Risk and Performance Estimation in Hedge Funds: Evidence from Errors in Variables*

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Abstract

This paper revisits the performance of hedge funds in presence of errors in variables. To reduce the bias induced by measurement error, we introduce an estimator based on cross sample moments of order three and four. This technique has significant consequences on the measure of factor loadings and the estimation of abnormal performance. Large changes in alphas can be attributed to measurement errors at the level of explanatory variables. Thanks to a recursive regression algorithm, we manage to keep the number of estimated coefficients reasonable while not significantly altering the economic relevance of the higher moment estimation procedure.

Keywords: Errors in variables; Measurement errors; Hedge fund performance; Asset pricing models

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1. Introduction

Early research on hedge fund performance, such as the papers by Fung and Hsieh (1997) and Liang (1999), attempted to decompose the required returns on hedge fund strategies through linear combinations of returns on different asset classes such as stocks, bonds, and commodities. Regardless of the strategy under study, these traditional sets of factors could not yield significance levels (as measured by the adjusted R-square) higher than 80%, even with as many as 11 risk premia.

To improve on the static factor model, two streams have developed in the literature. A first approach is to relax the assumption of constant exposures to the risk factors. This can be done by measuring regime-switching betas, as in Edwards and Caglayan (2001) and Capocci, Corhay and Hübner (2005) who measure different betas in up and down markets, or by allowing for time-varying betas. This approach is advocated by Fung and Hsieh (2004) and Posthuma and van der Sluis (2005) in a Kalman filtering approach. Amenc and Vaissié (2006) combine a mixture of Kalman smoothing and regime switching models.

The other approach aims at capturing the nonlinear risk exposures of hedge fund returns through the factor premia themselves, leaving the betas constant. Mitchell and Pulvino (2001) introduce piecewise linear regressions to account for non-linearities in hedge fund returns for risk arbitrage strategies. Fung and Hsieh (2000, 2004) introduce risk premia accounting for option straddles for trend-following funds, as these strategies tend to exhibit payoffs that resemble long option positions. In a similar vein, Agarwal and Naik

(2004) use a framework that applies the option strategies proposed by Glosten and Jagannathan (1994) to estimate the returns of exchange-traded calls and puts. Finally, Chan et al. (2005) apply a regime-switching multi-moments model to hedge fund returns.

Irrespective of the approach considered, a highly non-normal behavior of returns is likely to flaw statistical inference if there is evidence of measurement errors in the explanatory variables. These errors influence the point estimators of the risk factor loadings. Errors in the variables may lead to the non convergence of the OLS estimator, very often used in the financial literature, casting doubt on the results. Paradoxically, few theoretical and applied efforts have been made to reduce this important bias. Fama and Mac Beth (1973) try to reduce measurement errors, grouping equities in portfolios. Shanken (1992) suggests to adjust standard errors to correct biases induced by errors in variables. Kandel and Stambaugh (1995) use a GLS method, but a difficult estimation of covariance matrix is needed.

Unfortunately, the measurement error issue is very likely to arise in the analysis of hedge fund returns. In particular, the option-based factors used in the empirical specifications are highly prone to measurement errors as they combine the characteristics of being artificial variables and of following highly skewed and leptokurtic distributions. Furthermore, option-based factors tend to be highly correlated with their corresponding asset-based factors, raising potentials concerns for multicolinearity. In this context, as shown by Fung and Hsieh (2000, 2004) and by Agarwal and Naik (2004), neither the Sharpe ratio, nor Jensen’s alpha are likely to adequately measure abnormal performance with the Ordinary Least Squares (OLS). Any properly designed performance measure has indeed to account for the significant skewness and kurtosis displayed by hedge fund returns. Thus, the proper treatment of measurement errors appears to be of particular importance in the context of the assessment of hedge fund required returns and performance.

In this paper, we propose the use of estimators based on moments of order higher than two proposed by Cragg (1994, 1997), Dagenais and Dagenais (1997), and Lewbel (2006) to solve this issue. Dagenais and Dagenais's (1997) higher moment estimator (HM) belongs to the class of instrumental variables (IV) estimators. Although instrumental variables can resolve in principle the error-in-variables problem, in practice many difficulties remain. Among them, finding instruments and proving their validity is not always easy in practice[1].

An attractive feature of Dagenais and Dagenais estimator is that no extraneous information is required since instruments are constructed from the higher moments (skewness, kurtosis and over) of the original data. This approach should arouse interest not only because the method is quite simple to implement but also because an estimation technique based on the higher moments of asset returns echoes the fundamental contribution of Samuelson (1970), demonstrating that the first two moments of asset returns do not offer a complete description of portfolio risk. This point is well acknowledged in the financial literature[2].

Yet, the Dagenais and Dagenais (1997) method displays a practical drawback. For each independent variable used in the original return generating process, the corrected estimator generates a new regressor that specifically accounts for the estimated measurement error. This mechanical adjustment doubles the number of variables and may

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[1] See Pal (1980) for further details.

[2] The paradigm of portfolio selection based on the first two moments of the returns distribution does not describe well reality: see Huang and Litzenberger (1987) among others.

lead to a serious model overspecification. In that respect, the remedy could be worse than the pain. We propose a simple method to circumvent this issue by setting up a recursive regression algorithm that gradually unfolds the set of independent variables. This procedure allows us to reap the best of both the HM and OLS worlds, as it ensures a proper care of the measurement errors while limiting the inflation in the variables to what is strictly necessary to optimize the significance level of the regression.

We apply this approach to a set of hedge fund indexes constructed with equally weighted hedge fund portfolios. Unlike the investable indexes that can be retrieved by data providers, this database most closely resembles portfolio returns that researchers typically use in empirical studies. Doing so, we can assess the impact of our procedure for research purposes. We estimate the return generating process with a mix of asset- and option-based explanatory factors.

Our results indicate that the correction for measurement errors that we perform has a significant impact on the performance measurement of hedge fund strategies, especially when option-based strategies are considered. Thus, beyond the methodological improvements brought in by the higher moment estimation approach, it strongly modifies the vision of economic performance of the hedge funds industry. Furthermore, the recursive regressions algorithm practically reduces the number of variables in most cases, leaving the economic interpretation of the risk premia unchanged, while improving the significance of the return generating process.

The article is organized as follows. Section 2 introduces the econometric method. Section 3 contains the description of data, the risk factors (buy-and-hold and option-based) and the theoretical framework. In Section 4, we present the model in presence of error-in-variables, and the results are reported. Section 5 analyzes the choice of factor loadings when measurement errors are detected and discussed the stability of risk premia. Section 6 provides conclusive remarks and suggestions for future research.

2. Linear multifactor model with errors in the variables

2.1. Higher moment estimators

With the fundamental work of Frisch (1934), the analysis of measurement errors in the regressors, also called errors-in-variables (EIV), initially played a central at the early stages in econometrics. It is well known in the economic literature that EIV tend to lead to inconsistent ordinary least squares (OLS) estimators in linear regression models. Nevertheless, as underlined by Cragg (1994) and Dagenais and Dagenais (1997), the problem of EIV have been neglected thereafter. This general neglect of EIV arises from a certain misunderstanding of the problem. Treatments of measurement error are usually put in the context of a bivariate (i.e. one-factor) linear model. In this particular context, two effects can be reported. The first effect is labelled "attenuation effect" by Cragg (1994): measurement error biases the slope coefficient toward zero. The second effect is called "contamination effect": measurement error "*produces a bias of the opposite sign on the intercept coefficient when the average of the explanatory variables is positive*[3]". The contamination effect seems to be neglected and many focus only on the attenuation effect. Since the "attenuation effect" appears not to change coefficient sign, errors-in-variables seem at worst to give rise to conservative estimates. Moreover, given that the extent of the attenuation effect is negatively related to the regression R^2, High R^2 are indicative of negligible attenuation effect. As highlighted by Cragg (1994), the

3 Cragg (1994), p. 780.

conclusions of the bivariate case do not generalize easily to multiple regressions with measurement error in more than one variable. Cragg (1994, 1997) demonstrates that the bias of any given parameter depends on its own error (the attenuation effect) but also on the errors in all others variables (the contamination effect). Because of the contamination effect, all parameters of a multiple regressions are inconsistent even if only one variable is measured with error. Dagenais and Dagenais (1997) argue that errors-in-variables also have more perverse effects on confidence intervals and on the sizes of the type I errors.

Most data used in empirical economics suffer from the problem of errors-in-variables. In finance and especially for asset pricing models this problem is crucial. With the CAPM, and Roll's (1977) famous critique, the unobservability of the true market portfolio illustrates the presence of errors-in-variables. In this context, the market factor is measured with error, and estimated of the market beta certainly suffer from the problems listed in previous paragraphs. Theses problems can be generalized to more general linear multifactor model of asset returns such as Ross (1976)'s Arbitrage Pricing Theory or Fama and French (1993)'s model.

Errors-in-variable become important in the estimation of linear asset pricing models because they induce a correlation between residuals and regressors that lead to biased and inconsistent parameter estimates.

The problem of errors-in-variable in a finance context can be illustrated through the estimation of the following multifactor model of asset return[4], R_t.

$$R_t = \alpha + \sum_{k=1}^{K} \beta_k \cdot \tilde{F}_{kt} + u_t \qquad (1)$$

[4] Here, we consider only errors in independent variables. As it is well known in the econometric literature (see Davidson and MacKinnon (2004) for example), there is no bias when only the dependent variable is plagued with measurement errors.

where α is a constant term, $\tilde{F}_{tk}$ is factor *k* realization in period *t*, β_k is factor *k* loading and u_t is a residual idiosyncratic risk.

This formulation encompasses many popular models of asset returns. For instance, the CAPM is obtained if *K*=1 and $\tilde{F}_{1t}$ is the market return. The parameter α is known as the security's abnormal return, also called Jensen's alpha.

The parameters of model (1) can be consistently estimated by ordinary least squares (OLS) if the *K* factors $\tilde{F}_{kt}$ are observed by the analyst. Ordinary least squares are no longer consistent if some or all factors $\tilde{F}_{kt}$ are unknown and estimation and inference are based on observed factors F_{kt} instead. To demonstrate this point, suppose all factors are unobserved and the relationships between true and observed factors are additive.

$$F_t = \tilde{F}_t + v_t \qquad (2)$$

where F_t, $\tilde{F}_t$ and v_t are column vectors holding respectively the *K* observed factors, the *K* true factors and the *K* measurement errors. Assume further that v_t has mean zero and variance matrix equal to Σ_{VV}. The measurement errors (v_t) are moreover assumed to be independent through time and uncorrelated[5] with the true unobserved variables, $\tilde{F}_t$, and the residual idiosyncratic risk, u_t.

To highlight the consequence of measurement errors on estimation, we rewrite (1) in vector form.

$$R_t = \alpha + \tilde{F}_t \cdot \beta + u_t \qquad (3)$$

and substitute (2) in (3).

[5] The measurement error is said to be "classical" when it is uncorrelated with the true unobserved factor.

$$R_t = \alpha + F_t \cdot \beta + u_t - v_t \cdot \beta \qquad (4)$$

The OLS estimates $\hat{\alpha}$ and $\hat{\beta}$ are inconsistent because the compound error in (4), $u_t - v_t.\beta$, is correlated with the regressor F_t through the measurement error v_t [6]. In the presence of errors-in-variable, factor loading estimates are contaminated by attenuation and contamination bias mentioned above.

Without further assumptions, parameters of the errors-in-variable model (1) and (2) are not identified. As suggested by the literature, the standard solution to this identification problem is to introduce additional moment conditions. More specifically, if there are instrumental variables correlated with the true regressors but unrelated to the measurement errors, then adding these moments can help to solve the identification problem.

Many studies (see e.g. Fuller (1987), Bowden (1984) and Aigner et al. (1984)) have suggested the use of instrumental variables[7] to obtain consistent estimators, when information on the variances of these errors is not available. Despite these suggestions, instrumental variables techniques are often neglected and no special effort is made to test for the presence of error-in-variables[8]. As highlighted in Pal (1980), it may be not easy to verify that available instruments satisfy the required conditions to justify their use. But the main problem faced by researchers is the practical difficulty of finding valid instruments. On the other hand, as underlined by Klepper and Leamer (1984), they may

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[6] The nature and extend of the bias is obtained by computing the asymptotic value of the OLS estimates. They converge to their true value if true factors are observable. For a demonstration, see Carmichael and Coën (2006).

[7] Alternative approaches to the errors in variables problem may be mentioned: Frisch (1934), Klepper and Leamer (1984), Hausman and Watson (1985), and Leamer (1987) among others.

[8] Using for example Hausman's (1978) instrumental variable test.

feel that the cost of collecting additional data would be too large in comparison to the benefit derived from the fact of possibly producing more accurate estimators.

If the distributions of explanatory variables ($\tilde{F}_t$ in our financial context) are non Gaussian in the sense that they are skewed and have non Gaussian excess kurtosis, then Cragg (1997) and Dagenais and Dagenais (1997) show that own and cross third and fourth moments of these explanatory variables are valid instruments that can be used as additional moment restrictions to consistently estimate the model parameters α and β.

Following Durbin (1954) and Pal (1980), Dagenais and Dagenais (1997) introduce new unbiased higher moment estimators exhibiting "*considerably smaller standard errors*". Under the hypothesis of no measurement error in the variables, the estimators introduced by Durbin (1954) and Pal (1980) are unbiased. But, as demonstrated by Kendall and Stuart (1963) and Malinvaud (1978), these higher moments estimators have higher standard errors than the corresponding least squares estimators, and may be described as more erratic. Taking into account this feature, Dagenais and Dagenais (1997) develop a new instrumental variable estimator, β^{HM}, which is a linear matrix combination of the generalized version of β_d, Durbin's estimator, and $\beta_{p,}$ Pal's estimator.

Dagenais and Dagenais's estimator can most easily be computed by means of artificial regressions as suggested by Davidson and MacKinnon (1993). The first step consists in constructing estimates $\hat{F}_{kt}$ of the true regressors. This is done with K artificial regressions having F_{kt} as dependent variables and third and fourth moments (own and cross moments) of F_{kt} as regressors. These are then used to construct measures of the error-in-variables $\hat{w}_{kt} = F_{kt} - \hat{F}_{kt}$. The latter are then introduced as additional regressors, called the adjustment variables, in equation (5) as follows:

$$R_t = \alpha + \sum_{k=1}^{K} \beta_k^{HM} \cdot F_{kt} + \sum_{k=1}^{K} \psi_k \cdot \hat{w}_{kt} + \varepsilon_t \tag{5}$$

The contribution of this procedure is twofold. First, we can test the null hypothesis (H_0: $\hat{w}_{tk} = 0$, k = 1,...,K) that there are no errors-in-variables applying a Durbin-Wu-Hausman type test. Second, if errors-in-variables are detected, the estimator is automatically corrected to take into account this bias. As mentioned earlier, Dagenais and Dagenais (1997) demonstrate that this higher moment estimator (HME) (hereafter labelled β^{HM}) performs better than ordinary least squares estimators. Moreover, if there is no error in variables, then it is the same as OLS.

Therefore, we can implement the following decision rule in our asset pricing context. If H_0 cannot be rejected for factor loadings, we must use the OLS estimator, otherwise we use the higher moment estimator, β^{HM} developed by Dagenais and Dagenais (1997).

2.2. The recursive regression algorithm

The expanded regression model displayed in equation (5) accurately transforms the linear asset pricing model to account for measurement errors. Unfortunately, the cost of this operation is a considerable inflation in the number of independent variables. As each regressor is flanked with a twin variable, a K-factor model becomes a $2K$-modified model. Although this can be econometrically justified, the lack of significance of some adjustment variables might hinder the economic relevance of the expanded model.

We propose a recursive method to reduce the number of variables. The principle of the algorithm is to detect the adjustment variable that exhibits the lowest significance level. If the corresponding original variable were not prone to measurement error, it would have been more effective to use the OLS instead. As a check, we subtract the OLS term corresponding to this independent variable (regression coefficient times the observation) from the value of the dependent variable, and define a new dependent variable equal to this difference. We then run the HM estimation again on this new variable with the remaining regressors. The procedure stops when the significance level of the new model becomes lower than the former specification.

Formally, the algorithm goes as follows:

1. We start from the estimation of equation (5):

$$R_t = \hat{\alpha}^{HM} + \sum_{k=1}^{K} \hat{\beta}_k^{HM} \cdot F_{kt} + \sum_{k=1}^{K} \hat{\psi}_k \cdot \hat{w}_{kt} + \varepsilon_t \tag{6}$$

   which corresponds to the OLS specification:

$$R_t = \hat{\alpha}^{OLS} + \sum_{k=1}^{K} \hat{\beta}_k^{OLS} \cdot F_{kt} + \upsilon_t \tag{7}$$

   Note that, unlike equation (1), we use the observed values of the factors and not the (unobservable) true values $\tilde{F}_{kt}$.

2. We identify the risk premium F_i such that the estimated coefficient of the corresponding adjustment variable, $\hat{\psi}_i$, is the least significant (using the t-stat of the regression).[9]

[9] Alternatively, we could review all adjustment variables and proceed with steps 3 to 5 of the algorithm. The removed risk premium is the one that maximizes the pseudo-adjusted R^2 of the new regression. Our tests suggest that this increase in sophistication does not improve the results, as the final specification remains unchanged.

3. Then, we subtract the *i*-th value risk premium, estimated with the OLS regression (7), from the fund returns.
4. We then reuse the HM estimation equation on this new model:

$$R_t - \hat{\beta}_i^{OLS} \cdot F_{it} = \hat{\alpha}^{HM,1} + \sum_{\substack{k=1 \\ k \neq i}}^{K} \hat{\beta}_k^{HM,-i} \cdot F_{kt} + \sum_{\substack{k=1 \\ k \neq i}}^{K} \hat{\psi}^{-i}{}_k \cdot \hat{w}_{kt} + \vartheta_t \qquad (8)$$

5. If the significance level of the new regression, estimated by its adjusted R-squared, is higher than the one of the previous HM estimation model, we repeat the algorithm back from step 1 replacing equation (6) by equation (8); otherwise, we stop and keep the previous specification.

To estimate the significance level of this new regression equation with D removed variables ($D < K$), we get the unadjusted R^2 by simply computing $R^2 = 1 - \frac{\hat{\sigma}_\vartheta^2}{\hat{\sigma}_R^2}$, where $\hat{\sigma}_\vartheta^2$ is the variance of residuals from regression (6) and $\hat{\sigma}_R^2$ is the variance of the original returns. The pseudo-adjusted R^2 is then computed as Ps.$\overline{R}^2 = \frac{1-(2K-D)}{T-(2K-D)} + \frac{T-1}{T-(2K-D)} R^2$ where T is the number of observations, K is the number of original risk factors, and D is the number of adjustment variables removed from the model.

3. Data and empirical methods

3.1. Hedge Funds Data

We use the Barclay Group database with monthly net returns on 2,617 funds belonging to 11 strategies: Event Driven (EDR), Funds of Funds (FOF), Global (GLO), Global Emerging Markets (GEM), Global International Markets (GIN), Global Macro (GMA), Global Regional Established (GES), Long Only Leveraged (LOL), Market Neutral

(MKN), Sector (SEC), and Short Selling (SHO) for the period January 1994 to December 2002. Out of these funds, 1,589 were still alive at the end of the period and 1,028 funds had ceased reporting before the end of the time window. Funds that reported less than one consecutive year of returns have been removed from the database[10]. Data from the same period were used by Cappoci, Corhay, and Hübner (2005) with the Managed Account Reports (MAR) database, and have been found to be relatively reliable in returns of survivorship and instant return history biases.

The series of dependent variables in our regression are built by computing the equally weighted average monthly returns of all funds, either living or dead, that follow a particular strategy during a given month.

3.2. Risk Factors

To implement the estimation procedure and the recursive regression algorithm, we use an extended version of the Fama-French (1992) – Carhart (1997) linear asset pricing model. We start the implementation with the four-factor model proposed by Carhart (1997), supposedly achieving better significance levels than the Fama and French (1993) specification for hedge fund returns (see Agarwal and Naik, 2004; Capocci and Hübner, 2004). This market model is taken as the benchmark of a correctly specified model. Its equation is:

$$R_t = \alpha + \beta_m MKT_t + \beta_s SMB_t + \beta_h HML_t + \beta_u UMD_t + \varepsilon_t \qquad (9)$$

where R_t is the hedge fund return in excess of the 13-weeks T-Bill rate, MKT_t is the excess return on the market index proposed by Fama and French (1993), SMB_t is the

[10] This treatment explains why we have a lower number of funds remaining than in Capocci, Corhay, and Hübner (2005).

factor-mimicking portfolio for size (‘*small minus big*’), HML_t is the factor-mimicking portfolio for the book-to-market effect (*‘high minus low’*), and UMD_t = the factor-mimicking portfolio for the momentum effect (*‘up minus down’*). Factors are extracted from French's website.

This specification typically achieves significance levels that can easily be improved with style-based indexes. Among them, Capocci and Hübner (2004) show that an additional factor accounting for the emerging bond market investment strategy triggers a major shift in the explanatory power of the hedge fund return regressions. Consequently, we choose this particular asset-based index as the fifth regressor.

Finally, we introduce and option-based factor as the sixth regressor. To make sure that the way this variable is constructed does not unduly alter the analysis, we propose two alternative characterizations.

First, we construct monthly returns from index options with a procedure similar to the one put forward by Agarwal and Naik (2004) to build two series of actual returns of at-the-money (ATM) put and call options. As options are never perfectly ATM, we approximate each option closing price on the last trading day of the month with a linear interpolation of the closest in-the-money (ITM) and out-of-the-money (OTM) option prices. The next month, we use the same technique to obtain the closing price. This method ensures the time consistency of the series of options used. We apply a similar for OTM puts and calls, where the strike price is 5% away from the current value of the index. The choice of this degree of moneyness is consistent with the results empirically derived by Diez de los Rios and Garcia (2005). The variables corresponding to these series of options are called ACr, OCr, APr and OPr for ATM and OTM calls and ATM and OTM puts, respectively.

Next, we compute artificial option returns with a procedure that refines the one used by Glosten and Jagannathan (1994). Each month, we identify the value of the S&P500 index. We then construct four sets of synthetic options with one-month to maturity: an ATM put, an ATM call, an OTM put and an OTM call. The initial price of these options is proxied by using the Black-Scholes formula with the continuously compounded 1-month T-bill rate (risk-free rate), the historical volatility on the S&P500 (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 ACa, OCa, APa, OPa the series of realized returns on these artificial strategies.

The most comprehensive specification is a six-factor model depicted in equation (10).

$$R_t = \alpha + \beta_m MKT_t + \beta_s SMB_t + \beta_h HML_t + \beta_u UMD_t + \beta_e EMB_t + \beta_o Opt_t + \varepsilon_t \quad (10)$$

where *Opt* is the option-based factor among ACr, OCr, APr, OPr, ACa, OCa APa, and OPa that provides the highest level of information in the regression. The estimated regression coefficients will be noted $\hat{\alpha}^{OLS}$ and $\hat{\beta}_k^{OLS}$ for $k \in \{m, s, h, u, e, o\}$.

Similarly, the HM specification used to estimate the same model has the following form:

$$\begin{aligned} R_t &= \alpha + \beta_m MKT_t + \beta_s SMB_t + \beta_h HML_t + \beta_u UMD_t + \beta_e EMB_t + \beta_o Opt_t \\ &+ \psi_m \hat{w}_{mt} + \psi_s \hat{w}_{st} + \psi_h \hat{w}_{ht} + \psi_u \hat{w}_{ut} + \psi_e \hat{w}_{et} + \psi_o \hat{w}_{ot} + \varepsilon_t \end{aligned} \quad (11)$$

where $\hat{w}_{kt}$ are the adjustment variables for $k \in \{m, s, h, u, e, o\}$. Again, the estimated regression coefficients will be noted $\hat{\alpha}^{HM}$, $\hat{\beta}_k^{HM}$ and $\hat{\psi}_k$ obtained by applying Dagenais and Dagenais's (1997) artificial regression technique.

Thanks to this new approach, we shed a new light on absolute returns, comparing $\hat{\alpha}^{OLS}$ with $\hat{\alpha}^{HME}$. Furthermore, we can assess the value-added of the alternative estimation procedure by comparing their significance levels. We suggest the use of the following decision rule: if presence of errors in variables is statistically significant, use HM estimator; if not, OLS estimator can be used. We can note that HM estimator gives the same result as the OLS estimator in perfect absence of errors in variables. This point can be interpreted as an illustration of the superiority of HM and empirically confirms Dagenais and Dagenais' numerical and simulated results: "*The relative performance of HM estimators is always superior to that of OLS estimators, when there are errors in variables*[11]". Of course, the consequences of wrong decisions based on linear asset pricing models are straightforward in the financial industry.

3.3. Descriptive Statistics

The descriptive statistics of our sample are given in Table 1. Our database includes a substantially higher number of dead funds (+446) than in the MAR database used by Capocci, Corhay, and Hübner (2005), especially for the global established (+97 dead funds), funds of funds (+77), and market-neutral (+72) strategies.

[Please insert Tables 1/A and 1/B]

Consistently with previous studies, some strategies appear to achieve extremely favorable performance for all measures. Sector, Global Established, Global Emerging, and Market Neutral strategies exhibit average monthly returns greater than 1 percent. The Sharpe ratio of Market Neutral funds is up to eight times greater than that of the market proxy.

[11] Dagenais and Dagenais (1997), p. 209.

Event-Driven, Sector, Global Established, Macro and Funds of Funds strategies also obtain Sharpe ratios more than twice higher than the market proxy. Thus, a classical model-free performance measure suggests that there might be significant abnormal performance present in hedge fund returns.

[Please Insert Table 1/C]

As acknowledged by a growing literature, the two first moments of returns are insufficient to provide a good description of risk Descriptive statistics reported in Table 1/B confirm this view and cast doubt on the normality of the returns and the risk factor loadings. Errors in variables may be induced by this very restrictive assumption, suggested by traditional linear asset pricing models[12], but will be corrected with HM estimators. To test for the normality of the distributions we use a series of tests (Jarque-Bera, Lilliefors, Cramer-von Mises, Watson, and Anderson-Darling). Results are conclusive: we can reject the hypothesis of normality for all strategies (except short selling) and risk premia, with the exception of the HML factor. This indicates that higher moments (than the variance) of the regressors are highly likely to influence hedge funds performance measurement.

[Please insert Tables 2/A and 2/B]

The correlation between and among hedge and among risk factors is reported in Tables 2/A and 2/B. The correlations between the regressors and the hedge fund returns do not exceed 0.80, except Long Only Leveraged and Global Established, which display high correlations with the market proxy. The correlation among the asset-based regressors is low, thereby raising no serious concern about multicolinearity. Nevertheless, the introduction of an option-based factor induces a high correlation with the market excess

[12] The CAPM and the FF model are the common choice.

return variable (MKT), especially when an ATM option is used. Furthermore, these mutlicolinearity problems also exist among option-based factors. This feature of optional factors suggests that one should be particularly cautious when interpreting regression coefficients arising from a specification using several option-based factors, such as in Agarwal and Naik (2004) or Bailey, Li and Zhang (2004).

4. Multifactor Model and Results

The HM estimation procedure entails that the regression results are directly comparable with the OLS results for each original asset pricing specification. Thus, we run OLS on our four-, five- and six-factor models depicted above, and compare the significance levels achieved with the HME procedure. We use a standard F-test to detect the presence of errors-in-variables: we test for $\Sigma_k \psi_k = 0$. All F-stats are statistically significant at 1% level, highlighting the presence of errors-in-variables in all regressions. OLS estimates are biased. The results are presented in Table 3.

[Please insert Table 3]

We split this table in three panels: Panel A displays strategies for which the lowest significance levels are achieved ($\overline{R}^2$ below 70% for the 6-factor OLS model). In Panel B, results are displayed for $\overline{R}^2$ between 70% and 80%. Finally, strategies achieving the highest significance levels ($\overline{R}^2$ > 80%) are reported in Panel C.

Panel A reports a consistent result regarding the additional information brought by HME for the Market Neutral and three internationally driven (Global, Global International and Global Macro) strategies. The 6-factor HME specification always dominates the corresponding 6-factor OLS, with an increase in the $\overline{R}^2$ ranging between 0.1% and 5.4%, despite the fact that all variables are duplicated with the HM characterization, increasing the number of coefficients from 7 to 13. Significance levels are only close for the Global International strategy, as indicated by the insignificance of each coefficient of the adjustment variables. For the other three strategies displayed in the panel, there are between one and four significant loadings for the adjustment variables.

Some coefficients that used to be significant with OLS might not be anymore under HME. This phenomenon is particularly noteworthy for the Market Neutral strategy, where out of the five significant OLS coefficients, only two of them (the HML and EMB coefficients) remain significant with HME. The association of adjustment variables with the original factors may thus induce a dilution effect among the variables.

Oppositely, some coefficients that are insignificant with OLS may become significant with HME. This phenomenon happens with the UMD coefficient for the Global strategy and with the MKT coefficient for the Global Macro strategy. In such cases, the corresponding adjustment variables pick up most of the coefficient variance and the factor loading is estimated with greater precision.

Finally, some OLS coefficients are seen to lose their significance because the measurement error is responsible for the effect. This is the case with the option-based factor coefficient for the Global strategy and with the MKT coefficient for the Global Macro strategy. In these cases, the sign of the coefficients of the original and the adjustment factors are opposite.

In Panel B, we obtain qualitatively similar results for those strategies that had already fairly high significance levels with OLS. The significance gains are limited (between 0.9% and 3.2%) due to the fact that OLS performed relatively well already. We observe that with the option-based factor coefficient for Global Emerging and with the HML coefficient for Short Sales, the coefficient is insignificant with OLS but the coefficients for both the original factor and the adjustment variable become strongly significant, although with opposite signs, with the HME specification. For these strategies, our results suggest that the OLS coefficient hides two opposite effects, one for raw factor risk and one for measurement risk, that tend to compensate each other if the risk exposures are not separated.

Panel C displays a particular result regarding the Long Only Leveraged strategy: it is the only one for which the OLS specification dominates HME. Adjustment variable coefficients are insignificant, while some OLS coefficients lose their significance under HME. As this strategy most closely resembles long portfolios held by mutual funds whose market exposures are relatively well under control, such a result is not very surprising. For the other two strategies, the gains from HME are not very large but positive. For Sectors, as for the Global Emerging strategy in Panel B, the OLS coefficient of the HML variable is not significantly different from zero but both corresponding coefficients under HME are significant and of opposite signs.

When considering Table 3 globally, one also gets some useful insight in terms of strategy performance. Aside from the Long Only Leveraged strategy where OLS dominates, the account for measurement errors in the HME specification appears to generate higher alphas for all but the Sectors strategy, where it decreases by 25 bps per months. Yet, the level of alpha gains is limited, as they range from 2.6 bps (for Global International) to 25 bps (for Short Sales).[13] This finding reflects the underlying interpretation of the

[13] The peaking monthly 1.335% vs 0.338% for the Global strategy is a clear outlier with respect to the rest of the table. This is probably due to the fact that this strategy mostly consists of dead funds, as the funds

interference of measurement errors in the original OLS specification. Once their effect is removed and transferred in the adjustment variables, the sources of risk exposures are magnified and the generation of performance can be properly isolated.

Some variables also appear to be more prone to corrections for measurement errors than others. The coefficient of the adjustment variable for the MKT, SMB and option-based factors are significant for 6 out of 11 strategies. The other three variables (HML, UMD and EMB) trigger a significant loading for the adjustment variable in no more than two cases. For the HML variable, the adjustment variable coefficient is highly significant for the Global Macro and Sectors strategies regardless of the number of factors chosen. For the other nine strategies, this coefficient is consistently insignificant.

5. Optimal model specification

The previous section displays results that are globally in favor of the higher moment estimation method, but suffers from the inflation in the number of variables. The algorithm presented in Section 2 aims at mitigating this drawback but gradually reducing the number of variables.

We assess the quality of this procedure in two ways. First, we review the optimal number of adjustment variables to drop and observe the gains in overall regression significance. Next, we verify the evolution of the risk premia associated to each source of risk under the OLS, the HME and the optimal hybrid specification.

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belonging to this strategy have been reshuffled to the other “Global-based” strategies since 1999 (see Capocci and Hübner, 2004).

5.1. Gains in significance

Based on the HME results displayed in Table 3, we perform the recursive regression algorithm presented in Section 2.B on the 11 hedge fund strategies. The results are presented in Table 4, using the same types of panels as in Table 3.

[Please insert Table 4]

For the strategies with low significance levels (Panel A), the algorithm brings some improvement for the Global and Global International return indexes. The gains in significance, measured with the Pseudo-adjusted R-squared (Ps. $\overline{R}^2$), are 5.2% and 6.5%, respectively. Nevertheless, the sources of these gains are qualitatively very different. For the Global strategy, two adjustment variable coefficients are insignificant in the HME: they naturally fade away with the algorithm, leaving only the adjustment variables that account for a priced measurement error. For the Global International strategy, the HME globally (slightly) improves over the OLS, but without any significant loading for the new variables. Thus, it is likely that when they are taken individually, they are considered as superfluous. The remaining coefficients after three runs of the algorithm are not even significant yet. For these two strategies, the total improvement over the OLS $\overline{R}^2$ is 10.6% (for Global) and 6.6% (for Global International).

In Panel B, the algorithm increases the Pseudo-adjusted R-squared of the asset pricing specification for Funds of Funds (+3.9% with respect to HME, +4.8% wrt OLS), Global Emerging (+2.8% wrt HME, +4.8% wrt OLS) and Event Driven (+4.1% wrt HME, +7.3% wrt OLS). For each strategy, the same two coefficients cancel out: the adjustment variables corresponding to HML and UMD appear to be superfluous.

The results are much less interesting for Panel C, as the original specification (OLS for Long Only Leveraged, HME for the other two) does not appear to appreciate thanks to the application of the algorithm. For strategies with a high significance level obtained with OLS, the correction for measurement errors does not greatly reduce the residual variance of returns in our sample.

We do not witness any large variation in alphas when moving from HME to the optimal specification. It increases in three cases (+37.2 bps for Global, +8.1 bps for Global Emerging, +9.9 bps for Event Driven) and decreases in three cases (-17.3 bps for Global Macro, -3.8 bps for Funds of Funds, -12.9 bps for Sectors). As to the significance levels of the individual regression coefficients, they remain very stable for the original factors with two exceptions. For Global International, the significance levels of the MKT and EMB coefficients drop when the algorithm is applied, and for Global Emerging the (weakly) significant SMB coefficient becomes insignificant. In both cases however, this adverse effect is compensated through the replacement of an insignificant coefficient under HME with a significant OLS coefficient: for Global International, the HML coefficient of 0.152 is replaced with the corresponding highly significant value of 0.094 under OLS; for Global Emerging, the UMD coefficient of 0.078 is swapped with the highly significant value of 0.114 under OLS.

5.2. Stability or risk premia

Our results show that sensible gain in significance is documented in several cases. This gain results from the existence of measurement errors in factor risk loadings. By definition, such errors imply economically important uncertainty about factor risk premia.

Hence, we now have to consider whether the economic substance of the model is not altered by the passage from OLS to HME, then from HME to the optimal model specification.

We meet this objective by assessing, for every strategy, the stability of mean total excess return attributable to each primary source of risk, whether captured by the original observed factor or by the adjustment variable. For the OLS specification, the mean total risk premium of factor *k* for the whole sample period is just measured by the product of the estimated loading with the average factor value: $\text{PremTot}_k = \hat{\beta}_k^{OLS} \cdot \overline{F}_k$ for $k \in \{m, s, h, u, e, o\}$. For HME, the mean total risk premium is defined as $\text{PremTot}_k = \hat{\beta}_k^{HM} \cdot \overline{F}_k + \hat{\psi}_k \cdot \overline{\hat{w}}_k$. Of course, whenever the optimal specification is a hybrid, the mean total risk premium for each factor is either the one obtained with OLS or the one of HME, depending of whether the adjustment variable has been removes from the regression equation or not.

Table 5 compares mean total risk premia obtained with OLS regression technique with those generated by HM estimators and those generated by the application of the recursive algorithm, if applicable.

[Please insert Table 5]

As follows from the average increase in alphas, the risk premia associated with the factors decrease on average when migrating from the OLS to the HME. Yet, the evolution is not homogenous from one strategy to another or from one factor to another.

When individual hedge fund strategies are considered, two strategies experience dramatic changes in risk premia from the OLS to the HME specification: Global and Short Sellers. For both of them, several risk premium experience large swings: MKT (+37.4 bps), HML

(- 20.6 bps), EMB (-52.1 bps) and OPT (-72.5 bps) for Global, and MKT (+20.8 bps), HML (-49.1 bps), UMD (+13.2 bps), EMB (-11.9 bps) and OPT (+19.5 bps) for Short Sellers. The explanation of these two series of returns seems to suffer from significant alterations from the change in specifications. For the Global strategy, this could be reasonably explained by the very small number of live funds at the end of the sample period (only 1 live fund on December 2002) that weakens the economic significance of the strategy returns. For Short Sellers, the sample also suffers from a small number of funds and this may explain the instability of the risk premium.

For the other eight strategies (excluding Long Only Leveraged, for which HME does not dominate OLS), the stability of the first five risk premia is quite high. The average difference in mean total risk premium between HME and OLS is equal to 1.5 bps with a standard deviation of 7.7 bps (40 observations). Such evidence contrasts with the large decline in the option-based risk premium: from OLS to HME, it decreases on average by 14.3 bps, with only one positive value (Global Macro) and a standard deviation of 15.7 bps. Thus, accounting for measurement errors in option-based factors appears to decrease the average risk premium of these eight hedge fund strategies by a substantial yearly 1.7%.

The economic relevance of the recursive regression algorithm can also be assessed by considering the difference in risk premia between the HME and the optimal specifications. For the five strategies (excluding the Global strategy) for which the HME and optimal specification differ (Global International, Funds of Funds, Global Emerging, Event Driven, Sectors), the average difference between the HME risk premium and the new risk premium (calculated with HME) of the optimal specification is as low as 0.2 bp, with a standard deviation of 4.0 bps (20 observations). Hence, for our sample, we find no evidence that the application of the algorithm significantly alters the risk premium associated to each factor. This finding holds provided that the strategy return index features a sufficient number of funds, as shown by the inconclusive results for the Global and, to a lesser extent, the Short Sellers strategies.

6. Conclusion

The use of the higher moment estimators proposed by Dagenais and Dagenais (1997) has been overlooked in the empirical finance literature. In this paper, we provide some economic justification for the use of this very powerful statistical approach in the context of hedge fund generating processes. As we have small samples of usable data, with large nonlinearities in hedge fund returns, and as an increasing body of the literature uses option-based factors to explain hedge fund returns, the application of HME appears to be a natural and logical choice. Yet, the price to pay for an accurate account for error-in-variables is a substantial inflation in the number of coefficients to estimate. We have developed a new heuristic algorithm to circumvent one of the weaknesses of the proposed estimator.

The empirical test of the Dagenais and Dagenais (1997) method on a sample of hedge fund data provides very informative evidence on the applicability of the procedure. First, the results suggest that HME is relevant for most series of returns, as it improves the explanatory power of most OLS specifications. Second, the performance of hedge fund strategies is enhanced, on average, when measurement errors are properly taken into account. Third, it does not significantly alter the risk premia attributable to each source of risk except for the optional factor, where we find that the OLS tends to overestimate the exposure to option-based risk factors. These results are however limited by the fact that the series of hedge fund strategy returns has to result from a sufficiently large set of individual hedge funds.

Furthermore, the algorithm that we propose brings further improvements over the HME specification in the majority of the cases. We obtain improved significance levels in six cases out of eleven, and find evidence of very small changes in the factor risk premia with respect to HME. This procedure seems to bring the best of two worlds, by associating the rigor of HME with the parsimony of the OLS specification.

The scope of application of this approach seems to be very large. Given the fact that many data samples are too small to lend themselves easily to nonlinear estimation such as the use of dynamic or conditional betas, HME together with the recursive regression algorithm might serve as a very credible alternative. In the context of hedge fund research, the inflation in the number of candidate variables to explain hedge fund returns will probably soon call for a solution that reconciles robustness and parsimony. We view our contribution as a step in this direction.

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Table 1/A: Descriptive statistics of hedge fund strategies

	# funds	Living	Dead	Mean	Std Dev.	t(mean)	Median	Min	Max	M. exc.	t(m. exc.)	Sharpe
EDR	226	154	72	0.92	1.88	5.02	1.09	-8.45	4.96	0.55	3.01	0.49
FOF	599	410	189	0.70	1.76	4.06	0.61	-6.71	6.45	0.33	1.90	0.40
GLO	156	1	155	0.41	3.98	1.05	0.54	-28.39	13.90	0.04	0.10	0.10
GEM	147	100	47	1.09	4.95	2.25	1.75	-21.85	14.35	0.72	1.49	0.22
GIN	71	50	21	0.84	2.44	3.55	0.84	-6.80	8.92	0.47	1.99	0.35
GMA	129	52	77	0.81	2.21	3.74	0.53	-4.06	7.05	0.44	2.03	0.37
GES	467	306	161	1.23	3.23	3.90	1.07	-9.96	12.24	0.86	2.73	0.38
LON	32	19	13	0.88	5.89	1.52	1.37	-17.44	13.28	0.51	0.88	0.15
MKN	574	365	209	1.19	1.16	10.47	1.16	-3.49	3.86	0.82	7.20	1.02
SEC	182	111	71	1.63	4.44	3.76	2.06	-13.11	19.90	1.26	2.91	0.37
SHO	34	21	13	0.98	4.50	2.23	0.69	-13.63	13.24	0.61	1.38	0.22

This table shows the mean returns, t-stats for mean = 0, standard deviations, medians, minima, maxima, mean excess returns, t-stats for mean excess return = 0, Sharpe ratios for the individual hedge funds in our database following 11 active strategies for the sample period 1994:02 – 2002:12. Sharpe ratio is the ratio of excess return and standard deviation. # funds represent the number of funds following a particular strategy, living funds and dead funds represent the number of surviving and dead funds (in December 2002, without considering the new funds established in 12:2002). We calculate the mean excess return and the Sharpe ratio considering the Ibbotson Associates 1-month T-bills. Returns in the table are in percentages. EDR = Event Driven, FOF = Funds of Funds, GLO = Global, GEM = Global Emerging Markets, GIN = Global International Markets, GMA = Global Macro, GES = Global Regional Established, LON = Long Only Leveraged, MKN = Market Neutral, SEC = Sector, SHO = Short Selling.

Table 1/B: Descriptive statistics of risk premium

	Mean	Std Dev.	t(mean)	Median	Min	Max	M. exc.	t(m. exc.)	Sharpe	Skewness	Kurtosis
MKT	0.76	4.83	1.61	1.54	-15.69	8.33	0.39	0.83	0.16	-0.70	0.30
SMB	0.01	4.47	0.01	-0.41	-16.26	21.38	-0.36	-0.83	0.00	0.88	5.65
HML	0.64	4.19	1.57	0.77	-8.91	13.67	0.27	0.67	0.15	0.47	1.10
UMD	1.14	5.82	2.01	1.32	-25.13	18.21	0.77	1.36	0.20	-0.73	4.46
EMB	-0.60	7.35	-0.83	0.40	-34.65	12.71	-0.97	-1.35	-0.08	-1.12	3.56
ACr	0.01	0.82	0.06	-0.21	-0.98	1.88	-0.36	-4.58	0.01	0.46	-1.02
OCr	-0.01	1.28	-0.10	-0.58	-0.99	4.79	-0.38	-3.07	-0.01	1.76	2.95
APr	-0.17	0.89	-1.95	-0.59	-0.94	2.55	-0.54	-6.20	-0.19	1.33	0.77
OPr	-0.26	1.13	-2.32	-0.78	-0.97	5.17	-0.63	-5.66	-0.23	2.75	8.86
ACa	0.35	1.45	2.47	0.00	-1.00	4.18	-0.02	-0.14	0.24	0.68	-0.87
OCa	0.39	1.62	2.45	-0.26	-1.00	4.93	0.02	0.12	0.24	0.84	-0.62
APa	0.06	1.86	0.34	-1.00	-1.00	10.27	-0.31	-1.70	0.03	2.45	8.20
OPa	1.24	5.02	2.52	-1.00	-1.00	30.10	0.87	1.77	0.25	3.85	18.23

This table shows the mean returns (in percents), t-stats for mean = 0, standard deviations, medians, minima, maxima, mean excess returns, t-stats for mean excess return = 0, Sharpe ratios, skewness and kurtosis for the premia for the sample period 1994:02 – 2002:12. Sharpe ratio is the ratio of excess return and standard deviation. We calculate the mean excess return and the Sharpe ratio considering the Ibbotson Associates 1-month T-bills. Numbers in the table are in percentages. MKT = the market premium, SMB = Small Minus Low which is the difference between the returns on a portfolio of small stocks and a portfolio of large stocks, HML = High Minus Low which is the difference between the returns on a portfolio of high-book-to-market-equity stocks and a portfolio of low-book-to-market-equity stocks, UMD = Momentum factor (Carhart, 1997), EMB = MSCI emerging market index; ACr= return of a true ATM index call, OCr = return of a true 5% OTM index call; APr= return of a true ATM index put, OPr = return of a true 5% OTM index put; ACa = return of an artificial ATM index call; OCa = return of an artificial 5% OTM index call; APa = return of an artificial ATM index put; OPa = return of an artificial 5% OTM index put. The underlying index for all options is the S&P500.

Table 1/C: Normality tests of hedge funds strategies and risk premia

	Jarque-Bera		Lilliefors		Cramer-v. Mises		Watson		Anderson-Darling	
	Stat.	p-value	Stat.	p-value	Stat.	p-value	Stat.	p-value	Stat.	p-value
MKN	11.439	0.003	0.052	0.100	0.035	0.762	0.035	0.718	0.307	0.558
GLO	2943.61	0.000	0.131	0.000	0.607	0.000	0.590	0.000	4.143	0.000
GIN	9.453	0.008	0.077	0.100	0.089	0.159	0.086	0.146	0.642	0.092
GMA	4.100	0.128	0.097	0.016	0.155	0.020	0.141	0.021	0.817	0.034
FOF	42.027	0.000	0.072	0.100	0.122	0.055	0.120	0.043	0.892	0.022
GEM	58.384	0.000	0.064	0.100	0.090	0.152	0.086	0.145	0.622	0.102
EDR	111.499	0.000	0.061	0.100	0.079	0.214	0.070	0.244	0.622	0.103
SHO	2.045	0.359	0.049	0.100	0.037	0.727	0.036	0.703	0.285	0.621
LON	3.214	0.200	0.073	0.100	0.078	0.215	0.065	0.281	0.466	0.248
SEC	30.779	0.000	0.074	0.100	0.095	0.130	0.095	0.107	0.653	0.086
GES	10.630	0.004	0.057	0.100	0.050	0.507	0.050	0.467	0.435	0.295
MKT	8.557	0.013	0.105	0.006	0.182	0.009	0.150	0.015	1.071	0.008
SMB	137.387	0.000	0.091	0.031	0.176	0.011	0.162	0.011	1.312	0.002
HML	7.980	0.018	0.071	0.100	0.079	0.211	0.071	0.231	0.567	0.139
UMD	85.77	0.000	0.131	0.000	0.470	0.000	0.465	0.000	2.480	0.000
EMB	70.119	0.000	0.116	0.001	0.217	0.003	0.189	0.004	1.154	0.005
ACr	8.238	0.016	0.125	0.000	0.407	0.000	0.380	0.000	2.699	0.000
APr	32.192	0.000	0.211	0.000	1.456	0.000	1.275	0.000	8.062	0.000
OCr	85.549	0.000	0.221	0.000	0.138	0.000	1.194	0.000	7.999	0.000
OPr	436.781	0.000	0.285	0.000	2.576	0.000	2.320	0.000	13.167	0.000
ACa	11.207	0.003	0.214	0.000	0.978	0.000	0.916	0.000	6.161	0.000
APa	365.228	0.000	0.325	0.000	2.802	0.000	2.582	0.000	14.201	0.000
OCa	13.735	0.001	0.226	0.000	1.300	0.000	1.207	0.000	7.707	0.000
OPa	1563.87	0.000	0.328	0.000	3.529	0.000	3.303	0.000	17.665	0.000

This table reports the normality tests of the variables for the sample period 1994:02 – 2002:12: Jarque-Bera, Lilliefors, Cramer-von Mises, Watson and Anderson-Darling. EDR = Event Driven, FOF = Funds of Funds, GLO = Global, GEM = Global Emerging Markets, GIN = Global International Markets, GMA = Global Macro, GES = Global Regional Established, LON = Long Only Leveraged, MKN = Market Neutral, SHO = Short Selling, SEC = Sector; MKT = the market premium, SMB = Small Minus Low which is the difference between the returns on a portfolio of small stocks and a portfolio of large stocks, HML = High Minus Low which is the difference between the returns on a portfolio of high-book-to-market-equity stocks and a portfolio of low-book-to-market-equity stocks, UMD = Momentum factor (Carhart, 1997), EMB = MSCI emerging market index; ACr= return of a true ATM index call, OCr = return of a true 5% OTM index call; APr= return of a true ATM index put, OPr = return of a true 5% OTM index put; ACa = return of an artificial ATM index call; OCa = return of an artificial 5% OTM index call; APa = return of an artificial ATM index put; OPa = return of an artificial 5% OTM index put. The underlying index for all options is the S&P500.

Table 2/A: Correlations among hedge funds and between hedge funds and risk premia

	EDR	FOF	GLO	GEM	GIN	GMA	GES	LON	MKN	SEC	SHO
EDR	1.00										
FOF	0.85	1.00									
GLO	0.70	0.67	1.00								
GEM	0.70	0.80	0.76	1.00							
GIN	0.78	0.88	0.60	0.76	1.00						
GMA	0.74	0.88	0.50	0.63	0.81	1.00					
GES	0.87	0.87	0.61	0.69	0.83	0.84	1.00				
LON	0.83	0.80	0.60	0.67	0.72	0.78	0.91	1.00			
MKN	0.81	0.81	0.57	0.62	0.73	0.70	0.72	0.66	1.00		
SEC	0.82	0.82	0.55	0.62	0.75	0.79	0.93	0.87	0.65	1.00	
SHO	-0.68	-0.63	-0.51	-0.55	-0.61	-0.68	-0.83	-0.82	-0.50	-0.84	1.00
MKT	0.72	0.65	0.56	0.59	0.68	0.68	0.86	0.86	0.57	0.79	-0.78
SMB	0.51	0.47	0.30	0.33	0.36	0.40	0.47	0.42	0.36	0.57	-0.51
HML	-0.34	-0.31	-0.31	-0.32	-0.32	-0.37	-0.51	-0.55	-0.17	-0.51	0.57
UMD	-0.05	0.17	-0.06	-0.03	0.05	0.21	0.03	-0.08	0.04	0.13	-0.04
EMB	0.68	0.70	0.74	0.84	0.75	0.63	0.72	0.72	0.54	0.64	-0.60
ACr	0.53	0.48	0.41	0.41	0.51	0.56	0.65	0.69	0.45	0.54	-0.59
APr	0.41	0.38	0.35	0.31	0.40	0.47	0.52	0.54	0.39	0.42	-0.47
OCr	-0.64	-0.56	-0.50	-0.48	-0.58	-0.59	-0.73	-0.76	-0.51	-0.65	0.63
OPr	-0.62	-0.52	-0.56	-0.47	-0.54	-0.50	-0.65	-0.63	-0.47	-0.61	0.61
ACa	0.50	0.47	0.36	0.41	0.48	0.56	0.66	0.67	0.42	0.57	-0.60
APa	0.47	0.44	0.34	0.39	0.45	0.53	0.62	0.63	0.40	0.54	-0.57
OCa	-0.73	-0.64	-0.67	-0.57	-0.63	-0.59	-0.76	-0.75	-0.60	-0.69	0.65
OPa	-0.64	-0.57	-0.63	-0.51	-0.55	-0.51	-0.65	-0.63	-0.53	-0.58	0.54

This table reports the correlations among hedge fund returns and between hedge fund returns and risk premia for the sample period 1994:02 – 2002:12. EDR = Event Driven, FOF = Funds of Funds, GLO = Global, GEM = Global Emerging Markets, GIN = Global International Markets, GMA = Global Macro, GES = Global Regional Established, LON = Long Only Leveraged, MKN = Market Neutral, SHO = Short Selling, SEC = Sector; MKT = the market premium, SMB = Small Minus Low which is the difference between the returns on a portfolio of small stocks and a portfolio of large stocks, HML = High Minus Low which is the difference between the returns on a portfolio of high-book-to-market-equity stocks and a portfolio of low-book-to-market-equity stocks, UMD = Momentum factor (Carhart, 1997), EMB = MSCI emerging market index; ACr= return of a true ATM index call, OCr = return of a true 5% OTM index call; APr= return of a true ATM index put, OPr = return of a true 5% OTM index put; ACa = return of an artificial ATM index call; OCa = return of an artificial 5% OTM index call; APa = return of an artificial ATM index put; OPa = return of an artificial 5% OTM index put. The underlying index for all options is the S&P500.

Table 2/B: Correlations among risk premia

	MKT	SMB	HML	UMD	EMB	ACr	OCr	APr	OPr	ACa	OCa	APa	OPa
MKT	1.00												
SMB	0.14	1.00											
HML	-0.57	-0.26	1.00										
UMD	-0.19	0.19	0.09	1.00									
EMB	0.73	0.28	-0.45	-0.21	1.00								
ACr	0.82	-0.13	-0.43	-0.18	0.50	1.00							
APr	0.66	-0.16	-0.32	-0.13	0.37	0.90	1.00						
OCr	-0.90	-0.03	0.48	0.21	-0.64	-0.76	-0.55	1.00					
OPr	-0.79	-0.08	0.40	0.18	-0.61	-0.58	-0.41	0.88	1.00				
ACa	0.81	-0.07	-0.45	-0.14	0.49	0.93	0.84	-0.68	-0.51	1.00			
APa	0.78	-0.10	-0.43	-0.14	0.47	0.91	0.84	-0.63	-0.47	1.00	1.00		
OCa	-0.86	-0.15	0.43	0.14	-0.70	-0.61	-0.43	0.92	0.88	-0.54	-0.49	1.00	
OPa	-0.70	-0.15	0.36	0.06	-0.60	-0.49	-0.34	0.78	0.74	-0.42	-0.38	0.91	1.00

This table reports the correlations between risk premia for the sample period 1994:02 – 2002:12. MKT = the market premium, SMB = Small Minus Low which is the difference between the returns on a portfolio of small stocks and a portfolio of large stocks, HML = High Minus Low which is the difference between the returns on a portfolio of high-book-to-market-equity stocks and a portfolio of low-book-to-market-equity stocks, UMD = Momentum factor (Carhart, 1997), EMB = MSCI emerging market index; ACr= return of a true ATM index call, OCr = return of a true 5% OTM index call; APr= return of a true ATM index put, OPr = return of a true 5% OTM index put; ACa = return of an artificial ATM index call; OCa = return of an artificial 5% OTM index call; APa = return of an artificial ATM index put; OPa = return of an artificial 5% OTM index put. The underlying index for all options is the S&P500.

Table 3: OLS and HME regressions on hedge fund strategies

Panel A: Strategies with low significance levels ($\overline{R}^2 < 0.7$)

			Factors								Adjustment variables					
	$\overline{R}^2$	α	MKT	SMB	HML	UMD	EMB	Option		F-stat	w_m	w_s	w_h	w_u	w_e	w_o
MKN	0.448	0.681***	0.164***	0.086***	0.078***	0.018										
	0.468	0.713***	0.124***	0.073***	0.077***	0.023	0.038**									
	0.487	0.752***	0.065*	0.073***	0.068***	0.021	0.030*	APa	-0.189**							
	0.486	0.743***	0.187***	0.087***	0.146**	-0.054*				16.05***	-0.023	0.005	-0.050	0.107***		
	0.504	0.863***	0.100*	0.040	0.093	-0.003	0.095***			12.76***	0.029	0.047	0.001	0.054*	-0.076*	
	0.522	0.855***	0.090	0.046	0.123**	-0.010	0.095**	ACr	0.044	10.01***	-0.047	0.057	-0.035	0.061*	-0.072	0.687
GLO	0.342	-0.197	0.473***	0.207***	0.068	0.004										
	0.547	0.121	0.077	0.080	0.063	0.062	0.378***									
	0.604	0.338	-0.254**	0.079	0.014	0.047	0.334***	APa	-1.060***							
	0.395	-0.210	0.456***	0.241*	0.476*	-0.330***				12.89***	0.095	0.012	-0.334	0.461***		
	0.617	0.811***	-0.251	-0.169*	0.031	0.082	0.787***			8.98***	0.391*	0.349***	0.101	0.036	-0.512***	
	0.658	1.335***	-0.861***	-0.131	-0.152	0.085***	0.606***	APa	-1.721	8.54***	0.903***	0.320***	0.276	0.012	-0.341***	1.675**
GIN	0.540	0.202	0.378***	0.147***	0.095**	0.055*										
	0.674	0.359***	0.184***	0.085***	0.092**	0.083***	0.186***									
	0.677	0.391***	0.108	0.106***	0.094***	0.081***	0.192***	ACr	0.478							
	0.530	0.181	0.443***	0.071	0.163	0.050				24.57***	-0.062	0.112	-0.055	0.008		
	0.665	0.265	0.257***	0.038	0.130	0.090**	0.147**			19.57***	-0.082	0.078	-0.029	-0.019	0.049	
	0.678	0.417*	0.307***	0.025	0.152	0.085**	0.156***	APa	0.065	13.76***	-0.158	0.102	-0.053	-0.021	0.051	0.377
GMA	0.632	0.144	0.341***	0.129***	0.046	0.115***										
	0.666	0.218*	0.249***	0.100***	0.045	0.128***	0.088***									
	0.690	0.275**	0.112*	0.139***	0.047***	0.125***	0.099***	ACr	0.858***							
	0.636	0.201	0.239***	0.200***	0.001	0.053				22.33***	0.139*	-0.075	0.076	0.093*		
	0.660	0.314*	0.233***	0.137***	-0.093	0.136***	0.059			18.98***	0.000	-0.042	0.161	0.000	0.037	
	0.701	0.419***	-0.247	0.300***	-0.061	0.119***	0.154***	ACr	2.137***	13.28***	0.437***	-0.193***	0.112	0.020	-0.051	-1.366*

Panel B: Strategies with average significance levels (0.7 < $\overline{R}^2$ < 0.8)

	$\overline{R}^2$	α	Factors							F-stat	Adjustment variables					
			MKT	SMB	HML	UMD	EMB	Option			w_m	w_s	w_h	w_u	w_e	w_o
FOF	0.624	0.097	0.266***	0.144***	0.071**	0.069***										
	0.711	0.188*	0.153***	0.108***	0.069***	0.086***	0.108***									
	0.718	0.216**	0.087*	0.127***	0.070***	0.084***	0.113***	ACr	0.414*							
	0.623	0.116	0.235***	0.160***	0.101	0.014				23.39***	0.054	-0.005	-0.008	0.080*		
	0.704	0.300***	0.095	0.083	0.013	0.097	0.153			19.44***	0.068	0.041	0.076	-0.003	-0.056	
	0.727	0.380***	0.145	0.067	0.043	0.091***	0.146***	ACr	-0.192	13.57***	-0.097	0.085	0.041	0.007	-0.044	1.617***
GEM	0.393	0.374	0.624***	0.293***	0.107	0.027										
	0.736	0.881***	-0.006	0.091	0.098	0.119***	0.602***									
	0.739	0.788***	-0.119	0.120*	0.105	0.114***	0.614***	OCa	0.373							
	0.396	0.290	0.635***	0.212	0.398	-0.167				21.05***	0.078	0.180	-0.211	0.267		
	0.736	0.804***	0.038	-0.020	0.148	0.077	0.568***			18.42***	0.044	0.211	0.029	0.081	0.038	
	0.759	0.989***	0.636**	-0.224*	0.182	0.078	0.466***	ACr	-2.418**	11.79***	-0.890***	0.484***	-0.002	0.088	0.147	5.636***
EDR	0.709	0.378***	0.298***	0.194***	0.093***	-0.002										
	0.727	0.425***	0.240***	0.175***	0.092***	0.006	0.056***									
	0.748	0.488***	0.144***	0.175***	0.078***	0.002	0.043**	APa	-0.308***							
	0.732	0.461***	0.349***	0.153***	0.162**	-0.069**				18.61***	-0.048	0.068	-0.037	0.107***		
	0.765	0.633***	0.223***	0.084**	0.092	-0.004	0.136***			11.79***	0.008	0.134***	0.033	0.032	-0.103**	
	0.780	0.511***	0.329***	0.056	0.155***	-0.015	0.107**	ACr	-0.425	8.58***	-0.212*	0.176***	-0.037	0.042	-0.072	0.820
SHO	0.786	0.910***	-0.664***	-0.360***	0.091	-0.087***										
	0.787	0.953***	-0.717***	-0.377***	0.090	-0.079**	0.051									
	0.791	0.862***	-0.874***	-0.359***	0.086	-0.077**	0.053	APr	-0.903*							
	0.797	1.209***	-0.806***	-0.362***	-0.395***	0.043				20.61***	0.180	0.037	0.570***	-0.125		
	0.796	1.275***	-1.038***	-0.362***	-0.355**	0.017	0.143			16.52***	0.403***	0.025	0.536***	-0.082	-0.103	
	0.803	1.112***	-1.098***	-0.336***	-0.364***	0.008	0.105	OPa	-0.060	12.21***	0.445***	-0.008	0.540***	-0.069	-0.074	-0.212

Panel C: Strategies with high significance levels ($\overline{R}^2$ > 0.8)

			Factors								Adjustment variables					
	$\overline{R}^2$	α	MKT	SMB	HML	UMD	EMB	Option		F-stat	w_m	w_s	w_h	w_u	w_e	w_o
LON	0.816	0.108	0.987***	0.384***	-0.023	0.022										
	0.819	0.177	0.901***	0.357***	-0.025	0.035	0.082									
	0.832	0.291	0.630***	0.433***	-0.019	0.028	0.104**	ACr	1.697***							
	0.815	0.102	0.939***	0.435***	0.121	-0.122				24.20***	0.087	-0.044	-0.116	0.197		
	0.811	0.234	1.000***	0.350***	-0.013	-0.007	0.035			20.40***	-0.133	0.016	0.008	0.065	0.053	
	0.825	0.505	0.652**	0.459***	-0.060	-0.002	0.112	ACr	1.331	16.62***	-0.069	-0.031	0.049	0.066	-0.012	1.579
SEC	0.873	0.795***	0.716***	0.424***	0.021	0.150***										
	0.872	0.802***	0.707***	0.421***	0.020	0.152***	0.008									
	0.871	0.830***	0.756***	0.415***	0.022	0.151***	0.007	APr	0.280							
	0.886	0.491***	0.718***	0.518***	0.288**	0.108**				18.62***	-0.026	-0.167**	-0.365***	0.001		
	0.882	0.471***	0.890***	0.498***	0.251**	0.128***	-0.096			15.43***	-0.247*	-0.151*	-0.326***	-0.017	0.128	
	0.886	0.580***	0.804***	0.499***	0.250**	0.125***	-0.116	OPr	-0.548*	11.32***	-0.103	-0.170**	-0.320***	-0.009	0.151*	1.562**
GES	0.876	0.526***	0.577***	0.248***	0.045	0.070***										
	0.880	0.568***	0.525***	0.232***	0.044	0.077***	0.049**									
	0.884	0.604***	0.439***	0.256***	0.046	0.075***	0.056***	ACr	0.543**							
	0.878	0.469***	0.604***	0.232***	0.198**	-0.006				23.09***	-0.013	0.033	-0.147	0.098**		
	0.880	0.503***	0.641***	0.198***	0.153*	0.029	0.002			18.90***	-0.122	0.056	-0.099	0.065	0.053	
	0.894	0.747***	0.734***	0.148***	0.167**	0.033	0.001	OCr	-0.304	12.48***	-0.347***	0.131**	-0.106	0.059	0.059	1.520***

This table reports the regression results of hedge fund returns for the sample period 1994:02 – 2002:12. The OLS specifications take the form of equation $R_t = \hat{\alpha}^{OLS} + \sum_{k=1}^{K} \hat{\beta}_k^{OLS} \cdot F_{kt} + \upsilon_t$ with 4, 5 and 6 risk factors. The HME specifications take the form $R_t = \hat{\alpha}^{HM} + \sum_{k=1}^{K} \hat{\beta}_k^{HM} \cdot F_{kt} + \sum_{k=1}^{K} \hat{\psi}_k \cdot \hat{w}_{kt} + \varepsilon_t$ with 4, 5 and 6 risk factors and the corresponding adjustment variables. For both the OLS and HME specifications, we adopt as sixth risk premium the option-based factor that obtains the best value for the Akaike information criterion. The alpha is expressed in percents. F is a standard F test to detect EIV by testing for $\Sigma_\kappa \psi_\kappa = 0$. *** Significant at the 1% level, ** Significant at the 5% level and * Significant at the 10% level.

Table 4: Regression coefficients using the recursive regression algorithm

Panel A: Strategies with low significance levels ($\overline{R}^2$ < 0.7)

				Factors						Adjustment variables					
	Specification	Ps. $\overline{R}^2$	α	Mkt	SMB	HML	UMD	EMB	OPT	w_m	w_s	w_h	w_u	w_e	w_o
MKN	*OLS*	*0.487*	*0.752****	*0.065**	*0.073****	*0.068****	*0.021*	*0.030**	*-0.189***						
	HME	**0.522**	**0.855*****	**0.090**	**0.046**	**0.123****	**-0.010**	**0.095****	**0.044**	**-0.047**	**0.057**	**-0.035**	**0.061***	**-0.072**	**0.687**
	-1st fact. (MKT)	0.417	0.911***		0.037	0.094*	-0.004	0.117***	-0.022		0.070	-0.004	0.049	-0.093***	0.759**
	-2nd fact. (HML)	0.497	0.926***		0.033		0.002	0.118***	-0.074		0.070		0.043	-0.094***	0.801***
	-3rd fact. (UMD)	0.480	0.925***		0.022			0.127***	-0.120		0.091**			-0.101***	0.828***
GLO	*OLS*	*0.604*	*0.338*	*-0.254***	*0.079*	*0.014*	*0.047*	*0.334****	*-1.060****						
	HME	0.658	1.335***	-0.861***	-0.131	-0.152	0.085	0.606***	-1.721***	0.903***	0.320***	0.276	0.012	-0.341***	1.675**
	-1st fact. (UMD)	0.669	1.494***	-0.903***	-0.120	-0.161		0.640***	-1.709***	0.894***	0.311**	0.263		-0.371***	1.706**
	-2nd fact. (HML)	**0.710**	**1.707*****	**-1.063*****	**-0.098**			**0.895*****	**-1.551*****	**1.055*****	**0.238****			**-0.642*****	**1.719*****
	-3rd fact. (SMB)	0.703	1.957***	-1.081***				0.851***	-1.716***	1.102***				-0.580***	2.362***
GIN	*OLS*	*0.677*	*0.391****	*0.108*	*0.106****	*0.094****	*0.081****	*0.192****	*0.478*						
	HME	0.678	0.417*	0.307***	0.025	0.152	0.085**	0.156***	0.065	-0.158	0.102	-0.053	-0.021	0.051	0.377
	-1st fact. (UMD)	0.686	0.439*	0.295**	0.026	0.144		0.164**	0.068	-0.122	0.085	-0.037		0.033	0.358
	-2nd fact. (HML)	0.734	0.386*	0.325***	0.020			0.103	0.019	-0.166	0.093			0.097	0.337
	-3rd fact. (APa)	**0.743**	**0.244**	**0.308*****	**0.030**			**0.110**		**-0.114**	**0.076**			**0.084**	
GMA	*OLS*	*0.690*	*0.275***	*0.112**	*0.139****	*0.047*	*0.125****	*0.099****	*0.858****						
	HME	**0.701**	**0.419*****	**-0.247**	**0.300*****	**-0.061**	**0.119*****	**0.154*****	**2.137*****	**0.437*****	**-0.193*****	**0.112**	**0.020**	**-0.051**	**-1.366**
	-1st fact. (UMD)	0.680	0.271	-0.063	0.263***	-0.005		0.087	1.691***	0.214	-0.159*	0.039		0.029	-1.029
	-2nd fact. (EMB)	0.504	0.326**	-0.053	0.248***	-0.005			1.537***	0.209	-0.131	0.039			-0.505
	-3rd fact. (HML)	0.565	0.204	-0.096	0.235***				1.901***	0.301***	-0.111				-1.174

Panel B: Strategies with average significance levels (0.7 < $\overline{R}^2$ < 0.8)

				Factors							Adjustment variables					
	Specification	Ps. $\overline{R}^2$	α	Mkt	SMB	HML	UMD	EMB	OPT	w_m	w_s	w_h	w_u	w_e	w_o
FOF	*OLS*	*0.718*	*0.216^{**}*	*0.087^{*}*	*0.127^{***}*	*0.070^{***}*	*0.084^{***}*	*0.113^{***}*	*0.414^{*}*						
	HME	0.727	0.380^{***}	0.145	0.067	0.043	0.091^{***}	0.146^{***}	-0.192	-0.097	0.085	0.041	0.007	-0.044	1.617^{***}
	-1st fact. (UMD)	0.721	0.311^{*}	0.236	0.057	0.075		0.111	-0.396	-0.212	0.092	-0.002		-0.004	1.748^{***}
	-2nd fact. (HML)	**0.766**	**0.342^{***}**	**0.202**	**0.057**			**0.127**	**-0.331**	**-0.168**	**0.094**			**-0.019**	**1.659^{***}**
	-3rd fact. (EMB)	0.525	0.324^{***}	0.237^{***}	0.048				-0.451	-0.200^{**}	0.098^{*}				1.612^{***}
GEM	*OLS*	*0.739*	*0.788^{***}*	*-0.119*	*0.120^{*}*	*0.105*	*0.114^{***}*	*0.614^{***}*	*0.373*						
	HME	0.759	0.989^{***}	0.636^{**}	-0.225^{*}	0.182	0.078	0.466^{***}	-2.418^{**}	-0.890^{***}	0.484^{***}	-0.002	0.088	0.147	5.636^{***}
	-1st fact. (HML)	0.774	1.085^{***}	0.552^{*}	-0.224^{*}		0.109	0.506^{***}	-2.385^{**}	-0.862^{***}	0.459^{***}		0.039	0.107	5.588^{***}
	-2nd fact. (UMD)	**0.787**	**1.070^{***}**	**0.633^{*}**	**-0.153**			**0.486^{***}**	**-2.662^{**}**	**-0.982^{***}**	**0.446^{***}**			**0.114**	**5.863^{***}**
	-3rd fact. (EMB)	0.057	1.131^{***}	0.309	-0.153				-1.589	-0.604^{**}	0.346^{**}				3.489^{**}
EDR	*OLS*	*0.748*	*0.488^{***}*	*0.144^{***}*	*0.175^{***}*	*0.078^{***}*	*0.002*	*0.043^{**}*	*-0.308^{***}*						
	HME	0.780	0.511^{***}	0.329^{***}	0.061	0.155^{***}	-0.015	0.107^{**}	-0.425	-0.212	0.176^{***}	-0.037	0.042	-0.072	0.820
	-1st fact. (HML)	0.816	0.587^{***}	0.268^{***}	0.066		0.000	0.129^{***}	-0.375	-0.167	0.164^{***}		0.024	-0.093^{*}	0.827
	-2nd fact. (UMD)	**0.821**	**0.610^{***}**	**0.252^{**}**	**0.213^{***}**			**0.143^{***}**	**-0.358**	**-0.149**	**0.170^{***}**			**-0.107^{*}**	**0.810**
	-3rd fact. (Mkt)	0.686	0.753^{***}		0.060			0.213^{***}	-0.426^{*}		0.179^{***}			-0.189^{***}	1.189^{***}
SHO	*OLS*	*0.791*	*0.862^{***}*	*-0.874^{***}*	*-0.359*	*0.086*	*-0.077*	*0.053*	*-0.903*						
	HME	**0.803**	**1.112^{***}**	**-1.098^{***}**	**-0.233**	**-0.364**	**0.008**	**0.105**	**-0.060**	**0.445^{***}**	**-0.008**	**0.540*****	**-0.069**	**-0.074**	**-0.212**
	-1st fact. (SMB)	0.723	1.042^{***}	-1.010^{***}		-0.217	-0.006	0.068	-0.083	0.330^{*}		0.367*	-0.054	-0.018	-0.120
	-2nd fact. (EMB)	0.756	0.997^{***}	-0.981^{***}		-0.274	-0.007		-0.086	0.253		0.343*	-0.069		-0.144
	-3rd fact. (0/P)	0.775	1.197^{***}	-0.880^{***}		-0.274	0.014			0.157		0.400**	-0.092		

Panel C: Strategies with high significance levels ($\overline{R}^2$ > 0.8)

	Specification	Ps. $\overline{R}^2$	α	Factors						Adjustment variables					
				Mkt	SMB	HML	UMD	EMB	OPT	w_m	w_s	w_h	w_u	w_e	w_o
LON	***OLS***	***0.832***	***0.291***	***0.630******	***0.433******	***-0.019***	***0.028***	***0.104*****	***1.697******						
	HME	0.825	0.505	0.652**	0.439***	-0.060	-0.002	0.112	1.331	-0.069	-0.031	0.049	0.066	-0.012	1.579
	-1st fact. (EMB)	0.793	0.527*	0.720***	-0.029	-0.035	-0.031		0.993	-0.144	-0.011	0.024	0.091		1.847
	-2nd fact. (SMB)	0.764	0.566*	0.722***		-0.096	-0.087		0.990	-0.132		0.040	0.169		1.592
	-3rd fact. (HML)	0.764	0.543**	0.700***			-0.096		1.122	-0.109			0.174		1.407
SEC	*OLS*	*0.871*	*0.830****	*0.756****	*0.415****	*0.022*	*0.151****	*0.007*	*0.280*						
	HME	0.886	0.580***	0.804***	0.499***	0.415***	0.125***	-0.116	-0.548*	-0.103	-0.170**	-0.320***	-0.009	0.151*	1.562**
	-1st fact. (UMD)	**0.886**	**0.451***	**0.879*****	**0.482*****	**0.250****		**-0.161***	**-0.562***	**-0.183**	**-0.171****	**-0.353*****		**0.199****	**1.542****
	-2nd fact. (Mkt)	0.640	0.505*		0.254*	0.288**		-0.089	-0.822		-0.166**	-0.323**		0.128	1.700***
	-3rd fact. (EMB)	0.636	0.543**		0.485***	0.276**			-0.446*		-0.164**	-0.353***			0.868*
GES	*OLS*	*0.884*	*0.604****	*0.439****	*0.256****	*0.046*	*0.075****	*0.056****	*0.543***						
	HME	**0.894**	**0.747*****	**0.734*****	**0.148*****	**0.256*****	**0.033**	**0.001**	**-0.304**	**-0.347*****	**0.131****	**-0.106**	**0.059**	**0.059**	**1.520*****
	-1st fact. (EMB)	0.867	0.794***	0.637***	0.157***	0.167*	0.039		-0.190	-0.240**	0.113*	-0.103	0.047		1.232***
	-2nd fact. (HML)	0.877	0.846***	0.564***	0.178***		0.055		-0.094	-0.159*	0.081		0.036		1.019**
	-3rd fact. (UMD)	0.880	0.862***	0.605***	0.178***				-0.177	-0.223**	0.090				1.129***

This table reports the regression results of hedge fund returns for the sample period 1994:02 – 2002:12. The OLS specifications take the form of equation $R_t = \hat{\alpha}^{OLS} + \sum_{k=1}^{K} \hat{\beta}_k^{OLS} \cdot F_{kt} + \upsilon_t$ with 6 risk factors. The HME specifications take the form $R_t = \hat{\alpha}^{HM} + \sum_{k=1}^{K} \hat{\beta}_k^{HM} \cdot F_{kt} + \sum_{k=1}^{K} \hat{\psi}_k \cdot \hat{w}_{kt} + \varepsilon_t$ with 6 risk factors and the corresponding adjustment variables. For both the OLS and HME specifications, we adopt as sixth risk premium the option-based factor that obtains the best value for the Akaike information criterion. For each iteration of the recursive algorithm, we remove the OLS risk premium corresponding to the least significant coefficient $\hat{\psi}_i$ and re-estimate equation $R_t - \hat{\beta}_i^{OLS}.F_{it} = \hat{\alpha}^{HM,1} + \sum_{\substack{k=1 \\ k \neq i}}^{K} \hat{\beta}_k^{HM,1} \cdot F_{kt} + \sum_{\substack{k=1 \\ k \neq i}}^{K} \hat{\psi}^1{}_k \cdot \hat{w}_{kt} + \vartheta_t$.

Ps. $\overline{R}^2 = \frac{1-(2K-D)}{T-(2K-D)} + \frac{T-1}{T-(2K-D)} R^2$ where R^2 is the unadjusted coefficient of determination. For OLS and HME, Ps. $\overline{R}^2 \equiv \overline{R}^2$. The alpha is expressed in percentage. *** Significant at the 1% level, ** Significant at the 5% level and * Significant at the 10% level.

Table 5: Risk premia corresponding to the risk factors

			Mkt			SMB			HML			UMD			EMB			OPT		
	Specif.	α	factor	adjust.	total	factor	adjust.	total	factor	adjust.	total	factor	adjust.	total	factor	adjust.	total	factor	adjust.	total
MKN	OLS	0.752	0.025		0.025	0.001		0.001	0.050		0.050	0.025		0.025	-0.026		-0.026	0.002		0.002
	HME-Opt	0.855	0.035	-0.008	0.027	0.000	0.008	0.009	0.079	0.007	0.086	-0.011	-0.007	-0.018	-0.057	-0.036	-0.092	0.000	-0.051	-0.050
GLO	OLS	0.338	-0.099		-0.099	0.000		0.000	0.009		0.009	0.053		0.053	-0.199		-0.199	-0.065		-0.065
	HME	1.335	-0.336	0.611	0.275	-0.001	0.041	0.040	-0.097	-0.099	-0.197	0.098	-0.004	0.094	-0.361	-0.359	-0.720	-0.106	-0.683	-0.790
	Optimal	1.707	-0.415	0.752	0.337	-0.001	0.036	0.036	0.009		0.009	0.053		0.053	-0.534	-0.742	-1.276	-0.096	-0.733	-0.829
GIN	OLS	0.391	0.080		0.080	0.000		0.000	0.061		0.061	0.096		0.096	-0.112		-0.112	0.004		0.004
	HME	0.417	0.120	-0.107	0.013	0.000	0.013	0.013	0.097	0.019	0.116	0.097	0.007	0.104	-0.093	0.054	-0.039	0.004	-0.154	-0.150
	Optimal	0.244	0.120	-0.111	0.009	0.000	0.009	0.009	0.061		0.061	0.096		0.096	-0.066	0.116	0.051	0.004		0.004
GMA	OLS	0.275	0.044		0.044	0.001		0.001	0.030		0.030	0.143		0.143	-0.059		-0.059	0.004		0.004
	HME-Opt	0.419	-0.096	0.074	-0.022	0.002	-0.028	-0.027	-0.039	-0.021	-0.061	0.137	-0.002	0.134	-0.092	-0.026	-0.117	0.011	0.101	0.111
FOF	OLS	0.216	0.034		0.034	0.001		0.001	0.045		0.045	0.096		0.096	-0.068		-0.068	0.002		0.002
	HME	0.380	0.056	-0.016	0.040	0.000	0.012	0.013	0.028	-0.008	0.020	0.104	-0.001	0.103	-0.087	-0.022	-0.109	-0.001	-0.119	-0.120
	Optimal	0.342	0.079	-0.042	0.037	0.000	0.026	0.026	0.045		0.045	0.096		0.096	-0.076	-0.014	-0.090	-0.002	-0.128	-0.130
GEM	OLS	0.788	-0.055		-0.055	0.001		0.001	0.065		0.065	0.132		0.132	-0.366		-0.366	0.004		0.004
	HME	0.989	0.248	-0.152	0.097	-0.001	0.071	0.070	0.117	0.000	0.117	0.089	-0.010	0.079	-0.278	0.073	-0.205	-0.012	-0.415	-0.428
	Optimal	1.070	0.247	-0.247	0.000	-0.001	0.123	0.122	0.065		0.065	0.132		0.132	-0.290	0.085	-0.205	-0.013	-0.453	-0.466
EDR	OLS	0.488	0.064		0.064	0.001		0.001	0.060		0.060	0.005		0.005	-0.037		-0.037	0.002		0.002
	HME	0.511	0.128	-0.036	0.092	0.000	0.026	0.026	0.100	0.007	0.107	-0.017	-0.005	-0.022	-0.064	-0.036	-0.099	-0.002	-0.060	-0.063
	Optimal	0.610	0.098	-0.038	0.061	0.000	0.047	0.047	0.060		0.060	0.005		0.005	-0.086	-0.080	-0.166	-0.002	-0.063	-0.064
SHO	OLS	0.862	-0.294		-0.294	-0.002		-0.002	0.055		0.055	-0.095		-0.095	-0.026		-0.026	-0.066		-0.066
	HME-Opt	1.112	-0.429	0.343	-0.086	-0.002	-0.001	-0.003	-0.234	-0.203	-0.436	0.009	0.028	0.037	-0.062	-0.083	-0.145	-0.074	0.203	0.129
LON	OLS	0.291	0.246		0.246	0.003		0.003	-0.012		-0.012	0.032		0.032	-0.062		-0.062	0.009		0.009
SEC	OLS	0.830	0.268		0.268	0.002		0.002	0.012		0.012	0.174		0.174	-0.004		-0.004	0.032		0.032
	HME	0.580	0.314	-0.056	0.258	0.003	-0.035	-0.032	0.160	0.101	0.261	0.143	0.001	0.144	0.069	0.142	0.211	0.140	-0.300	-0.160
	Optimal	0.451	0.343	-0.090	0.253	0.003	-0.021	-0.018	0.185	0.101	0.285	0.174		0.174	0.096	0.173	0.270	0.144	-0.295	-0.152
GES	OLS	0.604	0.185		0.185	0.001		0.001	0.028		0.028	0.086		0.086	-0.033		-0.033	-0.003		-0.003
	HME-Opt	0.747	0.287	-0.155	0.132	0.001	0.017	0.017	0.107	0.029	0.137	0.037	-0.013	0.024	0.000	0.048	0.047	0.004	-0.246	-0.242

This table reports the value of the total mean risk premia (in percents) attributable to each risk factor for the sample period 1994:02 – 2002:12. For each specification, the alpha is the intercept of the regression. With OLS, the mean total risk premium of factor k is equal to $\hat{\beta}_k^{OLS}\overline{F}_k$. With HME, the mean total risk premium of factor k is equal to $\hat{\beta}_k^{HM}\overline{F}_k + \hat{\psi}_k\overline{\hat{w}}_k$. Under the optimal specification, the mean total risk premium of factor k is either the OLS risk premium if the variable has been removed from the HME estimation, or the mean total risk premium of the last pass of the HME.