.* (2003) show how the first three moments of the risk-neutral distribution alter the physical density. Consistent with the Theorem II developed by these authors, less risk-neutral skewness shows up in more physical kurtosis.

3.3. Factor Correlations

To support the variable selection, Table 5 displays the correlation among Hedge Funds, among risk factors, and between the Hedge Funds and the risk factors. The color of the cells is darker as correlations approach 1 and lighter as correlations tend to -1.

Table 5

Correlations among Hedge Funds, between Hedge Funds and risk factors, and among risk factors

Panel A: Correlations among Hedge Fund strategies

Strategy	HFR Classification			
	EH	ED	M	RV
EH				
ED				
M				
RV				
FF				

Panel B: Correlations between Hedge Fund strategies and risk factors

	Asset-based factors								Optional and distributional factors													Conditioning factors			
Strategy	RUS	SMB	HML	UMD	WEX	WGBI	EMB	RCI	DNVIX	LAMC	LAMP	LOMC	LOMP	AATMC	AATMP	AOTMC	AOTMC	DNKU	C	SK	KU	ZC	ZR	ZS	ZV
EH																									
ED																									
M																									
RV																									
FF																									

EH= Equity Hedge, ED = Event Driven, M = Macro, RV = Relative Value, FF = Funds of Funds
RUS = Russell, SMB = Size factor, HML = Book-to-market factor, UMD = Momentum factor, WEX = Worldwide Equity Market Index ex. US, WGBI = Worldwide Government Bond Index ex. US, EMB = Emerging Market Bond Index, RCI = Recession Index
AAMC, AAMP, AOMC, AOMP = At-the-money call and put, and out-of-the-money call and put
LAMC, LAMP, LOMC, LOMP = Lagged option-based factors
DNVIX, DNSK, DNKU = Risk-neutral volatility, skewness, and kurtosis index
C, SK, KU = ex-post covariance, coskewness, and cokurtosis premiums
ZC = Credit spread, ZR = 3-month T-bill, ZS = Term spread, ZV = Volatility Index (information variables)

Table 5 (continued)

Panel C: Correlations among risk factors

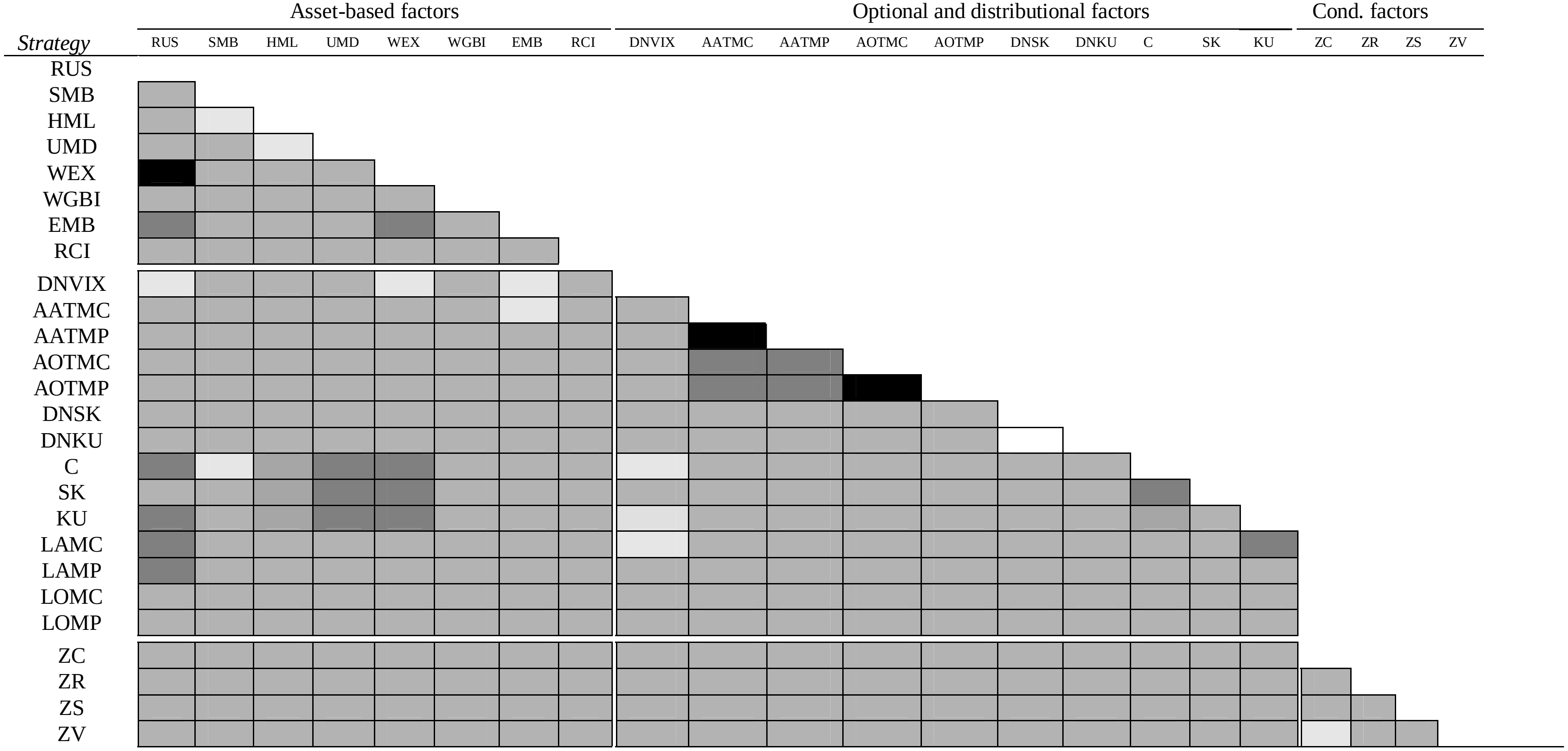

Table 5 reports the ranges of linear (Pearson) correlation coefficient ρ among Hedge Funds strategies (Panel A), between Hedge Funds strategies and risk factors (Panel B), and among risk factors (Panel C). Color codes for correlations are: strong positive correlation (ρ > 70%) in black ( ), moderate positive correlation (30% < ρ < 70%) in dark grey ( ), weak correlation (-30% < ρ < 30%) in medium grey ( ), moderate negative correlation (-70% < ρ < -30%) in light grey ( ), and strong negative correlation (ρ < -70%) in white ( ).

The interpretative value of the table is threefold. Panel A reports very high correlations among the five Hedge Fund portfolios. The Funds of Funds portfolio is highly correlated with all the other strategies, while the Equity Hedge portfolio displays a strong correlation with the Event Driven and the Macro portfolios. We expect to find similarities in risk exposures among these Hedge Fund strategies.

Panel B gives a first view on the return determinants of the five Hedge Funds portfolios analyzed. We obtain that very few strategies heavily load on one single factor, making it useful to introduce alternative risk premiums like optional or distributional factors into the model. Moreover, this analysis contributes to supply the framework against which we evaluate the significance of the risk premiums in the following sections.

First, most of the Equity Hedge Funds take directional bets in the worldwide stock market as expected from Chan *et al.* (2007). This explains the strong positive correlation of the funds returns with equity-style factors like the US and the worldwide market indexes. They are searching for undervalued securities and so express an above average positive correlation with the Fama and French size factor, are long in growth stocks, or invest in past winners. These results are intuitive as small caps are less invested in and thus tend to be more likely mispriced (Agarwal and Naik, 2000a; Jaeger and Wagner, 2005; Gatev *et al.*, 2006). To invest in past winners and growth stocks relies on the idea that stocks that have been penalized by the markets are likely to outperform. This explains the strong negative correlations of the strategy with the HML and UMD factors. With regard to the bond market, the style returns seem to be strongly related to the returns of the Emerging Market bonds. As a consequence, this portfolio displays a moderate positive correlation with the EMB factor. Moreover, strategies such as equity market neutral or long/short equity purposefully exploit tail risk in equity markets (Agarwal and Naik, 2000a; Amin and Kat, 2003b; Agarwal and Naik, 2004; Kat, 2005; Chan *et al.*, 2007). It is thus not surprising to find moderate levels of correlation of this investment style with artificial at-the-money options and the cokurtosis premium. The level of market volatility is also highly influencing this strategy as both the returns attached to the historical volatility and the level of volatility implied in option prices are moderately correlated with this Hedge Fund style.

Second, Event Driven Hedge Funds are actively searching for arbitrage in the stock and in the high yield bond markets, i.e. the Emerging Market bonds (Agarwal and Naik, 2000a,c; Jaeger and Wagner, 2005). This drives a very strong positive correlation with the Russell Index (Asness *et al.*, 2001) and moderate correlation levels with the MSCI Worldwide Market Index ex. US and the JP Morgan Emerging Market Bond Index. The important positive correlation with the size factor of Fama and French (1993) also finds support in Agarwal and Naik (2000b), Mitchell and Pulvino (2001), Agarwal and Naik (2004), and Jaeger and Wagner (2005). Besides, by focusing on risk arbitrage, Event Driven strategies are exposed to tail risk of the equity markets as it was the case for Equity Hedge Funds (Agarwal and Naik, 2000a; Amin and Kat, 2003b; Getmansky *et al.*, 2004; Kat, 2005). The strategy returns present significant relationship with artificial at-the-money options and with all the comoment premiums of Lambert and Hübner (2010). This comes in line with the results of Agarwal and Naik (2004) which record high level of excess kurtosis for this strategy. Finally, the exposure to market volatility appears also as a relevant fact to be exploited (Chan *et al.*, 2007).

Third, our Macro funds invest in the US and the worldwide stock markets, with a particular interest for small caps. High yield bond investments (proxied by the Emerging Market Bond Index) are also an integral part of their strategies. These results find support in Agarwal and Naik (2000a) and in Huber and Kaiser (2004). Contrary to both strategies exposed before, they exhibit very weak correlation with option-contract payoffs or distributional factors. They are however strongly influenced by the market volatility through moderate relationships with the VIX and the covariance premium.

Fourth, Relative Value funds exploit pricing discrepancies. They follow securities and/or bonds with similar fundamental values and, when their prices diverge, they buy undervalued securities and sell overvalued ones. From the table, Relative Value funds appear to be active in the US and the worldwide stock markets, with a particular interest for small caps and for implementing momentum strategies. Investments in high yield bonds are also important for this strategy. These correlations with the directional risk premiums are in line with the work of Agarwal and Naik (2000a, 2004), Jaeger and Wagner (2005), and Gatev *et al.* (2006). We record only weak levels of correlation with any of the non-directional premiums although high levels of negative skewness and strong excess kurtosis are expected for this strategy (Amin and Kat, 2003b; Agarwal and Naik, 2004; Huber and Kaiser, 2004; Getmansky *et al.*, 2004; Jaeger and Wagner, 2005).

Funds of Funds are active in quite a lot of equity and bond markets. They derive high levels of positive and negative correlation with the US and the worldwide stock markets, and also more specifically with factors such as the SMB, HML or UMD factors. High yield bonds are also invested in. Such a correlation structure is similar to the one displayed in Kouwenberg (2003). Moreover, Funds of Hedge Funds tend to exhibit lower skewness than the average individual fund (Amin and Kat, 2003b; Kat, 2005). Option-like features are thus expected in Hedge Fund return payoffs; it explains the moderate correlation of the Funds of Funds' portfolio with optional factors.

The last part of the table reports the correlations between the independent variables in order to investigate potential collinearity among the variables. Given the very large set of variables (8 asset-based factors, 14 option-based factors, and 5 conditioning variables that can be built with the choice between 4 instruments), it is necessary to ensure that the variables that are likely to be used simultaneously in a regression specification exhibit a reasonable degree of collinearity. We provide a visual summary of the results in the third Panel, highlighting in black and white the cells that are the most important.

Among asset-based factors, only the Russell and the WEX factors present a strong correlation. The problem is however more serious among the non-directional factors. We account for strong correlations between artificial at-the-money call and put, artificial out-of-the-money call and put, and finally between risk-neutral kurtosis and skewness. The problem is even more complex when we consider multiple moderate cross-correlations between the independent factors.

When used as independent variables in a time-series analysis, a complex correlated structure could mask some relevant and significant variables. Therefore, the methodology we construct to model the Hedge Fund return generating process must take the effects of collinearity into account. Moreover, historical higher-order comoments display multiple moderate correlations with traditional factors. Since there is evidence that the Fama and French empirical risk premiums could proxy for higher-order moment premiums (Barone-Adesi *et al.*, 2004; Chung *et al.*, 2006; and Hung, 2007), we do not consider the SMB, HML, and UMD factors as asset-based factors but through conditioning variables. Finally, due to the moderate correlation between the Russell index (or other stock market factors) and the covariance equity premium, we redefine the covariance premium as the residuals of the regression of the covariance premium on the market portfolio returns.

4. Performance Analysis

This section analyzes the different strategies according to the set of directional (i.e. asset-based and conditioning) and non-directional (i.e. distributional and optional) factors. Results are first presented for the five Hedge Fund investment styles using only asset-based factors coupled with information variables (see Table 6). We consider all possible combinations of variables, and finally select the one that maximizes (in absolute value) the Akaike Information Criterion for the linear regression[7]. We then proceed to find the "optimal" factor model which best fits each Hedge Fund style using a mixture of directional (asset-based and conditioning), distributional and optional factors (see Table 7). Finally, the marginal values of each family of non-directional factors, i.e. either the optional or the distributional factors with regard to directional factors are displayed (Table 8).

Our methodology departs from what has generally been done in the literature. Indeed, when confronted with such a large number of variables, most of the studies favour a stepwise regression approach (Liang, 1999; Agarwal and Naik, 2004) in order to select the explanatory variables. This approach starts with a general model that incorporates all variables and gradually eliminates the least relevant. However, given the presence of complex multicollinearities in the variables (see the results of Table 5) the stepwise regression procedure does not necessarily deliver an optimal output as it may result in the erroneous elimination of some interesting explanatory variables. Even though multi-collinearity does not interfere with the reliability of the model estimates, it almost surely affects the precision of our estimates. In other words, some significance can be masked by complex multicollinearity across variables and could lead to wrongly eliminate one relevant factor. It also does not even inform about which explanatory variables are redundant and which are in fact relevant among the non significant variables. Therefore, we prefer to perform all the possible regressions and identify the one that best describes each strategy.

[7] The AIC measures the goodness of fit of the model. It is defined as a negative function of the log likelihood of the model and it penalises the model for its number of factors.

4.1. Asset-Based Factors and Time-Varying Exposures

Table 6 presents, for each strategy, the combination of asset-based (with conditioning variables) factors that maximizes (in absolute value) the Akaike Information Criterion for the linear regression. The top half of the table displays the estimated coefficients for the asset-based factors and the bottom half presents the estimated coefficients for the information variables used to condition some of the directional exposures.

Table 6

Regression results using asset-based factors and conditioning variables

	HFR Classifications				FF
	EH	ED	M	RV	
Assets					
RUS	0.3105***	0.2153***			
WEX	0.1326***		0.2450***	0.0870***	0.1514***
WGBI			-0.2818	0.1783**	
EMB	0.0513*	0.0690***	0.2632***	0.0281*	0.0931
RCI					
Instruments					
ZCRUS				-2.7329**	
ZRRUS			59.4301**		27.2843*
ZVRUS					
ZCSMB					
ZRSMB	101.4266***	30.1275*		27.6097**	43.1398**
ZSSMB			1.7649		
ZCHML					
ZRHML	-48.68063**				-29.2844*
ZSHML				1.8384*	
ZCUMD	5.2813**				
ZRUMD					
ZSUMD				1.5492*	
ZVUMD			1.3162*		
ZCEMB					
ZREMB					
ZSEMB	-4.9171***	-2.7226***	-2.9654	-3.1493	-3.4592**
ZVEMB					
Adj. R^2	**74.22%**	**58.03%**	**55.91%**	**37.25%**	**55.64%**
Static α	**0.0084*** **	**0.0070*** **	**0.0076*** **	**0.0060*** **	**0.0037*** **
Dynamic α	**0.0084* **	**0.0070*** **	**0.0075*** **	**0.0060*** **	**0.0037*** **

Table 6 reports the estimated coefficients for the models made of the subset of directional and conditional factors that best describes each Hedge Fund strategy. The static and the dynamic alpha estimates can be modeled such as in eq. (7) (see infra). *, ** and *** stand for significant at 10%, 5%, and 1%, respectively. *See the list of acronyms at the end of this chapter for the names of the variables.*

The adjusted R-squares range from a low 37.25% for the Relative Value funds to a high 74.22% for the highly directional portfolio of Equity Hedge Funds. This is consistent with the descriptive statistics presented in Table 1, which has identified Relative Value funds as being the strategy that displays the most non-directional risk exposures. It is therefore not entirely surprising to find, for this strategy, poor explanatory power from a set of exposures to directional factors.

These results provide important information as to the source of the returns of the different strategies. The Emerging Market Bond Index, the Russell, the SMB factor, the MSCI World Index ex. US are the most common risk factors independently of the type of strategy. The sign and magnitude of the estimated coefficients are also coherent with our expectations.

First, as was expected from previous studies, Equity Hedge Funds mostly invest in equity markets. They continuously hold a certain level of investment in the domestic US market but also in worldwide stock markets. They also trade in stocks with particular risk profiles such as small capitalisations, growth stocks, and momentum stocks. Furthermore, they time their exposure to the Emerging Bond markets based on the liquidity of the market.

Second, the results for the Event Driven Hedge Fund portfolio are consistent with previous findings in the literature. This strategy focuses on identifying specific trading opportunities that are the result of inefficiencies or temporary market dislocations. Event Driven Hedge Funds focus heavily on trades within the domestic (RUS) equity market. One such trade that stands out is the exposure to the differential in performance between small and large stocks. They are also present in the Emerging bond markets, which are rich in market inefficiencies.

Third, the Macro Hedge Fund portfolio searches for macroeconomic trends in the domestic stock market, but also in the worldwide stock and Emerging bond markets. These funds present a particular interest in going long small caps and short big caps, long momentum stocks and short contrarian strategies. The bond market is also very attractive for this investment style.

Fourth, Relative Value funds search for valuation discrepancy in multiple securities (stocks and bonds). As expected, these Hedge Funds are active in the US and the worldwide equity and bond markets. They adjust their exposure to the US market with respect to the evolution of the credit quality of this market. Moreover, they attempt to profit from price disparities between small and big caps, growth and value caps, winners and losers. The importance of these investment opportunities will mostly vary according to the level of liquidity in the market.

Finally, Funds of Funds take multiple directional bets in the US domestic market, in the Emerging bond and the worldwide stock markets.

The last two lines report the alpha coefficients under two alternative specifications. The static alpha (penultimate line) represents the intercept of the regression that only uses the directional and conditioning risk premiums defined above (lagged instruments x risk premiums) as dependent variables, while the dynamic alpha (last line) represents the intercept of the same regression with the use of time-varying alphas to account for market timing of managers, as in Christopherson *et al.* (1998):

$$\alpha' = \alpha_0 + (Z_{t-1} - \overline{Z})\alpha_1 \tag{7}$$

where $\alpha_1 = 0$ for static α and $\alpha_1 \neq 0$ for the dynamic estimate of α .

The difference between the two series of alphas is very small, meaning that the full static alpha can be attributed to manager skills rather than to market timing.

The positive and mostly significant alpha coefficients would indicate that these indices offer superior returns. The magnitude varies from 37 basis points per month for the Funds of Funds to 84 basis points per month for the Equity Hedge Funds. This confirms the study of Liang (1999) on the impact of the double fee structure of Funds of Funds on their performance.

4.2. Directional and Non-Directional Factors

This section studies the relevance of adding non-directional factors to the directional regression-based analysis displayed in Table 6. To judge of the explanatory power of distributional factors, both directional (asset-based and conditioning factors) and non-directional (optional and distributional) exposures must be used together in a composite model in order to avoid an “exclusion-restriction” effect that would confuse market timing with nonlinearity of another nature (Jagannathan and Koraczyk, 1986).

Table 7 maps the risk exposures displayed by each Hedge Fund strategy of the *HFR* Classification. It presents the results of a model made of the best combination among all the asset-based, optional, distributional, and conditioning factors for pricing Hedge Funds. Put differently, the table displays, for each strategy, the subset of factors that best describes the Hedge Funds returns.

Table 7

Regression results using directional and non-directional factors

	HFR Classifications				FF
	EH	ED	M	RV	
Assets					
RUS	0.2870***	0.2110***	0.1210*	0.0699**	0.1131***
WEX	0.1410***		0.1489**	0.0667***	0.1213***
WGBI			-0.3884**	0.1697**	
EMB	0.0654**	0.06332***	0.3079***	0.0425**	0.0997***
RCI					
Non-directional					
AAMC				-0.0249***	
AAMP		-0.0151***			
AOMC	-0.0072**			0.0075***	-0.0075***
AOMP	0.0020**			-0.0023***	0.0022***
DNVIX	0.0912**		0.1392**	0.0472**	0.1087***
DNSK	0.0027*	0.0028***			0.0025**
DNKU					
C					
SK	0.0917*	0.1203***	0.1516**		
KU	0.0927**				
LAMC		-0.0129		-0.0338**	-0.0156*
LAMP				0.0205*	
LOMC					
LOMP					
Instruments					
ZCRUS					
ZRRUS	29.3294				
ZSRUS				-1.6934*	
ZVRUS			-1.4735*		
ZCSMB					
ZRSMB	110.3265***	45.3037***		27.2116**	60.2374***
ZSSMB			1.8376		
ZCHML					
ZRHML	-31.7758		-71.4007**		-29.0686**
ZSHML					
ZCUMD	5.3520**			2.2162*	3.4147**
ZRUMD			-39.6644		
ZSUMD					
ZVUMD					
ZCEMB					
ZREMB			64.4724**		
ZSEMB	-4.2737***	-2.1502**		-2.2446**	-2.9366***
ZVEMB					
Adj. R^2	**77.31%**	**63.84%**	**58.32%**	**41.36%**	**65.44%**
Static α	**0.0086*****	**0.0073*****	**0.0070*****	**0.0056*****	**0.0038*****
Dynamic α	**0.0086*****	**0.0072*****	**0.0068*****	**0.0056*****	**0.0037*****

Table 7 reports the estimated coefficients for the models made of the subset of directional, conditional, optional, and distributional factors that best describes each Hedge Fund style. The static and the dynamic alpha estimates can be modeled such as in eq. (7). *, ** and *** stand for significant at 10%, 5%, and 1%, respectively. *See the list of acronyms at the end of this chapter for the names of the variables.*

Given the large number of explanatory variables considered, we employ an iterative procedure. The iterations consist in limiting the conditioning variables to those selected in Table 6, while the subset of distributional, optional, and asset-based factors that maximises (in absolute value) the Akaike Information Criterion is extracted. Then, we find the subset of conditioning factors that maximises the Akaike Information Criterion for the previous selection of directional, distributional, and optional factors. Repeating this successively, we obtain the subset of factors that maximises the Akaike Information Criterion among all the possible regressions based on directional, optional, distributional and conditioning factors.

We compare the levels of explanatory power obtained in Table 7 to the ones displayed in Table 6 in order to infer the marginal explanatory power attached to non-directional factors. These nonlinear regressors raise the specification level of the model of each corresponding strategy from 2.41% (for the Macro funds), i.e. 58.32%-55.91%, up to 9.80% (for the Funds of Funds), i.e. 65.44%-55.64%. It is important to note that all Hedge Funds strategies maintain their exposure towards the directional factors, when non-directional factors are added.

Previous empirical studies show that Equity Hedge Funds tend to exhibit high volatility, mitigated levels of skewness[8] (depending on the sub-strategy that is followed), and significant positive excess kurtosis[9]. We record in our sample the expected high volatility and excess kurtosis, at the same time as slightly negative skewness (see Table 1). From our regression-based analysis, Equity Hedge Funds present a significant positive exposure to the changes in the risk-neutral volatility price. The main objective of Equity Hedge Funds is to identify mispricing in the equity market; it is only natural that the

[8] Mitigated levels in skewness risk is due to the heterogeneity in the exposures of the different funds within the category (Agarwal and Naik, 2001; Getmansky *et al.*, 2004). Equity hedge or short selling strategies for example are exposed to slightly positive skewness, whereas equity non-hedge strategies exploit tail risk in equity (Agarwal and Naik, 2000b; Liang, 2003; Agarwal and Naik, 2004)

[9] See Fung and Hsieh (1999), Agarwal and Naik (2000c), Asness *et al.* (2001), Favre and Galeano (2002), Amin and Kat (2003b), Agarwal and Naik (2004), and Kat (2005).

securities that they buy and sell exhibit higher volatility as their prices need to revert to their fundamental values. Moreover, Equity Hedge Funds style exhibits only a small left-asymmetry (compared to other Hedge Funds styles) over the period. On the one hand, under- and overvaluations are often found in not frequently traded stocks like small stocks or stocks in distress; therefore, by investing in these stocks they also buy negative skewness risk. Moreover, by being long in OTM put options and short in OTM call options, with more calls than puts, their strategy is similar to taking a short position in the underlying asset, i.e. S&P 500, with a residual short position in call options. Such a strategy is particularly exposed to tail risk: a large market increase would lead to huge losses. On the other hand, some sub-strategies hedge a part of their tail-risk exposure by taking a long position (of 0.27%) in positive skewness. Finally, by simultaneously purchasing volatility and skewness, they increase the dispersion in the tail of the distribution. These funds earn 9% of the coskewness risk premium and about the same percentage of the cokurtosis risk premium.

Liang (2003) provides evidence of strong nonlinearities in the return structure of Event Driven funds. In up markets, the performance of these funds is generally uncorrelated with the equity market, whilst in down markets, these strategies present a strong positive correlation. Our regression-based analysis confirms these expectations. By taking a short position in put options, the Event Driven Hedge Funds portfolio creates payoffs that are a concave function of the S&P 500. This is similar to selling positive skewness, or buying skewness risk. Indeed, if the underlying prices stay stable or increase, the strategy earns the premium from writing the put option. However, in time of huge volatility, a decrease in the level of the S&P 500 would lead to huge losses. This is why Event Driven portfolios are said to be long (negative) skewness risk. To hedge a part of their tail risk exposure, they buy positive skewness (as shown from their significant positive loading on the implied skewness factor). However, consistently with Table 1, Event Driven funds display a positive loading on the US equity coskewness premium. Although not statistically significant, the coefficient of the lagged artificial at-the-money call highlights the expected illiquid exposures of Event Driven strategies.

Third, Macro Fund managers are expected to experience slightly positive skewness and significant excess kurtosis[10]. However, the Descriptive Statistics displayed in Table 1 indicate a significant negative skewness for this strategy. This can be explained in part by the large proportion of the Emerging market funds that make up this category. Indeed, Emerging Market funds typically exhibit negative skewness but also large excess kurtosis (see Amin and Kat, 2003b). Like in Fung and Hsieh (1999), these funds principally bet on volatility in the markets they invest in; they present thus a positive loading on the implied volatility index. Macro funds attempt to identify macroeconomic trends in different markets. They generally lever their position and as a result, generate a left-skewed payoff profile. According to Dittmar (2002), skewness risk must be rewarded by a positive premium; the premium explains 15% of the Macro fund returns.

Fourth, the payoff distribution of the Relative Value portfolio is expected to be left- and fat-tailed[11] (see also Table 1). Furthermore, volatility levels similar to the ones displayed by bonds appear to be a relevant feature of the strategy (Amin and Kat, 2003b). From our composite model, Relative Value funds appear to display very small exposures to directional factors. Moreover, they are shown to trade actively in skewness risk. On the one hand, Relative Value Hedge Funds conduct a strategy that buys positive skewness (or sells skewness risk) by respectively taking a short OTM put and a long OTM call position on the S&P500. This is the opposite of what we observed for the Equity Hedge category. On the other hand, as a result of stale pricing, these Hedge Funds are still influenced by a

---

[10] See Agarwal and Naik (2001), Favre and Galeano (2002), Amin and Kat (2003b), Getmansky *et al.* (2004), Huber and Kaiser (2004).

[11] See Agarwal and Naik (2001), Barry (2002), Favre and Galeano (2002), Lhabitant and Learned (2002), Amin and Kat (2003b), Agarwal and Naik (2004), Huber and Kaiser (2004), Gupta and Liang (2005), Jaeger and Wagner (2005).

lagged long exposure to an ATM put option and a short exposure to an ATM call option; this is informative about the residual exposure of an earlier purchase of skewness risk. This explains why it is difficult to detect significant exposure to the US equity skewness premium, even though the payoff profiles of the funds that make up this category are particularly left-tailed. Finally, as they bet on the value convergence between different financial instruments they display a positive loading on the implied volatility index.

Applying the same reasoning as for Equity Hedge Funds with regard to their option-like strategy, Funds of Hedge Funds appear to be buyers of negative skewness. Like in Equity Hedge Funds, they hedge their exposure to tail risk by taking a long position in positive skewness, i.e. in the implied skewness factor of Bakshi *et al.* (2003). Moreover as Funds of Hedge Funds are conducting strategies like momentum, arbitrage, etc. whose success rely on sufficient market volatility, they are frequently trading in volatility risk. Therefore, they display a positive and significant exposure to the implied volatility of Bakshi *et al.* (2003). A significant exposure to a lagged ATM call option shows that risk is smoothed over time.

Having identified, using the different types of factors, the composite model that best explains Hedge Fund risk exposures for the different styles, we will now focus on the residual returns which cannot be explained by systematic exposures to risk factors. Under the assumption that the model is well-specified, this excess return is generally attributed to manager skill. The Equity Hedge portfolio outperforms all the other alternative strategies. The worse performer is our portfolio of Funds of Funds. This is not surprising as these funds operate a double-fee structure.

The final important issue that needs to be addressed regarding the two new sets of distributional factors is to decompose the marginal values of each family of non-directional factors in the composite model. Table 8 displays the incremental significance of all three families of non-directional factors regarding directional factors.

Table 8

Incremental significance of non-directional factors regarding directional factors (excess table)

Ptf.	Directional Factors R^2	Directional and Non-Directional Factors						$IUP_{NonDir.}$	$IUP_{Historic}$	$IUP_{Neutral}$
		Asset	Instruments	Optional	Distributional		R^2			
					Historic	Neutral				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
EH	74.22 %	+ 66.10 %	+ 8.07 %	+ 0.65 %	+ 0.71 %	+ 1.78 %	77.31 %	11.99 %	2.82 %	7.07 %
ED	58.03 %	+ 55.83 %	+ 2.2 %	+ 2.21 %	+ 2.03 %	+ 1.57 %	63.84 %	13.84 %	5.11 %	3.45 %
M	55.91 %	+ 53.33 %	+ 2.7 %	+ 0 %	+ 0.79 %	+ 1.5 %	58.32 %	5.47 %	1.80 %	3.41 %
RV	37.25 %	+ 26.72 %	+ 9.98 %	+ 3.3 %	+ 0 %	+ 1.36 %	41.36 %	6.55 %	0 %	2.27 %
FF	55.64 %	+ 46.95 %	+ 8.84 %	+ 3.18 %	+ 0 %	+ 6.47 %	65.44 %	22.09 %	0 %	15.77 %

Table 8 reports the incremental explanatory power of adding successively asset-based factors, instruments, optional factors and the two new sets of variables: the moment-related factors and the implied moments. The set of variables corresponds to those selected in Table 7. The table reports in column (8) the change in the adjusted R-square due to the introduction of the non-directional factors with regard to the directional factors, i.e. (7)-(2+3). Columns (9) and (10) compare the incremental R-square related to, respectively, historical comoment (5) or implied moment (6) premiums relatively to a model made of asset-based, option-based factors and instruments, i.e. (2) + (3) + (4). This information is summarized in the Incremental Unexplained Proportion (IUP) defined as

$$IUP = \frac{\overline{R}^2_{with} - \overline{R}^2_{no}}{1 - \overline{R}^2_{no}}$$

Neutral = Implied volatility index (DNVIX), implied skewness index (DNSK) and implied kurtosis index (DNKU); Historic = Cov (C), Skew (SK), Kurt (KU) premiums

EH = Equity Hedge, EV = Event Driven, M = Macro, RV = Relative Value, FF = Funds of Funds

Column (8) of Table 8. shows that all three families of non-directional factors significantly improve the explanatory power of a simple directional model. The strongest non-directional exposure is found in the portfolio of Funds of Hedge Funds. We record an increase in the adjusted R-square of more than 22% when adding non-directional factors in the directional model used for explaining this category of Hedge Fund. The improvement in R-square is also particularly high for Event Driven (13.84%) and the Equity Hedge strategies (11.99%). The improvement brought by the implied moments of Bakshi *et al.* (2003) on a traditional benchmark model used throughout the literature (i.e. a model made of directional, optional, and conditioning factors) is particularly interesting for the Fund of Hedge Funds (15.77%) and the Equity Hedge (7.07%) strategies; the implied volatility index is significant for all strategies but the Event Driven funds, while the implied skewness is relevant for estimating Funds of Funds, Equity Hedge and Event Driven funds. Finally, the backward-looking moment-related premiums, especially the coskewness premium, also improve the specification of a traditional benchmark model for the Equity Hedge, the Event Driven, and the Macro strategies.

5. Concluding Remarks

Hedge Funds display a strong nonlinear structure of returns, resulting in significant higher-order moments (than the variance statistic) in their return distribution. Without being exhaustive, the following reasons have been advanced in the literature for explaining this evidence. First, Hedge Funds follow very dynamic investment strategies, replicating option-like payoffs. Second, they have fewer restrictions on the use of leverage, short selling, and derivatives. Finally, they massively invest in not frequently traded securities.

As a consequence, some corrections should be made to traditional models (mostly based on linear comovements with market indexes) in order to take into account the nonlinear comovements of Hedge Funds with market indexes. The literature has been used to capture these nonlinearities by considering option-contract series in traditional asset pricing models.

In this paper, we evaluate the relevance of higher-order moment market models for evaluating the Hedge Fund nonlinear structure of returns, in addition to a set of factors frequently used in the literature on Hedge Fund asset pricing (asset-based, conditioning, and optional factors). Put another way, we examine whether systematic skewness (3rd comoment) and kurtosis (4th comoment) are priced in Hedge Fund returns. On the one hand, we evaluate the incremental explanatory value of the US higher-order comoment equity risk premiums of Lambert and Hübner (2010). These premiums are backward-looking estimates of the rewards attached to respectively a unitary covariance, coskewness, and cokurtosis with the stock market portfolios. On the other hand, we investigate the marginal explanatory power of the risk-neutral implied moments of Bakshi *et al.* (2003). These premiums are forward-looking estimates of the prices for volatility, skewness, and kurtosis in the US equity market.

It is shown that option-based factors are not able to capture all non-normalities in Hedge Fund returns. Especially, our findings suggest that US higher-moment systematic factors can help explaining the return-generating process of Hedge Funds. They can be usefully added to benchmark models for evaluating Hedge Funds.

References

Ackermann, C., McEnally, R. and Ravenscraft, D. (1999) The Performance of Hedge Funds: Risk, Return, and Incentives, *Journal of Finance* 54(3), 833-874.

Agarwal, V., Bakshi, G. and Huij, J. (2008), Higher-Moment Equity Risk and the Cross-Section of Hedge Fund Returns, unpublished working paper, London Business School.

Agarwal, V. and Naik, N. (2000a) Generalized Style Analysis of Hedge Funds, *Journal of Asset Management* 1(1), 93-109.

Agarwal, V. and Naik, N. (2000b) Multi-Period Performance Persistence Analysis of Hedge Funds, *Journal of Financial and Quantitative Analysis* 35(3), 327-342.

Agarwal, V. and Naik, N. (2000c) On Taking the “Alternative” Route: Risks, Rewards, and Performance Persistence of Hedge Funds, *Journal of Alternative Investments* 2(4), 6-23.

Agarwal, V. and Naik, N. (2001), Characterizing Hedge Fund Risks with Buy-and-Hold and Option-based Strategies, unpublished working paper, London Business School.

Agarwal, V. and Naik, N. Y. (2004) Risks and Portfolio Decisions Involving Hedge Funds, *Review of Financial Studies* 17(1), 63-98.

Ajili, S. (2005), Size and Book to Market Effects vs. Coskewness and Cokurtosis in Explaining Stock Returns, unpublished working paper, Université Paris IX Dauphine – CEREG, presented to the Northeast Business and Economics Association, 32nd annual conference, Newport, Rhode Island, USA.

Amenc, N., Martellini, L. and Vaissié, M. (2003) Benefits and Risks of Alternative Investment Strategies, *Journal of Asset Management* 4(2), 96-118.

Amin, G. and Kat, H. (2003) Stocks, Bonds, and Hedge Funds, not a Free Lunch, *Journal of Portfolio Management* 29(4), 113-120.

Ang, A., Bekaert, G. and Wei, M. (2007) Do Macro Variables, Asset Markets, or Surveys Forecast Inflation Better?, *Journal of Monetary Economics* 54(4), 1163-1212.

Arditti, F. D. (1967) Risk and the Required Return on Equity, *Journal of Finance* 22(1), 19-36.

Arditti, F. D. (1969) A Utility Function Depending on the First Three Moments: Reply, *Journal of Finance* 24(4), 720.

Asness, C., Krail, R. and Liew, J. (2001) Do Hedge Funds Hedge?, *The Journal of Portfolio Management* 28(1), 6-19.

Bakshi, G. and Madan, D. (2000) Spanning and Derivative-security Valuation, *Journal of Financial Economics* 55(2), 205-238.

Bakshi, G., Kapadia, N. and Madan, D. (2003) Stock Return Characteristics, Skew Laws, and the Differential Pricing of Individual Equity Options, *Review of Financial Studies* 16(1), 101-143.

Barone-Adesi, G., Gagliardini, P. and Urga, G. (2004) Testing Asset Pricing Models with Coskewness, *Journal of Business and Economic Statistics* 22(4), 474-485.

Barry, R. (2002), Hedge Funds: A Walk Through The Graveyard, unpublished working paper, MAFC Research Paper No. 25, Macquarie University Applied Finance Center.

Bondarenko, O. (2006), Market Price of Variance Risk and Performance of Hedge Funds, unpublished working paper, University of Illinois at Chicago, Northwestern University.

Brealey, R. A. and Kaplanis, E. (2001), Changes in the Factor Exposures of Hedge Funds, unpublished working paper, London Business School.

Busse, J. A. (1999) Volatility Timing in Mutual Funds: Evidence from Daily Returns, *Review of Financial Studies* 12(5), 1009-1041.

Capocci, D. and Hübner, G. (2004) Analysis of Hedge Fund Performance, *Journal of Empirical Finance* 11(1), 55-89.

Carhart, M. M. (1997) On Persistence in Mutual Fund Performance, *Journal of Finance* 52(1), 57-82.

Chan, N., Getmansky, M., Haas, S. and Lo, A. (2007), Systemic Risk and Hedge Funds, in: M. Carey and R. Stulz (eds.), *The Risks of Financial Institutions and the Financial Sector*, Chicago, IL: University of Chicago Press.

Chen, Y. and Liang, N. Y. (2007) Do Market Timing Hedge Funds Time the Market, *Journal of Financial and Quantitative Analysis* 42(4), 827-856.

Chen, Z. and Knez, P. (1996) Portfolio Performance Measurement: Theory and Applications, *Review of Financial Studies* 9(2), 511 – 555.

Christopherson, J.A., Ferson, W. E. and Glassman, D. (1998) Conditioning Manager Alphas on Economic Information: Another Look at the Persistence of Performance, *Review of Financial Studies* 11(1), 111–142.

Christopherson, J.A., Ferson, W.E. and Turner, A. L. (1999) Performance Evaluation Using Conditional Alphas and Betas, *Journal of Portfolio Management* 26(1), 59-72.

Chung, Y. P., Johnson, H. and Schill, M. J. (2006) Asset Pricing when Returns are Nonnormal: Fama-French Factors versus Higher-Order Systematic Comoments, *Journal of Business* 79(2), 923-940.

Conner, A. (2003) Asset allocation Effects of Adjusting Alternative Assets for Stale Pricing, *Journal of Alternative Investments* 6(3), 42-52.

Dennis, P. and Mayhew, S. (2002) Risk-neutral Skewness: Evidence from Stock Options, *Journal of Financial and Quantitative Analysis* 37, 471-493.

Dimson, E. (1979) Risk Measurement when Shares are Subject to Infrequent Trading, *Journal of Financial Economics* 7(2), 197-226.

Dittmar, R. F. (2002) Nonlinear Pricing Kernels, Kurtosis Preference, and Evidence from the Cross-Section of Equity Returns, *Journal of Finance* 57(1), 369-403.

Fama, E. F. (1965) The Behavior of Stock Market Prices, *Journal of Business* 38(1), 34-105.

Fama, E. F. and French, K. R. (1993) Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics* 33(1), 3-56.

Fama, E. and MacBeth, J. (1973) Risk, Return, and Equilibrium: Empirical Tests, *Journal of Political Economy* 81(3), 607-636.

Favre, L. and Galeano, J. A. (2002) Mean-Modified Value-at-Risk Optimization with Hedge Funds, *Journal of Alternative Investments* 5(2), 21-25.

Ferson, W. and Schadt, R. (1996) Measuring Fund Strategy and Performance in Changing Economic Conditions, *Journal of Finance* 51(2), 425-461.

Fisher, L. (1966) Some New Stock-Market Indexes, *Journal of Business* 39(1), 191-226.

Fung, W. and Hsieh, D. (1997) Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds, *Review of Financial Studies* 10(2), 275-302.

Fung, W. and Hsieh, D. (1999) A Primer on Hedge Funds, *Journal of Empirical Finance* 6(3), 309-331.

Fung, W. and Hsieh, D. (2001) The Risk in Hedge Fund Strategies: Theory and Evidence from Trend-followers, *Review of Financial Studies* 14(2), 313-341.

Fung, W. and Hsieh, D. (2002a) Risk in Fixed-Income Hedge Fund Styles, *Journal of Fixed Income* 12(2), 6-27.

Fung, W. and Hsieh, D. (2002b) Asset-Based Style Factors for Hedge Funds, *Financial Analysts Journal* 58(5), 16-27.

Gatev, E., Goetzmann, W. N. and Rouwenhorst, K. G. (2006) Pairs Trading: Performance of a Relative-Value Arbitrage Rule, *Review of Financial Studies* 19(3), 797-827.

Getmansky, M., Lo, A. and Makarov, I. (2004) An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns, *Journal of Financial Economics* 74(3), 529-609.

Glosten, L. and Jagannathan, R. (1994) A Contingent Claim Approach to Performance Evaluation, *Journal of Empirical Finance* 1(2), 133-160.

Gupta, A. and Liang, B. (2005) Do Hedge Funds have Enough Capital? A Value-at-Risk Approach, *Journal of Financial Economics* 77(1), 219-253.

Harvey, C. R. and Siddique, A. (2000) Conditional Skewness in Asset Pricing Tests, *Journal of Finance* 55(3), 1263-1295.

Huber, C. and Kaiser, H. (2004) Hedge Funds Risk Factors with Option-like Structures: Examples and Explanations, *Journal of Wealth Management*, 7(3), 49-60.

Hung, D. C.-H. (2007), Momentum, Size and Value Factors versus Systematic Comoments in Stock Returns, unpublished working Paper, Durham University.

Ibbotson, R. G. (1975) Price Performance of Common Stock New Issues, *Journal of Financial Economics* 2(3), 235-272.

Jaeger, L. and Wagner, C. (2005) Factor Modeling and Benchmarking of Hedge Funds: Can Passive Investments in Hedge Funds Strategies Deliver?, *Journal of Alternative Investments* 8(3), 9-36.

Jagannathan, R. and Korajczyk, R. A. (1986) Assessing the Market Timing Performance of Managed Portfolios, *Journal of Business* 59(2), 217-235.

Jean, W. H. (1971) The Extension of Portfolio Analysis to Three or More Parameters, *Journal of Financial and Quantitative Analysis* 6(1), 505-515.

Kat, H. (2005) Integrating Hedge Funds into the Traditional Portfolio, *Journal of Wealth Management* 7(4), 51-57.

Kat, H. and Miffre, J. (2002), Performance Evaluation and Conditioning Information: the Case of Hedge Funds, unpublished working Paper, ICMA Centre Discussion Papers in Finance, School of Business, Reading University.

Kat, H. and Miffre, J. (2006), Hedge fund performance: The Role of Non-Normality Risks and Conditional Asset Allocation, unpublished working Paper, Cass Business School, City University, London Faculty of Finance.

Kazemi, H. and Schneeweis, T. (2003), Conditional Performance of Hedge Funds, unpublished working Paper, University of Massachusetts at Amherst.

Kole, E. and Verbeek, M. (2006), Crash Risk in the Cross Section of Stock Returns, unpublished working Paper, Erasmus University Rotterdam.

Kouwenberg, R. (2003) Do Hedge Funds Add Value to a Passive Portfolio? Correcting for Non-Normal Returns and Disappearing Funds, *Journal of Asset Management* 3(4), 361–382.

Lambert, M. and Hübner, G. (2010), Comoment Risk and Stock Returns, unpublished working Paper, Luxembourg School of Finance, University of Luxembourg.

Latané, H. A. and Rendleman, R. J. (1976) Standard Deviations of Stock Price Ratios Implied in Option Prices, *The Journal of Finance* 31(2), 369-381.

Leland, H. E. (1999) Beyond Mean-Variance: Performance Measurement in a Nonsymmetrical World, *Financial Analysts Journal* 55(1), 27-36.

Levy, H. E. (1969) Comment: A Utility Function Depending on the First Three Moments, *Journal of Finance* 24(4), 715-719.

Lhabitant, F. S. and Learned, M. (2002) Hedge Fund Diversification: How Much is Enough?, *Journal of Alternative Investments* 5(3), 23-46.

Liang, B. (1999) On the Performance of Hedge Funds, *Financial Analysts Journal* 55(4), 72-85.

Liang, B. (2003), On the Performance of Alternative Investments: CTAs, Hedge Funds, and Funds-of-Funds, unpublished working Paper, University of Massachusetts at Amherst – Department of Finance & Operations Management, China Academy of Financial Research (CAFR).

Lintner, J. (1965) The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets, *Review of Economics and Statistics* 47(1), 13-37.

Lo, A. (2002) The Statistics of Sharpe Ratios, *Financial Analysts Journal* 58(4), 36-52.

Mitchell, M. and Pulvino, T. (2001) Characteristics of Risk and Return in Risk Arbitrage, *Journal of Finance* 56(6), 2135-2175.

Moreno, D. and Rodriguez, R. (2009) The Coskewness Factor: Implications for Performance Evaluation, *Journal of Banking and Finance* 33(9), 1664-1676.

Mossin, J. (1966) Equilibrium in a Capital Asset Market, *Econometrica* 34(4), 768-783.

Rubinstein, M. E. (1973) The Fundamental Theorem of Parameter-Preference Security Valuation, *Journal of Financial and Quantitative Analysis* 8(1), 61-69.

Scholes, M. and Williams, J. (1977) Estimating Betas from Nonsynchronous Data, *Journal of Financial Economics* 5(3), 309–328.

Schwert, G. W. (1977) Stock Exchange Seats as Capital Assets, *Journal of Financial Economics* 4(1), 51-78.

Scott, R. C. and Horvath, P. A. (1980) On the Direction of Preference for Moments of Higher Order than the Variance, *Journal of Finance* 35(4), 915-919.

Sharpe, W. F. (1964) Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk, *Journal of Finance* 19(3), 425-442.

Weisman, A. and Abernathy, J. (2000) The Dangers of Historical Hedge Fund Data, *Journal of Investment Consulting* 4(1).