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Risk and performance estimation in hedge funds revisited: Evidence from errors in variables[☆]

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ABSTRACT

This paper revisits the performance of hedge funds in the presence of errors in variables. To reduce the bias induced by measurement error, we introduce an estimator based on cross sample moments of orders three and four. This Higher Moment Estimation (HME) 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, while we emphasize some shifts in the economic contents of the equity risk premiums by switching from OLS to HME.

1. Introduction

It is well known in the economic literature that measurement errors in the regressors, also called errors-in-variables (EIV), tend to lead to inconsistent ordinary least squares (OLS) estimators in linear regression models.[2] Measurement errors generally arise from the use of observable proxies for unobserved variables. Nevertheless, as underlined by Cragg (1994) and Dagenais and Dagenais (1997), the problem of EIV has been largely neglected. To present the problem, two effects can be underlined. The first effect, labelled “attenuation effect” by Cragg (1994), is the measurement error that 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] 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 other 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 EIV also have more perverse effects on confidence intervals and on the sizes of the type I errors.

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2 See Fuller (1987), Klepper and Leamer (1984), and Leamer (1987) among others.
3 Cragg (1994), p. 780.

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As underlined by Frisch (1934), most data used in empirical economics suffer from the problem of EIV. 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 EIV. In this context, the market factor is measured with error, and the estimation of the market beta certainly suffers from the problems listed previously. These problems can be generalized to more general linear multifactor models of asset returns such as Ross (1976)'s Arbitrage Pricing Theory or Fama and French (1993)'s model. As underlined by Fama and French (1997) "estimates of the cost of equity for the three-factor model of FF (1993) are imprecise". By construction and lack of theoretical foundations, premiums related to the size, book-to-market, and momentum (Carhart, 1997) effects are designated candidates for EIV.

The measurement error issue is very likely to arise in the analysis of hedge fund returns, based on empirical linear asset pricing models. In particular, the option-based factors used in the empirical specifications are highly prone to measurement errors as they are defined as artificial variables. In this context, as shown by Fung and Hsieh (2001, 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). Thus, the proper treatment of EIV appears to be a challenge in the context of assessment of hedge fund required returns and performance. If linear asset pricing models are the common choices, recent evidence suggests, however, that they do not give a good description of expected returns. All the Fama–French inspired theoretical models are expressed in terms of expectations for the explanatory variables as well as for the dependent variable. In fact, if the estimated return generating models use realizations of returns, these realizations can be interpreted as the expectations measured with error. Thus, there is no theoretical reason for thinking that OLS would ever be consistent, and so an instrumental variable approach (IV) approach should always be used. Paradoxically, few theoretical and applied efforts have been made to reduce the important bias induced by EIV.[4]

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 (HM) estimator 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.[5] An attractive feature of Dagenais and Dagenais's 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,[6] especially in the hedge fund industry.

We apply this approach to a set of hedge fund indices that represent the major hedge fund strategies belonging to the directional, non-directional and event-driven classes. These indices are amongst the most widely studied in the academic literature and used in market practice. Doing so, we can assess the impact of our procedure for research purposes, but also regarding the actual implications for reporting purposes. We estimate the return generating process with a mix of asset- and option-based explanatory factors. We refer to the extant literature dealing with hedge fund returns in order propose a parsimonious modeling choice based on a stepwise variable selection. Starting from this selection of relevant explanatory factors, the purpose our analysis is to document how EIV can be corrected for a combination of independent variables (hedge fund returns) and independent variables (asset-based and option-based risk premiums) that is highly prone to this type of issue.

Our results indicate that the correction for measurement errors that we perform has a significant impact on the performance measurement and on the systematic risk exposures of hedge fund strategies, especially regarding the equity risk premium. 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.

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 the presence of EIV, and the results are reported. Section 5 analyzes the choice of factor loadings when measurement errors are detected and discussed the stability of risk premiums. Section 6 provides conclusive remarks and suggestions for future research.

2. Linear multifactor model with errors in the variables

EIV are 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[7] of asset return,[8]

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

[4] Exception to be quoted are Fama and MacBeth (1973), Shanken (1992), Kandel and Stambaugh (1995) and more recently Erickson and Whited (2000, 2002) with various results.

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

[6] The paradigm of portfolio selection based on the first two moments of the returns distribution does not describe well reality: see Huang and Litzenberger (1988) among others.

[7] This formulation encompasses many popular linear asset pricing models.

[8] We may mention that we consider here 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.

Table 1A
Descriptive statistics of hedge fund strategies

	Mean	Std dev.	t (mean)	Median	Min	Max	M. exc.	t (m. exc.)	Sharpe	Skewness	Kurtosis
SHO	−0.18	4.93	−0.44	−0.64	−8.69	22.71	−0.50	−1.24	−0.10	0.90	2.31
EME	0.79	4.35	2.21	1.49	−23.03	15.34	0.47	1.31	0.11	−1.17	6.03
GLB	1.23	3.06	4.89	1.19	−11.55	10.60	0.91	3.61	0.30	0.04	3.56
LON	1.13	2.89	4.75	1.07	−11.43	13.01	0.81	3.39	0.28	0.16	4.33
CNV	0.84	1.30	7.83	1.09	−4.68	3.57	0.51	4.81	0.40	−1.62	4.63
MNE	0.89	0.79	13.71	0.82	−1.15	3.26	0.56	8.72	0.72	0.45	0.60
FIX	0.57	1.04	6.71	0.75	−6.96	2.05	0.25	2.94	0.24	−3.39	19.76
DIS	1.16	1.77	7.99	1.23	−12.45	4.10	0.84	5.77	0.47	−3.35	23.46
MUL	0.95	1.72	6.68	0.99	−11.52	4.66	0.62	4.41	0.36	−2.80	18.49
RIS	0.65	1.21	6.55	0.62	−6.15	3.81	0.33	3.31	0.27	−1.24	6.69

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 10 active strategies for the sample period 1994:12–2007:03. 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. Returns in the table are in percentages. SHO = DedShort, EME = Emerging Markets Index, GLB = Global Macro, LON = Long/Short Equity, CNV = Convertible Arbitrage, MNE = Equity Market Neutral, FIX = Fix Arbitrage, DIS = Distressed Securities Index, MUL = Multi Strategy Index, RIS = Risk Arbitrage.

where α is a constant term defined as the security's abnormal return, or Jensen's alpha, $\tilde{F}_{tk}$ is factor k realization in period t, β_k is factor k loading and u is a residual idiosyncratic risk.

If the K factors $\tilde{F}_{kt}$ are observed, the parameters of model (1) can be consistently estimated by ordinary least squares (OLS). 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.

$$F_t = \tilde{F}_t + v_t \tag{2}$$

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. The measurement errors (v_t) are moreover assumed to be independent through time and uncorrelated[9] 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 Eq. (1) in vector form.

$$R_t = \alpha + \tilde{F}_t \cdot \beta + u_t \tag{3}$$

and substitute Eq. (2) in Eq. (3).

$$R_t = \alpha + F_t \cdot \beta + u_t - v_t \cdot \beta \tag{4}$$

The OLS estimates $\hat{\alpha}$ and $\hat{\beta}$ are inconsistent because the compound error in Eq. (4), $u_t - v_t \cdot \beta$, is correlated with the regressor F_t through the measurement error v_t.[10] In the presence of EIV, factor loading estimates are contaminated by attenuation and contamination bias mentioned above.

Without further assumptions, parameters of the EIV models (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.

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, β^{HM}, exhibiting "considerably smaller standard errors". The instruments are $z_1 = f*f$, $z_2 = f*f*f - 3f[E(f'f/N)*I_K]$ and a constant. f_{ij} are the elements of the matrix f and $f = AF$ where $A = I_N - ii'/N$. The matrix f is the $T \times K$ matrix F calculated in mean deviation, standing for the matrix of K factor loadings where T is here the number of observations. The symbol * is the Hadamard element-by-element matrix multiplication operator.

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 independent

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

[10] 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 formal proof, see Carmichael and Coën (2008).

Table 1B
Descriptive statistics of risk premium

	Mean	Std dev.	*t* (mean)	Median	Min	Max	M. exc.	*t* (m. exc.)	Sharpe	Skewness	Kurtosis
RUS	0.88	4.04	2.64	1.27	−11.71	12.68	0.55	1.67	0.14	−0.44	0.66
SMB	0.22	4.07	0.64	−0.18	−16.70	22.18	−0.11	−0.32	−0.03	0.84	6.97
HML	0.47	3.65	1.56	0.44	−12.80	13.80	0.15	0.49	0.04	0.00	2.71
UMD	0.79	5.25	1.82	0.79	−25.05	18.40	0.46	1.08	0.09	−0.65	5.00
EMB	1.07	5.78	2.26	1.35	−26.56	13.47	0.75	1.58	0.13	−0.98	2.79
BAA	2.13	0.58	44.29	1.89	1.29	3.79	1.81	37.58	3.09	0.77	−0.41
MEM	0.59	6.54	1.11	0.72	−27.34	17.88	0.27	0.51	0.04	−0.65	1.85
MLU	0.68	1.93	4.25	0.95	−7.63	6.65	0.35	2.23	0.18	−0.88	4.73
WGB	0.52	1.91	3.32	0.29	−4.28	5.94	0.20	1.27	0.10	0.32	0.22
LHM	0.41	0.88	5.72	0.48	−2.51	3.15	0.09	1.28	0.11	−0.18	0.75
LHC	0.28	1.88	1.81	0.46	−7.37	7.49	−0.04	−0.28	−0.02	−0.56	4.40
SBD	−1.74	14.29	−1.48	−5.19	−25.36	68.86	−2.07	−1.76	−0.14	1.61	4.25
SFX	0.21	19.09	0.13	−4.00	−30.00	90.27	−0.11	−0.07	−0.01	1.42	3.11
STK	−5.21	13.03	−4.87	−6.80	−30.19	46.15	−5.54	−5.17	−0.42	1.06	2.34
ACe	0.27	1.49	2.20	−0.34	−1.00	6.05	−0.05	−0.43	−0.04	1.13	0.79
OCm	−0.19	2.84	−0.83	−1.00	−1.00	24.91	−0.52	−2.20	−0.18	5.96	44.62
OCe	0.24	3.46	0.85	−1.00	−1.00	25.73	−0.08	−0.29	−0.02	4.20	22.36
APm	−0.12	1.80	−0.80	−1.00	−1.00	11.13	−0.44	−2.97	−0.24	3.32	14.69
APe	−0.08	1.90	−0.48	−1.00	−1.00	10.78	−0.40	−2.55	−0.21	2.97	10.65
APr	5.40	25.28	2.60	−1.00	−1.00	265.17	5.07	2.44	0.20	8.24	78.93

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 premiums for the sample period 1994:12–2007:03. 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. RUS = the Russell 3000 index, SMB = Fama and French size factor, HML = Fama and French book-to-market factor, UMD = Momentum factor (Carhart, 1997), EMB = Emerging Bond Market Index; BAA = Moody's Baa bond yield — US Treasury 10y CM bond yield, MEM = MSCI Emerging Market Index, MLU = ML US high yield total return index, WGB = WD Citigroup WGBI world all mats index, LHM = Lehman global-agg. sec-US MBS, LHC = Lehman global aggregate corporate, SBD = Return of PTFS Bond lookback straddle, SFX = Return of PTFS Currency Lookback Straddle, STK = Return of PTFS Stock Index Lookback Straddle, ACe = return of an artificial ATM index call: underlying index is the MSCI Emerging Market Index, OCm = return of an artificial 5% OTM index call: underlying index is the S&P500, OCe = return of an artificial 5% OTM index call: underlying index is the MSCI Emerging Market Index, APm = return of an artificial ATM index put: underlying index is the S&P500, APe = return of an artificial ATM index put: underlying index is the MSCI Emerging Market Index, AP = return of an artificial ATM index put: the underlying index is the BAA — 10y T-Bond. Only the factors that are selected in the stepwise analysis are presented.

variables. These are then used to construct measures of the EIV $\hat{w}_{kt}=F_{kt}-\hat{F}_{kt}$. The latter are then introduced as additional regressors,[11] called the adjustment variables, in Eq. (5) as follows:

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

The contribution of this procedure is twofold. First, we can test the null hypothesis (H_0: $\psi_k=0, k=1,\ldots,K$) that there are no EIV applying a Durbin–Wu–Hausman (DWH thereafter) type test.[12] Second, if EIV 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 labeled 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).

3. Data and empirical methods

3.1. Hedge funds data

We use monthly return data from CSFB/Tremont. This vendor provides fund information extracted from the TASS database. This is one of the three most extensively used data providers in hedge fund research, together with CISDM and HFR (see Chen and Liang, 2007 for a discussion).

Given the scope of this paper, we opt for a direct analysis of CSFB/Tremont hedge fund indices rather than composites obtained from the individual funds that can be contaminated with severe survivorship bias. The CSFB/Tremont indices provide full transparency about their constituents. Moreover, unlike equally-weighted indices, the CSFB/Tremont asset-weighted indices do not underweight top performers and underweight decliners.

We only select the broader indices that can be classified in three distinct groups: Directional, Non-Directional and Event Driven. The Directional group comprises Dedicated Short Sellers (SHO), Emerging Markets (EME), Global Macro (GLB) and Long/Short Equity (LON). The Non-Directional group features Convertible Arbitrage (CNV), Equity Market Neutral (MNE) and Fixed Income

[11] An appendix for more details is available from the authors upon request.

[12] See Hausman (1978) for more details.

Table 1C
Normality tests of hedge funds strategies and risk premiums

	Jarque–Bera		Lilliefors		Cramer–von Mises		Watson		Anderson–Darling	
	Stat.	*p*-value	Stat.	*p*-value	Stat.	*p*-value	Stat.	*p*-value	Stat.	*p*-value
SHO	49.35	0.00	0.06	0.10	0.10	0.12	0.07	0.23	0.78	0.04
EME	239.29	0.00	0.11	0.00	0.47	0.00	0.44	0.00	2.49	0.00
GLB	71.24	0.00	0.12	0.00	0.76	0.00	0.76	0.00	4.24	0.00
LON	106.47	0.00	0.10	0.06	0.27	0.00	0.27	0.00	1.75	0.00
CVN	184.10	0.00	0.17	0.00	0.98	0.00	0.86	0.00	5.35	0.00
EMN	6.88	0.04	0.08	0.02	0.14	0.03	0.12	0.04	0.85	0.02
FIX	2518.7	0.00	0.16	0.00	1.19	0.00	1.03	0.00	6.77	0.00
DIS	3428.9	0.00	0.12	0.00	0.52	0.00	0.46	0.00	3.65	0.00
MUL	2150.6	0.00	0.15	0.00	0.66	0.00	0.62	0.00	4.07	0.00
RIS	291.64	0.00	0.12	0.00	0.33	0.00	0.32	0.00	1.96	0.00
RUS	6.95	0.03	0.07	0.05	0.14	0.03	0.12	0.05	0.95	0.01
SMB	293.84	0.00	0.08	0.02	0.20	0.00	0.19	0.00	1.50	0.00
HML	41.11	0.00	0.08	0.01	0.31	0.00	0.31	0.00	1.82	0.00
UMD	151.57	0.00	0.12	0.00	0.66	0.00	0.66	0.00	3.56	0.00
EMB	66.68	0.00	0.07	0.07	0.16	0.01	0.13	0.004	1.00	0.01
BAA	15.35	0.00	0.17	0.00	0.82	0.00	0.73	0.000	4.82	0.000
WGB	2.70	0.26	0.06	0.10	0.05	0.53	0.04	0.60	0.35	0.48
MLU	145.48	0.00	0.12	0.00	0.71	0.00	0.68	0.00	4.09	0.00
MEM	29.21	0.00	0.08	0.02	0.15	0.02	0.13	0.03	0.84	0.03
LHC	117.06	0.00	0.09	0.00	0.48	0.00	0.46	0.00	3.00	0.00
LHM	3.67	0.16	0.05	0.10	0.05	0.56	0.44	0.55	0.30	0.58
STK	57.44	0.00	0.08	0.04	0.15	0.02	0.11	0.07	1.39	0.00
SBD	164.65	0.00	0.12	0.00	0.69	0.00	0.55	0.00	3.97	0.00
SFX	102.75	0.00	0.11	0.00	0.60	0.00	0.47	0.00	3.56	0.00
OCm	12307	0.00	0.44	0.00	8.27	0.00	7.95	0.00	43.19	0.00
OCe	3296	0.00	0.40	0.00	7.18	0.00	6.76	0.00	34.61	0.00
ACe	34.15	0.00	0.20	0.00	1.53	0.00	1.39	0.00	9.05	0.00
APm	1502.7	0.00	0.33	0.00	4.68	0.00	4.36	0.00	23.29	0.00
APe	861.33	0.00	0.33	0.00	4.89	0.00	4.52	0.00	24.38	0.00
APr	37492	0.00	0.40	0.00	7.76	0.00	7.53	0.00	41.84	0.00

This table reports the normality tests of the variables for the sample period 1994:12–2007:03: Jarque–Bera, Lilliefors, Cramer–von Mises, Watson and Anderson–Darling. SHO = DedShort, EME = Emerging Markets Index, GLB = Global Macro, LON = Long/Short Equity, CNV = Convertible Arbitrage, MNE = Equity Market Neutral, FIX = Fix arbitrage, DIS = Distressed Securities Index, MUL = Multi Strategy Index, RIS = Risk Arbitrage, RUS = the Russell 3000 index, SMB = Fama and French size factor, HML = Fama and French book-to-market factor, UMD = Momentum factor (Carhart, 1997), EMB = Emerging Bond Market Index; BAA = Moody's Baa bond yield — US Treasury 10y CM bond yield, MEM = MSCI Emerging Market Index, MLU = ML US high yield total return index, WGB = WD Citigroup WGBI world all mats index, LHM = Lehman global-agg. sec-US MBS, LHC = Lehman global aggregate corporate, SBD = Return of PTFS Bond lookback straddle, SFX = Return of PTFS Currency Lookback Straddle, STK = Return of PTFS Stock Index Lookback Straddle, ACe = return of an artificial ATM index call: underlying index is the MSCI emerging market index, OCm = return of an artificial 5% OTM index call: underlying index is the S&P500, OCe = return of an artificial 5% OTM index call: underlying index is the MSCI emerging market index, APm = return of an artificial ATM index put: underlying index is the S&P500, APe = return of an artificial ATM index put: underlying index is the MSCI emerging market index, APr = return of an artificial ATM index put: the underlying index is the Baa — 10y T-Bond.

Arbitrage (FIX). Although the Event Driven category has its own index, we break it up with the Distressed (DIS), Multi Strategy (MUL) and Risk Arbitrage (RIS) sub-categories. This characterization is consistent with the depiction of the indices provided by CSFB/Tremont. Data was collected from January 1994 to August 2007 (164 months).

3.2. Risk factors

The choice of risk factors is driven by the joint motivation of providing a reasonable characterization of hedge fund returns, while not letting the number of variables inflate so as to achieve the highest possible significance levels. Therefore, we choose to restrict the number of explanatory variables to a maximum of eight.[13]

Consistently with a large body of the extant literature, we start with the four-factor model proposed by Carhart (1997) as a common basis for all hedge fund indices.[14] Its equation is:

$$R_t = \alpha + \beta_r \mathrm{RUS}_t + \beta_s \mathrm{SMB}_t + \beta_h \mathrm{HML}_t + \beta_u \mathrm{UMD}_t + \varepsilon_t \quad (6)$$

where R_t is the hedge fund return in excess of the 13-weeks T-Bill rate, RUS_t is the Russell 3000 index,[15] SMB_t is the 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.

[13] The literature on hedge fund performance regularly uses two-digit return generating models, e.g. 11 factors for Capocci and Hübner (2004), 13 factors for Agarwal and Naik (2004), and even 24 factors (including dummy variables) for Fung et al. (2006).
[14] See Agarwal and Naik (2004), Capocci and Hübner (2004) and Chen and Liang (2007) among others.
[15] This market proxy is used by Agarwal and Naik (2004) and Capocci and Hübner (2004) among others.

Table 2A
Correlations among hedge funds and between hedge funds and risk premiums

	SHO	EME	GLB	LON	CNV	MNE	FIX	DIS	MUL	RIS
SHO	1.00									
EME	−0.56	1.00								
GLB	−0.11	0.43	1.00							
LON	−0.71	0.63	0.41	1.00						
CNV	−0.24	0.32	0.27	0.26	1.00					
MNE	−0.34	0.34	0.21	0.34	0.28	1.00				
FIX	−0.05	0.30	0.42	0.17	0.55	0.10	1.00			
DIS	−0.61	0.59	0.31	0.57	0.48	0.35	0.30	1.00		
MUL	−0.57	0.73	0.42	0.66	0.57	0.31	0.42	0.77	1.00	
RIS	−0.51	0.44	0.13	0.53	0.41	0.34	0.15	0.58	0.67	1.00
RUS	−0.74	0.50	0.19	0.59	0.11	0.39	−0.02	0.53	0.52	0.46
SMB	−0.42	0.33	0.11	0.54	0.19	0.01	0.10	0.31	0.36	0.34
HML	0.59	−0.32	−0.06	−0.60	−0.01	−0.16	0.05	−0.24	−0.23	−0.13
UMD	0.10	0.02	0.19	0.30	−0.05	−0.11	0.07	−0.13	0.00	−0.10
EMB	−0.67	0.79	0.24	0.61	0.20	0.35	0.12	0.61	0.64	0.48
BAA	−0.04	0.01	−0.11	−0.15	−0.01	−0.14	−0.11	−0.09	−0.13	−0.17
MEM	−0.66	0.78	0.18	0.60	0.15	0.34	0.06	0.58	0.62	0.49
MLU	−0.50	0.39	0.18	0.38	0.36	0.20	0.24	0.61	0.51	0.40
WGB	0.13	−0.24	0.02	−0.11	−0.13	−0.11	0.02	−0.19	−0.17	−0.18
LHM	0.07	−0.10	0.21	0.03	0.07	0.12	0.11	−0.03	−0.06	0.02
LHC	−0.40	0.34	0.21	0.35	0.33	0.26	0.24	0.56	0.46	0.41
SBD	0.08	−0.22	−0.07	−0.13	−0.14	0.09	−0.09	−0.27	−0.34	−0.31
SFX	0.02	−0.08	0.15	0.03	−0.04	0.15	−0.09	−0.02	−0.04	0.00
STK	0.10	−0.14	0.07	−0.02	−0.04	0.16	0.06	−0.16	−0.17	−0.23
Ace	−0.43	0.60	0.25	0.45	0.11	0.29	0.07	0.36	0.43	0.29
OCm	−0.29	0.24	0.26	0.35	0.07	0.29	0.02	0.20	0.20	0.12
OCe	−0.17	0.38	0.23	0.23	0.15	0.22	0.09	0.19	0.25	0.19
APm	0.74	−0.56	−0.31	−0.63	−0.19	−0.31	−0.07	−0.65	−0.59	−0.47
APe	0.58	−0.66	−0.30	−0.52	−0.17	−0.32	−0.13	−0.55	−0.53	−0.36
Apr	0.00	−0.24	−0.18	−0.06	−0.12	0.04	−0.30	0.01	−0.22	−0.13

This table reports the correlations among hedge fund returns and between hedge fund returns and risk premiums for the sample period 1994:12–2007:03. SHO = DedShort, EME = Emerging Markets Index, GLB = Global Macro, LON = Long/Short Equity, CNV = Convertible Arbitrage, MNE = Equity Market Neutral, FIX = Fix Arbitrage, DIS = Distressed Securities Index, MUL = Multi Strategy Index, RIS = Risk Arbitrage, RUS = the Russell 3000 index, SMB = Fama and French size factor, HML = Fama and French book-to-market factor, UMD = Momentum factor (Carhart, 1997), EMB = Emerging Bond Market Index; BAA = Moody's Baa bond yield — US Treasury 10y CM bond yield , MEM = MSCI Emerging Market Index, MLU = ML US high yield total return index, WGB = WD Citigroup WGBI world all mats index, LHM = Lehman global-agg. sec-US MBS, LHC = Lehman global aggregate corporate, SBD = Return of PTFS Bond Lookback Straddle, SFX = Return of PTFS Currency Lookback Straddle, STK = Return of PTFS Stock Index Lookback Straddle, ACe = return of an artificial ATM index call: underlying index is the MSCI Emerging Market Index, OCm = return of an artificial 5% OTM index call: underlying index is the S&P500, OCe = return of an artificial 5% OTM index call: underlying index is the MSCI emerging market index, APm = return of an artificial ATM index put: underlying index is the S&P500, APe = return of an artificial ATM index put: underlying index is the MSCI Emerging Market Index, APr = return of an artificial ATM index put: the underlying index is the Baa — 10y T-Bond.

Next, we implement a stepwise variable selection procedure with a number of candidate dependent variables that have proven to bring explanatory power in previous research.

These candidate variables are asset-based and option-based.

As asset-based variables, we exploit the JP Morgan Emerging Bond Market Index (EMB) introduced by Capocci and Hübner (2004); the four factors introduced by Fung and Hsieh (2001), namely the MSCI Emerging Markets (MEM), the spread of the Moody's Baa bond yield over the US Treasury 10 years constant maturity bond yield (BAA), the Goldman Sachs Commodity Index (GSC), and the Trade Weighted Exchange Index (TWE).[16] Finally, in line with the study by Agarwal and Naik (2004), we also include four fixed income factors: one for high yield bonds (the ML US high yield total return index (MLU)), one for world government bonds (the WD Citigroup WGBI all mats index (WGB)), one for mortgage-backed securities (the Lehman global-agg. sec-US MBS index (LHM) and one for corporate bonds (the Lehman global aggregate corporate index (LHC)).

Besides the asset-based risk factors, option-based factors may provide significant explanatory power. Consistently with the extant literature on hedge funds returns, we choose two types of factors that mimic option-related strategies.

First, we use the returns from lookback straddles on five asset-based factors (bond (SBD), currency (STK), commodity (SCO), interest rate (SIR) and stock index (SFX)) similar to those used in Fung and Hsieh (2001) and extracted from David Hsieh's data library[17].

Second, we construct monthly returns from index options with a procedure similar to the one put forward by Agarwal and Naik (2004) to build four series of returns of at-the-money (ATM) and out-of-the-money (OTM) put and call options on all asset-based

[16] The last two variables (GSC and TWE) are not retained in any of the specifications subsequently presented. Detailed results of the stepwise regressions are available upon request.

[17] Only the bond, currency and stock index straddles are retained in the stepwise analysis. These data series can be downloaded at http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls.

Table 2B
Correlations among risk premiums

	RUS	SMB	HML	UMD	EMB	BAA	MEM	MLU	WGB	LHM	LHC	SBD	SFX	STK	ACe	OCm	OCe	APm	APe	APr
RUS	1.00																			
SMB	0.11	1.00																		
HML	−0.48	−0.51	1.00																	
UMD	−0.27	0.18	−0.06	1.00																
EMB	0.68	0.33	−0.40	−0.22	1.00															
BAA	−0.17	0.08	0.01	−0.06	0.02	1.00														
MEM	0.70	0.34	−0.40	−0.22	0.96	0.05	1.00													
MLU	0.52	0.23	−0.21	−0.29	0.52	−0.07	0.49	1.00												
WGB	−0.10	0.00	0.04	−0.01	−0.17	0.01	−0.15	0.06	1.00											
LHM	0.00	−0.16	0.05	0.16	−0.18	−0.01	−0.18	0.14	0.16	1.00										
LHC	0.44	0.19	−0.20	−0.26	0.43	−0.11	0.39	0.88	−0.02	0.31	1.00									
SBD	−0.06	−0.05	−0.04	−0.05	−0.12	0.15	−0.15	−0.16	−0.05	0.10	−0.09	1.00								
SFX	−0.05	0.03	0.07	0.10	−0.12	0.01	−0.09	−0.11	0.07	0.04	−0.11	0.16	1.00							
STK	−0.17	−0.11	0.07	0.10	−0.27	−0.11	−0.24	−0.20	−0.03	0.15	−0.21	0.24	0.25	1.00						
ACe	0.50	0.29	−0.27	−0.24	0.78	−0.02	0.76	0.37	−0.15	−0.19	0.27	−0.02	−0.05	0.02	1.00					
OCm	0.38	−0.02	−0.22	−0.04	0.19	−0.04	0.20	0.14	−0.10	0.10	0.15	0.12	0.02	0.14	0.19	1.00				
OCe	0.27	0.22	−0.21	−0.25	0.49	0.03	0.47	0.24	−0.15	−0.13	0.22	−0.06	0.01	0.03	0.77	0.11	1.00			
APm	−0.72	−0.24	0.42	0.10	−0.69	0.10	−0.66	−0.50	0.09	0.04	−0.42	0.23	0.08	0.33	−0.39	−0.14	−0.18	1.00		
APe	−0.55	−0.21	0.33	0.03	−0.81	−0.03	−0.77	−0.41	0.10	0.06	−0.34	0.14	0.08	0.34	−0.42	−0.14	−0.18	0.72	1.00	
APr	0.00	−0.08	−0.07	−0.01	−0.12	−0.12	−0.11	−0.02	0.03	0.11	0.01	0.23	0.01	0.14	−0.06	0.00	−0.05	0.00	0.11	1.00

This table reports the correlations between risk premiums for the sample period 1994:12–2007:03. RUS = the Russell 3000 index, SMB = Fama and French size factor, HML = Fama and French book-to-market factor, UMD = Momentum factor (Carhart, 1997), EMB = Emerging Bond Market Index; BAA = Moody's Baa bond yield — US Treasury 10y CM bond yield, MEM = MSCI Emerging Market Index, MLU = ML US high yield total return index, WGB = WD Citigroup WGBI world all mats index, LHM = Lehman global-agg. sec-US MBS, LHC = Lehman global aggregate corporate, SBD = Return of PTFS Bond lookback straddle, SFX = Return of PTFS Currency Lookback Straddle, STK = Return of PTFS Stock Index Lookback Straddle, ACe = return of an artificial ATM index call: underlying index is the MSCI emerging market index, OCm = return of an artificial 5% OTM index call: underlying index is the S&P500, OCe = return of an artificial 5% OTM index call: underlying index is the MSCI emerging market index, APm = return of an artificial ATM index put: underlying index is the S&P500, APe = return of an artificial ATM index put: underlying index is the MSCI emerging market index, APr = return of an artificial ATM index put: the underlying index is the BAA — 10y T-Bond.

indices. As all these indices have derivatives markets that broadly differ in size and liquidity, 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 corresponding 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 approximated by using the Black–Scholes formula with the continuously compounded 1-month T-bill rate (risk-free rate), the historical volatility on the index (volatility) and the contemporaneous value of the 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. The choice of this degree of moneyness is consistent with the results empirically derived by Diez de los Rios and Garcia (2005). We call AC*i*, OC*i*, AP*i*, OP*i* the series of realized returns on these artificial strategies, with *i* corresponding to the type of underlying index.[18] Following Agarwal and Naik (2004) and Fung and Hsieh (2001), we identify the dominant risk factors using a stepwise regression “adding and/or deleting variables sequentially depending on the *F*-value”[19] to the four-factor model (RUS, SMB, HML, UMD). We specify a 5% (or at least 10%) significance level for including an additional variable in the stepwise regression procedure while identifying significant risk factors from the fifth risk factor. Significance is determined using the White (1980) heteroskedasticity-consistent covariance matrix estimators (HCCME).

The most comprehensive specification is a factor model depicted in Eq. (7).

$$R_t = \alpha + \beta_r \mathrm{RUS}_t + \beta_s \mathrm{SMB}_t + \beta_h \mathrm{HML}_t + \beta_u \mathrm{UMD}_t + \sum_{j=1}^{n^*} \beta_j F_{jt} + \varepsilon_t \tag{7}$$

where F_j is each of the n^* additional factors, $0 \le n^* \le 4$, that provide the highest level of information in the regression. The estimated regression coefficients will be noted $\hat{\alpha}^{\mathrm{OLS}}$ and $\hat{\beta}_k^{\mathrm{OLS}}$ for $k \in \{r, s, h, u, j\}$.

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

$$R_t = \alpha + \beta_r \mathrm{RUS}_t + \beta_s \mathrm{SMB}_t + \beta_h \mathrm{HML}_t + \beta_u \mathrm{UMD}_t + \sum_{j=1}^{n^*} \beta_j F_j t + \psi_r \hat{w}_{rt} + \psi_s \hat{w}_{st} + \psi_h \hat{w}_{ht} + \psi_u \hat{w}_{ut} + + \sum_{j=1}^{n^*} \psi_j \hat{w}_{jt} + \varepsilon_t \tag{8}$$

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

[18] For the subsequent analysis, only options written on the market proxy (indexed by *m*), the MSCI Emerging market (indexed by *e*) and the corporate spread (indexed by *s*) are retained in the stepwise procedure.

[19] Agarwal and Naik (2004), pp.74.

Table 3
OLS and HME regressions on hedge fund indices

Panel A.1 Directional Strategies — Dedicated Short Sellers: SHO

		Common factors				Factor 5	Factor 6	Factor 7	Factor 8	DWH
$\bar{R}^2$	α	RUS	SMB	HML	UMD	BAA	EMB	STK	OCe	
0.672	0.202	−0.800***	−0.327***	0.182**	−0.021					
0.685	2.559***	−0.840***	−0.311***	0.170*	−0.039	−1.083***				
0.695	2.268***	−0.708***	−0.257***	0.184**	−0.050	−0.938**	−0.135**			
0.701	2.281***	−0.713***	−0.265***	0.174**	−0.047	−1.015***	−0.154***	−0.035*		
0.729	2.117***	−0.664***	−0.286***	0.190***	−0.005	−0.993**	−0.255***	−0.049***	0.294***	
0.699	1.094*	−1.484***	−0.346	−0.266	−0.119*					17.140
		[0.766***]	[−0.052]	[0.530]	[0.061]					[0.001]
0.720	5.925***	−1.728***	−0.312	−0.344	−0.239***	−2.112***				22.840
		[0.990***]	[−0.046**]	[0.638**]	[0.190]	[1.524*]				[0.000]
0.736	6.022***	−2.059***	−0.484**	−0.494*	−0.220***	−2.108***	0.257			27.919
		[1.454***]	[0.165]	[0.799***]	[0.235***]	[1.980**]	[−0.345]			[0.000]
0.736	4.957***	−1.191***	0.041	0.159	−0.235***	−1.877***	−0.045	0.052		25.875
		[0.547*]	[−0.352***]	[0.115]	[0.229***]	[1.038]	[−0.040]	[−0.118***]		[0.000]
0.740	4.270***	−1.085***	−0.047	0.155	−0.158	−1.646**	−0.062	0.042	0.123	13.511
		[0.453]	[−0.271]	[0.118]	[0.144]	[0.844]	[−0.176]	[−0.114*]	[0.564]	[0.095]

Panel A.2 Directional Strategies — Emerging Markets: EME

		Common factors				Factor 5	Factor 6	Factor 7	Factor 8	DWH
$\bar{R}^2$	α	RUS	SMB	HML	UMD	EMB	SBD	STK	OCm	
0.320	−0.251	0.583***	0.325***	0.120	0.102*					
0.658	−0.374	−0.018	0.056	0.060	0.163***	0.641***				
0.667	−0.394	−0.025	0.048	0.038	0.154***	0.629***	−0.033*			
0.676	−0.237	−0.026	0.055	0.044	0.148***	0.648***	−0.040***	0.036**		
0.685	−0.200	−0.081	0.066	0.054	0.141***	0.651***	−0.044**	0.029*	0.185**	
0.350	−1.191	1.298***	0.606*	0.621	0.124					10.809
		[−0.783*]	[−0.323]	[−0.520]	[0.054]					[0.028]
0.668	−0.370	−0.117	−0.169	−0.194	0.272***	0.794***				9.193
		[0.088]	[0.224]	[0.282]	[−0.183***]	[−0.202]				[0.101]
0.678	−0.393	−0.100	−0.200	−0.217	0.280***	0.741***	−0.045*			10.741
		[0.059]	[0.259]	[0.281]	[−0.224***]	[−0.144]	[0.031]			[0.096]
0.685	−0.246	−0.093	−0.176	−0.215	0.253***	0.760***	−0.056**	0.034		11.296
		[0.074]	[0.247*]	[0.315*]	[−0.178***]	[−0.152]	[0.040]	[0.003]		[0.126]
0.700	−0.230	−0.177	−0.183	−0.213**	0.243***	0.764***	−0.058**	0.017	0.162**	15.022
		[0.133]	[0.258*]	[0.328**]	[−0.186***]	[−0.162]	[0.040]	[0.013]	[−0.534]	[0.058]

Panel A.3 Directional Strategies — Global Macro: GLB

		Common factors				Factor 5	Factor 6	Factor 7	Factor 8	DWH
$\bar{R}^2$	α	RUS	SMB	HML	UMD	LHM	EMB	SFX	OCe	
0.089	0.485*	0.249***	0.088	0.142*	0.154***					
0.112	0.257	0.239***	0.115*	0.143*	0.132**	0.596**				
0.142	0.183	0.097	0.058	0.129	0.141***	0.715***	0.149***			
0.159	0.194	0.080	0.044	0.112	0.134***	0.712***	0.165***	0.024**		
0.185	0.163	0.112	0.035	0.127	0.160***	0.705***	0.105*	0.021	0.184***	
0.116	0.668	0.052	0.371	0.193	0.032					8.368
		[0.230]	[−0.386]	[0.001]	[0.153]					[0.078]
0.122	0.815	−0.059	0.245	−0.004	0.012	0.205				6.687
		[0.347]	[−0.213]	[0.216]	[0.157***]	[0.239]				[0.245]
0.236	1.044***	−1.201***	−0.407***	−0.564***	0.179***	0.664	0.795***			23.495
		[1.394***]	[0.405**]	[0.786***]	[−0.087]	[−0.299]	[−0.725***]			[0.000]
0.238	0.873**	−1.074***	−0.288*	−0.420**	0.162***	0.692	0.758***	0.041*		21.707
		[1.249***]	[0.265]	[0.626***]	[−0.073]	[−0.338]	[−0.672***]	[−0.019]		[0.003]
0.267	0.752*	−0.925***	−0.232	−0.323*	0.179**	0.646	0.691***	0.040*	0.042	23.689
		[1.085***]	[0.238]	[0.515**]	[−0.128]	[−0.082]	[−0.650***]	[−0.025]	[−0.339]	[0.002]

Panel A.4 Directional Strategies — Long/Short Equity: LON

		Common factors				Factor 5	Factor 6	Factor 7	Factor 8	DWH
$\bar{R}^2$	α	RUS	SMB	HML	UMD	EMBI	STK	APm		
0.716	0.251*	0.428***	0.248***	−0.090*	0.215***					
0.756	0.223*	0.289***	0.185***	−0.103***	0.229***	0.149***				
0.772	0.358**	0.290***	0.193***	−0.095**	0.225***	0.167***	0.030***			
0.790	0.477***	0.209***	0.186***	−0.092**	0.211***	0.132***	0.039***	−0.362***		
0.722	−0.129	0.639***	0.473***	0.218	0.219***					7.106
		[−0.226]	[−0.261]	[−0.320]	[0.010]					[0.130]

(continued on next page)

Table 3 (*continued*)

Panel A.4 Directional Strategies — Long/Short Equity: LON

		Common factors				Factor 5	Factor 6	Factor 7	Factor 8	DWH
$\bar{R}^2$	α	RUS	SMB	HML	UMD	EMBI	STK	APm		
0.757	0.301	0.018	0.169	−0.128	0.255***	0.292***				5.584
		[0.281]	[−0.003]	[0.026]	[−0.057]	[−0.154]				[0.349]
0.781	0.247	0.166	0.280***	0.006	0.246***	0.267***	0.025			11.394
		[0.117]	[−0.138*]	[−0.121]	[−0.041]	[−0.123]	[0.019]			[0.077]
0.793	0.337*	0.244***	0.308***	0.015	0.229***	0.134	0.034*	−0.322		8.623
		[−0.051]	[−0.178**]	[−0.128]	[−0.041]	[−0.007]	[0.011]	[−0.053]		[0.2808]

Panel B.1 Non-Directional Strategies — Convertible Arbitrage: CNV

		Common factors				Factor 5	Factor 6	Factor 7	Factor 8	DWH
$\bar{R}^2$	α	RUS	SMB	HML	UMD	MLU	WGB.			
0.057	0.423***	0.050	0.098***	0.075*	−0.012					
0.148	0.313***	−0.014	0.061*	0.050	0.006	0.253***				
0.167	0.367***	−0.024	0.060*	0.048	0.005	0.270***	−0.104*			
0.111	0.068	0.301*	0.245*	0.276	0.000					12.793
		[−0.272*]	[−0.180]	[−0.200]	[0.008]					[0.012]
0.167	0.114	0.313	0.314	0.333	−0.023	−0.118				8.240
		[−0.350]	[−0.267]	[−0.288]	[0.020]	[0.389]				[0.143]
0.214	0.819***	−0.161	−0.036	−0.184	−0.007	0.291	−0.502***			14.525
		[0.116]	[0.090]	[0.239]	[−0.003]	[0.031]	[0.467***]			[0.024]

Panel B.2 Non-Directional Strategies — Equity Market Neutral: MNE

		Common factors				Factor 5	Factor 6	Factor 7	Factor 8	DWH
$\bar{R}^2$	α	RUS	SMB	HML	UMD	STK	SFX	APe		
0.133	0.498***	0.075***	−0.001	0.003	−0.001					
0.176	0.558***	0.082***	0.005	0.007	−0.004	0.013**				
0.190	0.551***	0.080***	0.002	0.003	−0.005	0.011*	0.006			
0.254	0.601***	0.047***	−0.004	0.003	−0.011	0.016***	0.006**	−0.133***		
0.117	0.548***	0.032	0.010	0.010	−0.024*					1.572
		[0.046]	[−0.009]	[−0.009]	[0.030]					[0.813]
0.164	0.597***	0.058	0.025	0.015	−0.032**	0.014				2.991
		[0.032]	[−0.019]	[−0.002]	[0.044**]	[0.001]				[0.701]
0.195	0.584***	0.034	0.017	0.004	−0.035***	0.006	0.013***			6.892
		[0.055]	[−0.010]	[0.014]	[0.047***]	[0.008]	[−0.013*]			[0.330]
0.241	0.658***	0.001	−0.013	−0.030	−0.029	0.013	0.010**	−0.159***		4.525
		[0.056]	[0.017]	[0.050]	[0.029]	[0.004]	[−0.009]	[0.009]		[0.717]

Panel B.3 Non-Directional Strategies — Fixed Income Arbitrage: FIX

		Common factors				Factor 5	Factor 6	Factor 7	Factor 8	DWH
$\bar{R}^2$	α	RUS	SMB	HML	UMD	MLU	EMB	APr		
0.004	0.202**	0.010	0.047*	0.045	0.010					
0.087	0.116	−0.040	0.019	0.026	0.024	0.198*				
0.101	0.116	−0.071	0.006	0.024	0.027	0.183*	0.037*			
0.184	0.195**	−0.066**	−0.002	0.009	0.026	0.191***	0.025	−0.012***		
0.008	0.004	0.150	0.123	0.151	0.024					4.611
		[−0.151]	[−0.093]	[−0.105]	[−0.006]					[0.329]
0.082	0.129	−0.176	−0.127	−0.127	0.076	0.448				4.201
		[0.142]	[0.147]	[0.156]	[−0.064]	[−0.294]				[0.521]
0.207	0.252**	−0.450*	−0.301*	−0.292*	0.114*	0.445	0.190***			25.190
		[0.389*]	[0.318*]	[0.325*]	[−0.137*]	[−0.312]	[−0.180***]			[0.000]
0.217	0.104	−0.142	−0.097	−0.044	0.096	0.388	0.042	−0.013		13.071
		[0.071]	[0.099]	[0.048]	[−0.118]	[−0.243]	[−0.031]	[0.000]		[0.070]

Panel C.1 Event Driven Strategies — Distressed: DIS

		Common factors				Factor 5	Factor 6	Factor 7	Factor 8	DWH
$\bar{R}^2$	α	RUS	SMB	HML	UMD	MLU	MEM	SBD	ACe	
0.347	0.541***	0.252***	0.159***	0.105**	−0.008					
0.457	0.376*	0.156***	0.105***	0.068*	0.019	0.381***				
0.494	0.425***	0.073**	0.067**	0.058	0.025	0.356***	0.082**			
0.510	0.418***	0.077*	0.067**	0.049	0.019	0.334***	0.074***	−0.018***		
0.519	0.460***	0.075**	0.074**	0.054	0.013	0.331***	0.109**	−0.016	−0.201	
0.530	−0.265	0.776***	0.497***	0.718***	−0.024					59.882
		[−0.578***]	[−0.357***]	[−0.664***]	[0.084*]					[0.000]
0.549	−0.033	0.655**	0.554*	0.709*	−0.092	−0.119				34.463
		[−0.519*]	[−0.431]	[−0.680*]	[0.162*]	[0.422]				[0.000]

Table 3 (*continued*)

Panel C.1 Event Driven Strategies — Distressed: DIS

		Common factors				Factor 5	Factor 6	Factor 7	Factor 8	DWH
$\bar{R}^2$	α	RUS	SMB	HML	UMD	MLU	MEM	SBD	ACe	
0.586	0.328	0.082	0.007	0.232	0.067*	0.102	0.351***			37.522
		[−0.020]	[0.102]	[−0.199]	[−0.045]	[0.190]	[−0.304**]			[0.000]
0.626	0.252	0.213	0.103	0.314***	0.040	−0.055	0.289***	−0.038***		50.775
		[−0.152]	[0.002]	[−0.285*]	[−0.024]	[0.347]	[−0.242***]	[0.043***]		[0.000]
0.585	0.383**	0.142	0.078	0.178	0.019	0.240	0.193***	−0.030*	−0.416*	30.134
		[−0.082]	[0.025]	[−0.150]	[−0.002]	[0.058]	[−0.177*]	[0.035***]	[0.661*]	[0.000]

Panel C.2 Event Driven Strategies — Multi Strategy: MUL

		Common factors				Factor 5	Factor 6	Factor 7	Factor 8	DWH
$\bar{R}^2$	α	RUS	SMB	HML	UMD	MLU	EMB	SBD	APr	
0.404	0.249	0.273***	0.183***	0.142***	0.038*					
0.450	0.142	0.210***	0.148***	0.117***	0.055***	0.247***				
0.530	0.141	0.105***	0.103***	0.111***	0.063***	0.194***	0.126***			
0.576	0.139	0.106***	0.100***	0.096***	0.054***	0.160***	0.119***	−0.027***		
0.586	0.190	0.109***	0.095***	0.088***	0.055***	0.170***	0.112***	−0.024*	−0.008	
0.487	−0.323	0.655***	0.437***	0.520**	0.044*					27.366
		[−0.416*]	[−0.295*]	[−0.392]	[0.030]					[0.000]
0.491	−0.193	0.654*	0.548*	0.593	−0.015	−0.208				16.509
		[−0.459]	[−0.416]	[−0.483]	[0.090]	[0.383]				[0.005]
0.546	0.084	0.097	0.093	0.119	0.093***	0.092	0.227			11.014
		[0.004]	[0.008]	[−0.005]	[−0.068]	[0.061]	[−0.133]			[0.088]
0.618	0.038	0.225*	0.150	0.180	0.076***	−0.083	0.174**	−0.047***		22.408
		[−0.137]	[−0.049]	[−0.085]	[−0.072*]	[0.247]	[−0.083]	[0.036**]		[0.002]
0.641	−0.077	0.406***	0.276***	0.328***	0.061**	−0.148	0.100	−0.049***	−0.001	29.625
		[−0.340**]	[−0.190*]	[−0.262**]	[−0.052]	[0.328*]	[−0.007]	[0.039**]	[0.011]	[0.000]

Panel C.3 Event Driven Strategies — Risk Arbitrage: RIS

		Common factors				Factor 5	Factor 6	Factor 7	Factor 8	DWH
$\bar{R}^2$	α	RUS	SMB	HML	UMD	LHC	SBD			
0.382	0.085	0.174***	0.145***	0.129***	−0.002					
0.398	0.074	0.154***	0.134***	0.123***	0.005	0.102**				
0.456	0.061	0.145***	0.127***	0.109***	−0.001	0.091**	−0.021***			
0.427	−0.228	0.344***	0.341***	0.396***	−0.006					15.136
		[−0.184]	[−0.226***]	[−0.280**]	[0.019]					[0.004]
0.446	−0.397*	0.501***	0.513***	0.582***	−0.025	−0.277				17.219
		[−0.363**]	[−0.396**]	[−0.476**]	[0.026]	[0.325]				[0.004]
0.514	−0.312***	0.402***	0.394***	0.452***	−0.006	−0.237	−0.035***			22.813
		[−0.275***]	[−0.272***]	[−0.358***]	[−0.025]	[0.301*]	[0.029***]			[0.000]

This table reports the regression results of hedge fund index returns for the sample period 1994:12–2007:03. The OLS specifications (reported in the first part of each panel) take the form of equation $R_t = \hat{\alpha}^{\text{OLS}} + \sum_{k=1}^{K} \hat{\beta}_k^{\text{OLS}} \cdot F_{kt} +_t$ with the four Fama–French factors and 2 to 4 additional risk factors chosen by stepwise regression. The HME specifications (reported in the second part of each panel) take the form $R_t = \hat{\alpha}^{\text{HM}} + \sum_{k=1}^{K} \hat{\beta}_k^{\text{HM}} \cdot F_{kt} + \sum_{k=1}^{K} \hat{\psi}_k \cdot \hat{w}_{kt} + \varepsilon_t$ with the four Fama–French factors, 2 to 4 additional risk factors and the corresponding adjustment variables (in brackets). The alpha is expressed in percents. DWH (acronym for Durbin–Wu–Hausman) is a standard χ_{q^2} where q is the number of adjustment variables to detect EIV by testing $\boldsymbol{\psi}_k = 0$ The DWH test is a heteroskedasticity robust test. Below the DWH statistic is the p-value in brackets. All HME and OLS statistics are computed with White (1980) H_0 heteroskedasticity-consistent covariance matrix estimators (HCCME). *** Significant at the 1% level, ** significant at the 5% level and * significant at the 10% level.

RUS = the Russell 3000 index, SMB = Fama and French size factor, HML = Fama and French book-to-market factor, UMD = Momentum factor (Carhart, 1997), EMB = Emerging Bond Market Index; BAA = Moody's Baa bond yield — US Treasury 10y CM bond yield, MEM = MSCI Emerging Market Index, MLU = ML US high yield total return index, WGB = WD Citigroup WGBI world all mats index, LHM = Lehman global-agg. sec-US MBS, LHC = Lehman global aggregate corporate, SBD = Return of PTFS Bond lookback straddle, SFX = Return of PTFS Currency Lookback Straddle, STK = Return of PTFS Stock Index Lookback Straddle, ACe = return of an artificial ATM index call: underlying index is the MSCI emerging market index, OCm = return of an artificial 5% OTM index call: underlying index is the S&P500, OCe = return of an artificial 5% OTM index call: underlying index is the MSCI emerging market index , APm = return of an artificial ATM index put: underlying index is the S&P500, APe = return of an artificial ATM index put: underlying index is the MSCI emerging market index , APr = return of an artificial ATM index put: the underlying index is the Baa — 10y T-Bond.

Thanks to this new approach, we shed a new light on absolute returns, comparing $\hat{\alpha}^{\text{OLS}}$ with $\hat{\alpha}^{\text{HME}}$. 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's numerical and simulated results: "The relative performance of HM estimators is always superior to that of OLS estimators, when there are errors in variables".[20] 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 Tables 1A, 1B and 1C. Our database includes the Credit Suisse First Boston/Tremont indices. Namely, we select the following indices; Dedicated Short Sellers (SHO), Emerging Markets Index (EME), Global Macro (GLB), Long/Short Equity (LON), Convertible Arbitrage (CNV), Equity Market Neutral (MNE), Fixed Income Arbitrage (FIX), Distressed Securities Index (DIS) Multi Strategy Index (MUL) and Risk Arbitrage (RIS).

Consistently with previous studies, some strategies appear to achieve extremely favorable performance for all measures. Global Macro, Long/Short Equity, and Distressed Securities strategies exhibit average monthly returns greater than 1%. The Sharpe ratio of Market Neutral funds is up to five times greater than that of the market proxy, (Russell 3000 Index). Global Macro, Long/Short Equity, Convertible Arbitrage, Multi 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.

As acknowledged by a vast body literature, the first two moments of returns are insufficient to provide a good description of risk. Descriptive statistics reported in Table 1B confirm this view and cast doubt on the normality of the returns and the risk factor loadings. 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 and risk premiums, with the exception of the WGB (world government bond) and the LHM (MBS) factors. This indicates that higher moments (than the variance) of the regressors are highly likely to influence hedge funds performance measurement.

The correlation between and among hedge and among risk factors is reported in Tables 2A and 2B. The correlations between the independent variables and the hedge fund returns do not exceed 0.80. The correlation among the asset-based regressors is quite low, except for EMB and MEM as already thereby raising no serious concern about multicolinearity in so far as they are never combined in the different specifications.[21] Moreover, as underlined by Dagenais (1994), if explanatory variables are strongly correlated, the problem of measurement errors is much more severe: OLS estimators are biased. A correction for EIV is strongly requested.

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-, six-, seven and eight-factor models depicted above, and compare the significance levels achieved with the HME procedure.

As mentioned earlier we identify the dominant risk factors using a stepwise regression and we determine the significance using the White (1980) heteroskedasticity-consistent covariance matrix estimators (HCCME). In this case as demonstrated by Davidson and MacKinnon (2004), the DWH statistic, under H_0 (no EIV), is asymptotically distributed as a χ_{q^2} where q is the number of adjustment variables. The DWH test is also a heteroskedasticity robust test. All DWH-stats are statistically significant at 5% level (except for the Equity Market Neutral strategy), highlighting the presence of EIV in nine regressions to ten.[22] OLS estimates are inconsistent. The results are presented in Table 3.

We split this table in three panels: Panel A displays Directional strategies: Dedicated Short Sellers, Emerging Markets, Global Macro, and Long/Short Equity. In Panel B, results are displayed for Non-Directional strategies: Convertible Arbitrage, Equity Market Neutral, and Fixed Income Arbitrage. Finally, Event Driven strategies are reported in Panel C: Distressed, Multi Strategy and Fixed Arbitrage.

Panel A reports a consistent result regarding the additional information brought by HME for Directional Strategies. The 4–8 factor HM specifications always dominate the corresponding 4–8 OLS with an increase in the $\bar{R}^2$ ranging between 0.3% for Long/Short Equity and 8.2% for Global Macro. The DWH-stats and t-stats detect in all cases the presence of EIV. For the four strategies displayed in the panel, there are between one and three significant loadings for the adjustment variables.

Moreover the artificial regression approach we use gives a good illustration of the contamination and attenuation effects described by Cragg (1994). For the Dedicated Short Sellers strategy, the addition of the fifth factor (BAA) indeed introduces contamination effects. Factors BAA, HML, SMB and RUS are contaminated by EIV (as underlined by significant t-stats and the DWH-stats), whereas only the RUS factor is statistically contaminated in the four-factor specification. On the other hand, the optional factor OCe tends to significantly decrease the impact of EIV even if they are still statistically present. Only the factor STK is statistically the source of EIV (at 10%) while it is statistically significant at 1% in a seven-factor specification.

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

[21] Furthermore, these multicolinearity 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 et al. (2004). Details not reported here, are available upon request.

[22] For Equity Market Neutral strategy EIV are detected for individual risk-factors using t-stat especially in the five-factor specification. EIV cannot be ignored in this case, even if the DWH-stat is not statistically significant. We recommend a prudent rule.

Besides, some coefficients that used to be significant with OLS might not be anymore under HME. This phenomenon is particularly noteworthy for the Dedicated Short Sellers strategy where out of seven significant coefficients, only two of them (RUS and BAA) remain significant with HME. Oppositely, other coefficients that are not significant with OLS may be significant with HME. This phenomenon happens with RUS and UMD coefficients for Global Macro and with HML and UMD for Emerging Markets. In such cases, the corresponding adjustment variables pick up most of the coefficient variance.

In Panel B, devoted to Non-Directional Strategies, we obtain qualitatively similar results. The presence of EIV is detected by DWH tests or t-stats. The relatively weak adjusted R^2 underline the weak contribution of RUS, SMB, HML and UMD to returns explanation. The use of the stepwise procedure shows the importance of factors related to high-yield interests, trend following, and non-linearities as reported the t-stats of the optional factors (significant at 1%); APr for Fixed Income Arbitrage, and APe for Equity Market Neutral. Like in Panel A, the addition of new variables can induce contamination effects, such as with WGB, SFX and EMB respectively for Convertible Arbitrage, Equity Market Neutral and Fixed Income Arbitrage. On the other hand, MLU, APr and especially APe introduce attenuation effects. This phenomenon is particularly noteworthy for Equity Market Neutral. The APe variable leads to non-significant EIV, as reported by the DWH test and by non-significant t-stats. We cannot reject the absence of EIV at 10%. In this case, the OLS specification should be preferred to HME. Nevertheless, we suggest a prudent approach: the five and the six-factor specifications report significant EIV for UMD that seem to vanish with the addition of APe.

For Convertible Arbitrage and Fixed Income Arbitrage, the DWH-stats are statistically significant and strongly command the use of HME. The alphas for these two strategies suggest a new interpretation of absolute returns. For Convertible Arbitrage, the alpha is much higher and significant with HME specification than with OLS. Oppositely, for Fixed Income Arbitrage, significant absolute returns vanish with HME. These results suggest that OLS should be used and interpreted with great caution. IV procedures and especially HME are likely to provide substantially different insight over hedge fund performance, especially when – like for the Non-Directional Strategies – the basic model specification is relatively poor.

Panel C displays results regarding Event Driven Strategies, whose average significance levels with OLS (50.2%) largely exceed those of Non-Directional Strategies (20.2%). In all cases, HME specification dominates OLS, with an average increase in $\bar{R}^2$ of 6.0%. Results confirm Dagenais and Dagenais (1997) main conclusions for EIV tests: "The performance of the EIV tests improves significantly when $\bar{R}^2$ increases". The DWH tests are statistically significant for the three strategies. As expected, the addition of new factors induces attenuation and contamination effects. Thus, the HME specification reveals a statistically significant abnormal return of −0.312 for Risk Arbitrage whereas the OLS shows a positive abnormal return of 0.061. The impact of MLU is noteworthy, very significant with OLS and non-significant with HME for Distressed and Multi strategies. MLU contributes nevertheless to the attenuation effect: the DWH-stat for the Distressed strategy decreases from 59.88 for the 4-factor specification to 34.46 (but still very significant) for the five-factor specification. Focusing on Risk Arbitrage, the explanatory variable, LHC, is not significant anymore but induce a contamination effect as shown by the DWH-stat that increases from 15.136 (significant at 1%) for the four-factor specification to 17.219 (significant at 1%).

When considering Table 3 globally, one also gets some useful insight in terms of strategy performance. The reported results clearly show that EIV are not a pure econometric curiosity but a real issue that must be solved to avoid misleading investment decisions. Attenuation and contamination effects may be underlined for all hedge fund strategies. There is no theoretical reason for thinking that OLS would ever be consistent, and so an instrumental variable approach should always be used. Dagenais and Dagenais' (1997) estimator is a good candidate to make better inference and improve portfolio management.

To shed light on the consequences of EIV on asset management, we illustrate in the next section the main differences between risk premiums estimated by OLS and HME.

5. Stability of risk premiums

Our results show that sensible gains in significance from the change in specification are documented for all cases but one. These gains presumably result from the existence of measurement errors in factor risk loadings. By definition, such errors imply economically important uncertainty about factor risk premiums, and the associated performance measures such as the alpha. Hence, we now have to consider whether the economic implications for portfolio management purposes are not altered by the passage from OLS to HME.

We address 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: $\mathrm{PremTot}_k = \hat{\beta}_k^{\mathrm{OLS}} \cdot \bar{F}_k$ for $k \in \{r, s, h, u, j\}$ where j is the increment for each of the n^* additional factors, $0 \leq n^* \leq 4$, providing the highest information level in the regression. For HME, the mean total risk premium is defined as $\mathrm{PremTot}_k = \hat{\beta}_k^{\mathrm{HM}} \cdot \bar{F}_k + \hat{\psi}_k \cdot \bar{\hat{w}}_k$.

Table 4 compares mean total risk premiums obtained with OLS regression technique with those generated by HM estimators.

For Directional strategies, the switch from OLS to HME substantially alters the performance diagnostics for the Dedicated Short Sellers and (to a lesser extent) for the Global Macro strategies. This has to be related to the important drop of the market risk premium for these strategies. This premium, along with the SMB premium, is even negative for three strategies (SHO, EME and GLB) although only the first one is dedicated to have a negative market exposure.

As could be expected from the weak significance levels, premiums for Non-Directional strategies do not experience important changes due to the passage from OLS to HME, with an average change of 2.0 bps per risk factor. All of the Russell risk premiums slightly fall.

Table 4
Total premiums corresponding to the risk factors

Directional strategies										
SHO	Specif.	α	RUS	SMB	HML	UMD	BAA	EMB	STK	OCe
	OLS	2.117	−0.582	−0.062	0.089	−0.004	−2.113	−0.274	0.257	0.071
	HME	4.270	−0.951	−0.010	0.072	−0.124	−3.502	−0.066	−0.219	0.030
EME	Specif.	α	RUS	SMB	HML	UMD	EMB	SBD	STK	OCm
	OLS	−0.200	−0.071	0.014	0.025	0.111	0.699	0.076	−0.152	−0.036
	HME	−0.230	−0.155	−0.039	−0.100	0.191	0.820	0.100	−0.089	−0.031
GLB	Specif.	α	RUS	SMB	HML	UMD	LHM	EMB	SFX	OCe
	OLS	0.163	0.099	0.007	0.060	0.126	0.292	0.113	0.004	0.044
	HME	0.752	−0.811	−0.050	−0.152	0.141	0.268	0.742	0.008	0.010
LON	Specif.	α	RUS	SMB	HML	UMD	EMB	STK	APm	
	OLS	0.477	0.209	0.186	−0.092	0.211	0.132	0.039	−0.362	
	HME	0.337	0.214	0.066	0.007	0.181	0.144	−0.179	0.038	
Non-Directional strategies										
CNV	Specif.	α	RUS	SMB	HML	UMD	MLU	WGB		
	OLS	0.367	−0.021	0.013	0.023	0.004	0.182	−0.054		
	HME	0.819	−0.141	−0.008	−0.086	−0.005	0.197	−0.262		
MNE	Specif.	α	RUS	SMB	HML	UMD	STK	SFX	APe	
	OLS	0.601	0.041	−0.001	.001	−0.009	−0.082	0.001	0.010	
	HME	0.658	0.001	−0.003	−0.014	−0.023	−0.070	0.002	0.012	
FIX	Specif.	α	RUS	SMB	HML	UMD	MLU	EMB	APr	
	OLS	0.195	−0.058	−0.001	0.004	0.020	0.129	0.027	−0.066	
	HME	0.104	−0.124	−0.021	−0.021	0.076	0.262	0.045	−0.070	
Event Driven strategies										
DIS	Specif.	α	RUS	SMB	HML	UMD	MLU	MEM	SBD	ACe
	OLS	0.460	0.066	0.016	0.025	0.011	0.224	0.065	0.027	−0.054
	HME	0.383	0.124	0.017	0.084	0.015	0.163	0.115	0.052	−0.112
MUL	Specif.	α	RUS	SMB	HML	UMD	MLU	EMB	SBD	APr
	OLS	0.190	0.095	0.021	0.041	0.043	0.115	0.120	0.042	−0.042
	HME	−0.077	0.356	0.059	0.154	0.048	−0.100	0.107	0.085	−0.008
RIS	Specif.	α	RUS	SMB	HML	UMD	LHC	SBD		
	OLS	0.061	0.127	0.027	0.051	−0.001	0.025	0.036		
	HME	−0.312	0.353	0.085	0.212	−0.005	−0.066	0.061		

This table reports the value of the total mean risk premiums (in percents) attributable to each risk factor for the sample period 1994:12–2007:03. For each specification, the alpha is the intercept of the regression. With OLS, the mean total risk premium of factor k is equal to $\hat{\beta}_k^{\mathrm{OLS}}\,\overline{F}_k$. With HME, the mean total risk premium of factor k is equal to $\hat{\beta}_k^{\mathrm{HM}}\overline{F}_k+\hat{\psi}_k\,\overline{w}_k$.

The analysis is more insightful for the Event Driven strategies. In sharp contrast to the other two categories, all market risk premiums (Russell, SMB and HML) increase from OLS to HME. The average change in the market risk premium is 18.2 bps, 3.2 bps for SMB and 11.1 bps for HML, which sums up to a total of 3.9% in annual terms. Besides, all three alphas concomitantly fall by an average of 23.9%, or −2.9% in annual terms. Thus, accounting for EIV contributes to modifying the risk exposure and performance characteristics of these types of strategies. They statistically behave much more as mildly directional strategies under the HME specification, to the detriment of their performance.

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.

The empirical test of the Dagenais and Dagenais (1997) method on a set of hedge fund indices provides informative evidence on the applicability of the procedure. First, the results suggest that HME is not only relevant as a methodological treatment of EIV, but it also improves the explanatory power of most OLS specifications. Second, the performance of hedge fund strategies is largely modified – without any systematic direction – when measurement errors are properly taken into account. Third, it does indeed often alter the risk premiums attributable to the equity market source of risk, while EIV has no clear impact on the other sources of risk.

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 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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