CFR-Working Paper NO. 10-07

Do Higher-Moment Equity Risks Explain Hedge Fund Returns?

V. Agarwal • G. Bakshi • J. Huij

centre for financial research
Look deeper

Do Higher-Moment Equity Risks Explain Hedge Fund Returns?*

Vikas Agarwal[a†] Gurdip Bakshi[b‡] Joop Huij[c§]

[a]*Robinson College of Business, Georgia State University Atlanta GA 30303, USA*

[b]*Smith School of Business, University of Maryland, College Park, MD 20742, USA*

[c]*RSM Erasmus University, Room T9-49, Burgemeester Oudlaan 50, P.O. Box 1738, 3000 DR Rotterdam, the Netherlands*

This version, August 6, 2009

Abstract

Hedge funds are fundamentally exposed to equity volatility, skewness, and kurtosis risks based on the systematic pattern and significant spread in alphas from the existing models that do not control for the higher-moment risks. The spread and pattern in alphas do not disappear with bootstrap simulation, Bayesian analysis to account for potential estimation error, adjustment for backfilling bias, and the inclusion of additional systematic factors. Significant cross-sectional variation in higher-moment exposures is observed across fund styles with equity-oriented styles displaying more extreme exposures. Investable higher-moment factors explain the time series behavior of returns of a large number of Managed Futures, Event Driven, and Long/Short Equity hedge funds. Average exposure sensitivities for higher-moment factors are statistically significant in an estimation that accounts for style fixed effects and fund random effects.

*We thank Andrew Ang, Ravi Bansal, Nick Bollen, Stephen Brown, Zhiwu Chen, Nishant Dass, James Doron, Antonio Diez de los Rios, Cheol Eun, Bill Fung, Rene Garcia, Daniel Giamouridis, Steve Heston, Danling Jiang, Aneel Keswani, Robert Kosowski, Bong-Soo Lee, Suzanne Lee, Minqiang Li, Dilip Madan, Narayan Naik, Reza Mahani, Anna Obizhaeva, George Panayotov, Tarun Ramadorai, Lemma Senbet, George Skoulakis, David Thesmar, Isabel Tkatch, Joel Vanden, Russ Wermers, Liuren Wu, and seminar participants at Florida State University, Georgia Institute of Technology, HEC Paris, London Business School, RSM Erasmus University, University of Arkansas, and participants of the June 2007 Bank of Canada-Rotman School of Management Workshop on Advances in Portfolio Management, Ist Annual Conference on Econometrics of Hedge Funds, University of Toronto, for helpful comments and constructive suggestions. We acknowledge financial support from BNP Paribas Hedge Fund Center at the Singapore Management University. This research was supported, in part, by a research grant from the Robinson College of Business, Georgia State University. Agarwal is also grateful for the support from the Research Fellowship position at the Centre for Financial Research (CFR) at the University of Cologne. We welcome comments, including references to related papers we have inadvertently overlooked.

†Tel.: +1-404-413-7326; fax: +1-404-413-7312. *E-mail address:* vagarwal@gsu.edu

‡Tel.: +1-301-405-2261; fax: +1-301-405-0359. *E-mail address:* gbakshi@rhsmith.umd.edu

§Tel.: +31-10-408-1358; fax: +31-10-408-9017. *E-mail address:* jhuij@rsm.nl

The premise that hedge fund returns depend nonlinearly on the market return has a firm footing in the investments literature (Fung and Hsieh (1997, 2001, 2004b), Mitchell and Pulvino (2001), Amin and Kat (2003), Agarwal and Naik (2004), Hasanhodzic and Lo (2007), and Fung, Hsieh, Naik, and Ramadorai (2008)). Fung and Hsieh (2001, 2004b) emphasize option-like traits of hedge fund returns and advocate the inclusion of lookback straddle returns as systematic factors in their model. In addition, Mitchell and Pulvino (2001) show that returns from risk arbitrage resemble the payoff from selling uncovered index put options. In their quest for superior performance, hedge funds often employ derivatives, short-selling, and leverage (i.e., Fung and Hsieh (2001), Weisman (2002), Bondarenko (2004), and Diez and Garcia (2006)) to generate returns during extreme states of the equity market, and this can lead to hedge funds being exposed to higher-moment risks of the equity market.

Such observations motivate us to build on the extant literature by examining how hedge fund returns are connected to the higher-order laws of the market return distribution, with the view to pose specific research questions: To what extent are hedge funds exposed to higher-moment equity risks? Are the spreads in hedge fund alphas from existing models related to the differences in funds' higher-moment exposures? Which fund styles exhibit extreme higher-moment exposures? Are trend followers, most of which are included in the Managed Futures category, substantively exposed to the volatility factor, given the work of Fung and Hsieh (2001)? Do our results generalize to Event Driven and Long/Short Equity (the other two big styles)? Our thrust is to investigate variation in higher-moment exposures across fund styles, and to examine the impact of investable higher-moment factors on hedge fund returns using individual funds as well as a panel estimation procedure that accommodates style fixed effects and hedge fund random effects.

Our empirical investigation employs higher-moment factors, and yields findings that are supportive of our themes. First, hedge funds are fundamentally exposed to higher-moment risks. Using a multifactor model that does not account for higher-moment equity risks, we find significant dispersion and systematic patterns in alphas between the top and bottom portfolios of hedge funds, sorted on their exposures to volatility, skewness, and kurtosis risks.

Second, the alpha spreads and alpha patterns remain even after including additional systematic factors such as lookback straddles on interest rates and equity, out-of-the-money index put options, and liquidity. We allow for potential estimation error through Bayesian analysis and test for the validity of our results after accounting for the backfilling bias. Furthermore, we perform a bootstrap simulation using the residual and factor resampling approach of Kosowski, Timmermann, Wermers, and White (2006) to show that the documented significance of higher-moment risks is not a consequence of data-driven spurious inferences.

Third, style-by-style analysis reveals that five of the ten styles – Long/Short Equity, Emerging Markets, Managed Futures, Global Macro, and Dedicated Short – exhibit extreme positive/negative higher-moment exposures. These findings accord with the intuition that higher-moment risks matter more for those fund styles that tend to apply their strategies to the equity markets and are less relevant for styles in which equity risk is not the primary exposure. A statistical resampling technique that accounts for differences in the number of funds across styles validates these findings for the three styles with the largest number of funds.

Finally, we construct investable higher-moment factors and evaluate their ability to explain the time series of hedge fund returns. This allows us to explicitly address the puzzling finding in Fung and Hsieh (2001), who document that none of the Managed Futures are significantly exposed to the equity lookback straddle in their sample. We explore this issue further by conducting a comprehensive analysis of individual Managed Futures to show that the volatility factor is positive and statistically significant, and our results indicate that the volatility factor can be useful for describing their return dynamics.

Examining the wider generality of the higher-moment factors, we extend our analysis of individual funds to the other two big styles, according to which a large number of Event Driven funds have significant negative skewness and negative kurtosis exposures, while Long/Short Equity funds have significant negative skewness and positive kurtosis exposures. Estimation with style fixed effects and fund random effects substantiate the relevance of higher-moment factors for the three big hedge fund styles, as we find evidence in favor of statistically significant average exposure sensitivities.

Overall, our study contributes to the body of theoretical and empirical research that suggests that higher-moment risk dimensions may be important for a certain class of assets.[1] Our empirical evidence on the ability of investable higher-moment factors to describe hedge funds returns can have implications for performance evaluation and risk management in the money management industry.

In what follows, Section 1 motivates the presence of higher-moment exposures while Section 2 describes the data and return factors. Section 3 relates higher-moment exposures to hedge fund returns, and empirically characterizes alphas from the Fung and Hsieh (2004b) model. Here we also investigate variation in higher-moment exposures across fund styles. Section 4 analyzes Managed Futures, Event Driven, and Long/Short funds and relates their returns to the higher-moment factors. Finally, Section 5 concludes.

1. Proxies and motivation for higher-moment equity exposures

Since our risk proxies for market volatility, skewness, and kurtosis are not directly traded, we extract them from S&P 500 index options. This construction is based on the cost of reproducing the payoffs of the proxies using out-of-the-money calls and puts as shown in Theorem 1 of Bakshi, Kapadia, and Madan (2003) (and as in Britten-Jones and Neuberger (2000), Carr and Madan (2001), and Demeterfi, Derman, Kamal, and Zou (1999) in the case of variance swaps). Specifically, for equity index price S_t, τ–period index return $R_{t,t+\tau} \equiv \ln S_{t+\tau} - \ln S_t$ and interest rate r^f, we characterize the value of the payoffs as:

$$\mathbb{M}_{2,t} \equiv e^{-r^f \tau}\,\mathbb{E}^{\mathbb{Q}}\left((R_{t,t+\tau} - \mathbb{M}_{1,t})^2\right), \quad \text{Value of Second Central Return Moment Payoff} \tag{1}$$

$$\mathbb{M}_{3,t} \equiv e^{-r^f \tau}\,\mathbb{E}^{\mathbb{Q}}\left((R_{t,t+\tau} - \mathbb{M}_{1,t})^3\right), \quad \text{Value of Third Central Return Moment Payoff} \tag{2}$$

$$\mathbb{M}_{4,t} \equiv e^{-r^f \tau}\,\mathbb{E}^{\mathbb{Q}}\left((R_{t,t+\tau} - \mathbb{M}_{1,t})^4\right), \quad \text{Value of Fourth Central Return Moment Payoff} \tag{3}$$

[1] While our focus is on assessing the impact of equity higher-moments, it is possible that higher-moments of commodity, currency, and bond returns are also potentially important sources of hedge fund returns. However, due to the lack of availability of comparable options data in these markets, it is harder to construct higher-moment proxies in markets other than equity.

where $\mathbb{E}^{\mathbb{Q}}(.)$ is expectation under the risk-neutral valuation measure and $\mathbb{M}_{1,t}$ reflects the intrinsic value of the claim to $(\ln S_{t+\tau} - \ln S_t)$.

In our setting, $\mathbb{M}_{k,t}$, for $k = 2, \ldots, 4$, are the arbitrage-free values of the claim to the central moment payoff $(\ln S_{t+\tau} - \ln S_t - \mathbb{M}_{1,t})^k$. Furthermore, $\mathbb{M}_{2,t}$, $\frac{\mathbb{M}_{3,t}}{(\mathbb{M}_{2,t})^{3/2}}$, and $\frac{\mathbb{M}_{4,t}}{(\mathbb{M}_{2,t})^2}$ are the arbitrage-free values of the claims to market variance, skewness, and kurtosis respectively. Since we find that the mean, $\mathbb{M}_{1,t}$, does not materially influence the estimates of higher-moments, we follow the tradition in the variance swap literature and henceforth set $\mathbb{M}_{1,t} = 0$.

To see how the time series of claim prices $\mathbb{M}_{2,t}$, $\frac{\mathbb{M}_{3,t}}{(\mathbb{M}_{2,t})^{3/2}}$, and $\frac{\mathbb{M}_{4,t}}{(\mathbb{M}_{2,t})^2}$ can be cost replicated through a static portfolio of traded calls and puts on the market index, we fix notation and let $C[K]$ and $P[K]$ represent the market price of call and put options with strike price K and τ-periods to expiration. Tapping the model-free approach (in Bakshi, Kapadia, and Madan (2003), Britten-Jones and Neuberger (2000), and Carr and Madan (2001)), the price of the volatility contract is:

$$\mathbb{M}_{2,t} = \int_{K>S_t} \omega^{vo}[K]\, C[K]\, dK \;+\; \int_{K<S_t} \omega^{vo}[K]\, P[K]\, dK, \quad \text{with} \quad \omega^{vo}[K] \equiv \frac{2\left(1 - \ln\left(\frac{K}{S_t}\right)\right)}{K^2}, \tag{4}$$

where discounted expectation under the risk-neutral density, $q[R_{t+\tau}]$, gives the value of the underlying payout (i.e., $\mathbb{M}_{2,t} = \int_{-\infty}^{+\infty} R_{t+\tau}^2\, q[R_{t+\tau}]\, dR_{t+\tau}$). Proceeding to the cost of reproducing the cubic and quartic contracts, we have,

$$\mathbb{M}_{3,t} = \int_{K>S_t} \omega^{sk1}[K]\, C[K]\, dK \;-\; \int_{K<S_t} \omega^{sk2}[K]\, P[K]\, dK, \quad \text{where} \tag{5}$$

$$\omega^{sk1}[K] \equiv \frac{6\ln\left(\frac{K}{S_t}\right) - 3(\ln\left(\frac{K}{S_t}\right))^2}{K^2} \quad \text{and} \quad \omega^{sk2}[K] \equiv \frac{6\ln\left(\frac{K}{S_t}\right) + 3(\ln\left(\frac{K}{S_t}\right))^2}{K^2}, \tag{6}$$

and furthermore,

$$\mathbb{M}_{4,t} = \int_{K>S_t} \omega^{ku}[K] C[K] dK + \int_{K<S_t} \omega^{ku}[K] P[K] dK, \quad \text{where} \quad \omega^{ku}[K] \equiv \frac{12(\ln\left(\frac{K}{S_t}\right))^2 - 4(\ln\left(\frac{K}{S_t}\right))^3}{K^2}. \tag{7}$$

Hence, we may construct the price of skewness and kurtosis as $\frac{\mathbb{M}_{3,t}}{(\mathbb{M}_{2,t})^{3/2}}$, and $\frac{\mathbb{M}_{4,t}}{(\mathbb{M}_{2,t})^{2}}$.[2] It may be noted from (5)-(6) that $\frac{\mathbb{M}_{3,t}}{(\mathbb{M}_{2,t})^{3/2}} < 0$, reflecting the fact that puts are more expensive than calls, and the weighting on puts exceeds the call counterpart (i.e, $\omega^{sk2}[K] > \omega^{sk1}[K]$).

Consistent with the extant literature where first differences in market index implied volatility (from CBOE) are used to proxy market volatility risk (e.g., Ang, Hodrick, Xing, and Zhang (2006)), we define,

$$\Delta\text{VOL}_t \equiv \sqrt{\mathbb{M}_{2,t}} - \sqrt{\mathbb{M}_{2,t-1}}, \tag{8}$$

$$\Delta\text{SKEW}_t \equiv \frac{\mathbb{M}_{3,t}}{(\mathbb{M}_{2,t})^{3/2}} - \frac{\mathbb{M}_{3,t-1}}{(\mathbb{M}_{2,t-1})^{3/2}}, \tag{9}$$

$$\Delta\text{KURT}_t \equiv \frac{\mathbb{M}_{4,t}}{(\mathbb{M}_{2,t})^{2}} - \frac{\mathbb{M}_{4,t-1}}{(\mathbb{M}_{2,t-1})^{2}}. \tag{10}$$

We deploy ΔVOL_t, ΔSKEW_t and ΔKURT_t as proxies for higher-moment risks in the cross-sectional analysis of hedge fund returns. Risk proxies such as ΔVOL_t are not to be confused with powers of market returns used in market timing specifications (e.g., Ferson and Schadt (1996)). It is equally important to differentiate higher-moment payoffs, and their intrinsic values, from lookback straddles, as the latter are path–dependent claims on the maximum and the minimum asset prices. Further, higher-moment proxies in (8)-(10) are not combinations of option returns of differing strikes, and hence are theoretically distinct from selecting option returns of specific moneyness as in Agarwal and Naik (2004). Through our empirical investigation, we argue that they are also empirically distinct. Finally, it is just as important to realize that ΔVOL_t, ΔSKEW_t and ΔKURT_t are respectively the first difference of the price of two traded portfolios and should not be regarded as constructs under the risk-neutral measure.

Why do we postulate that there is a role to be played by higher-moment risks in explaining hedge fund returns? Appreciate that the negative market volatility risk premium is theoretically tenable as long equity investors dislike volatility (Coval and Shumway (2001), Bakshi and Kapa-

[2] Details on the Riemann integral approximation of (4)-(7) and related implementation issues are addressed in Dennis and Mayhew (2002), Jiang and Tian (2005), and Bakshi and Madan (2006). Implementation with a finite grid of out-of-the-money calls and puts is reasonably accurate with small approximation errors (Dennis and Mayhew (2002)).

dia (2003), and Carr and Wu (2009)), and some hedge funds may be earning returns by being net sellers of market volatility. Other hedge funds may employ the opposite trade with the view of a rise in market volatility. Furthermore, as long equity investors hate negative skewness (e.g., Kraus and Litzenberger (1976) and Harvey and Siddique (2000)), some hedge funds can earn returns by being sellers of negative skewness. Analogously, those hedge funds with negative exposures to kurtosis risk will experience positive returns as the kurtosis risk premium is negative.

In sum, hedge funds have the expertise, as well as the risk appetite, to seek exposures to a multitude of factors with the hope of earning a risk premium. However, the extent to which hedge funds are exposed to higher-moment risks remains an open question that can only be addressed empirically. Thus, one goal of this paper is to gauge the strength of the exposures to higher-moment risks in the cross section of hedge funds, and across hedge fund styles. Then, we assess whether properly constructed investable higher-moment factors can explain the time-series behavior of hedge fund returns within a style.

What we do here is also motivated by the study of Fung and Hsieh (2001), who document nonlinearity in the returns of Managed Futures, and observe that lookback straddles in bond, currency, and commodity markets, but not lookback straddles on equity, can explain the returns of Managed Futures. Building on their insights, we investigate the hypothesis that a higher-moment equity factor, specifically the volatility factor, may be significantly linked to returns of Managed Futures.

Our inquiry is not about higher-moments of hedge funds' returns, but instead about the exposures of hedge fund returns to equity higher-moments. Hence, one should not interpret the test of variance neutrality presented in Patton (2008) to mean neutrality with respect to equity volatility exposures. As we shall see, our measures of shifts in tail movement, tail asymmetry, and tail size outlined in (8)-(10) can contribute to our understanding of how tail risks impact hedge fund returns in general.

2. Hedge fund sample and Fung and Hsieh (2004b) factors

We use monthly net-of-fee returns of hedge funds from the 2004 Lipper TASS Hedge Fund Database over the period January 1994 to December 2004. Excluded in our analysis are funds that do not report on a monthly basis, and funds with less than 12 consecutive returns over the entire sample period. Our resulting sample covers 3,771 individual hedge funds. This sample universe is free from survivorship bias as documented by Brown, Goetzmann, Ibbotson, and Ross (1992) and Brown and Goetzmann (1995) since it includes dead/defunct funds.[3] As noted elsewhere, hedge funds in the database could be missing due to reasons other than poor performance, such as merger, restructuring, and voluntary stopping of reporting (e.g., Fung and Hsieh (2000), Liang (2000), and Getmansky, Lo, and Makarov (2004)).

To measure risk-adjusted performance of hedge funds, we employ the Fung and Hsieh (2004b) seven-factor model (henceforth, FH-7). Drawing from the notation adopted in Fung, Hsieh, Naik, and Ramadorai (2008), the FH-7 model can be represented as:

$$\begin{aligned} r_t^i &= \alpha^i + \beta^{1,i}\,\mathrm{SNPMRF}_t + \beta^{2,i}\,\mathrm{SCMLC}_t + \beta^{3,i}\,\mathrm{BD10RET}_t + \beta^{4,i}\,\mathrm{BAAMTSY}_t \\ &\quad + \beta^{5,i}\,\mathrm{PTFSBD}_t + \beta^{6,i}\,\mathrm{PTFSFX}_t + \beta^{7,i}\,\mathrm{PTFSCOM}_t + \varepsilon_t^i, \end{aligned} \tag{11}$$

where r_t^i is the excess return of fund i over the riskfree rate in month t and ε_t^i is fund i's residual return in month t. The systematic risk factors in the FH-7 model are provided by David Hsieh:

- SNPMRF_t is S&P 500 index return minus the riskfree rate in month t;
- SCMLC_t is the Frank Russell 2000 index return minus the S&P 500 index return in month t;
- $\mathrm{BD10RET}_t$ reflects the return difference between the 10-year Treasury bond and the riskfree rate;

[3] In our analysis, we control for backfilling bias resulting from a fund initiating to report their performance to a database at a later date once they have existed for some time and have done well (Ackermann, McEnally, and Ravenscaft (1999) and Fung and Hsieh (1997, 2000)). Accordingly, we remove the initial two years' of return history of each fund. Since this action reduces the sample size to 3,243 hedge funds, these results are reported as a part of validation checks.

- BAAMTSY_t measures the credit spread defined as Moody's Baa bond return minus the 10-year Treasury bond return;
- PTFSBD_t, PTFSFX_t, and PTFSCOM_t are returns of lookback straddles on bonds, currencies, and commodities respectively in month t.

Total returns of the Barclays 1-3 month Treasury index is the proxy for the riskfree rate.

3. Higher moments of equity risk in the cross section of hedge fund returns

For the empirical investigation, we invoke standard asset pricing tests, relying on pooled time-series cross-sectional data on hedge fund returns. First, we estimate individual funds' exposures to ΔVOL, ΔSKEW, and ΔKURT using time-series regressions. Then we perform independent sorts on each of the higher-moment risk exposures. Given the correlation between these exposures, we suggest a three-way sort that may be more appropriate for isolating the effect of each of the higher-moment risks. Second, we evaluate the sorted portfolios' out-of-sample performance and estimate the spread between the alphas of extreme portfolios after controlling for risk factors in the FH-7 model. Third, we perform bootstrap simulation to show that the spreads in alphas are not statistical artifacts. Fourth, we examine the cross-sectional variation in higher-moment exposures across hedge fund styles to determine which styles are more inclined towards taking on higher-moment risks. Finally, we evaluate whether spreads and patterns in alphas from the FH-7 model remain after accounting for potential estimation error, backfilling, and additional systematic factors. Our objective is to describe how the higher-moment risks systematically influence the cross section of hedge fund returns.

3.1. *Independent sorts on higher-moment exposures reveal pronounced patterns and spreads in alphas*

In order to construct a set of base assets that display significant dispersion in their sensitivities to higher-moment risks, we form decile portfolios of hedge funds in the following way. Each month, all available hedge funds are sorted into ten mutually exclusive portfolios, based on their exposures to (i) volatility (ΔVOL), (ii) skewness (ΔSKEW), and (iii) kurtosis (ΔKURT). Specifically, we obtain the funds' exposures by estimating rolling CAPM-type regressions with excess return on the S&P 500 index, i.e., RMRF, augmented by $\Delta\mathrm{VOL}_t$, $\Delta\mathrm{SKEW}_t$, and $\Delta\mathrm{KURT}_t$, over the past 12 months:

$$r_t^i \;=\; \alpha_{4F}^i + \beta_{\mathrm{RMRF}}^i \mathrm{RMRF}_t + \beta_{\Delta\mathrm{VOL}}^i \Delta\mathrm{VOL}_t + \beta_{\Delta\mathrm{SKEW}}^i \Delta\mathrm{SKEW}_t + \beta_{\Delta\mathrm{KURT}}^i \Delta\mathrm{KURT}_t + \varepsilon_t^i, \tag{12}$$

where r_t^i is the excess return of hedge fund i over the riskfree rate.

Ang, Hodrick, Xing, and Zhang (2006) and Lewellen and Nagel (2006) argue that a suitably short estimation window offers a compromise between inferring coefficients with a reasonable degree of precision and estimating conditional coefficients in a setting with time-varying factor loadings. It is desirable to adopt shorter estimation windows for hedge funds to allow for frequent changes in their risk exposures, as they employ dynamic trading strategies often utilizing leverage in response to changes in macroeconomic conditions and arbitrage opportunities (Avramov, Kosowski, Naik, and Teo (2007), Bollen and Whaley (2008), Hasanhodzic and Lo (2007), and Jagannathan, Malakhov, and Novikov (2006)).[4]

Given our approach to estimate loadings, it is crucial to keep the number of factors to a minimum in constructing the portfolios. To maintain parsimony, we employ the equity market factor along with higher-moment risk proxies in the formation period, but we are careful to control for

[4]When we experiment with 24-month windows to estimate exposures, we observe a small reduction in the magnitudes of exposures and a minor narrowing of post-ranking alphas between the extreme portfolios. Assuming the constancy of the exposures over longer windows weakens the link between exposures and future returns and results in greater empirical misspecification, a point also made by Ang, Hodrick, Xing, and Zhang (2006). Later we also address the possibility of estimation error in factor sensitivities induced through estimation windows by exploiting a Bayesian framework.

other risk factors using the Fung and Hsieh (2004b) model in the post-formation period.

Based on the hedge funds' exposures to higher–moments, the funds are sorted into deciles whereby the top decile, D1, contains the ten percent of funds exhibiting the highest (most positive) exposure to the relevant higher–moment risk and the bottom decile, D10, comprises funds with the lowest (most negative) exposure to that moment. Then, we compute out-of-sample returns of each of these deciles to avoid spurious correlation between the estimated exposures and returns. Furthermore, we account for illiquidity associated with hedge fund investments with the understanding that the presence of lockup, notice, and redemption periods deter capital withdrawals. Hence, we allow for three months' wait for reformation of the portfolios to make our analysis consistent with frictions associated with hedge fund investing (Aragon (2007) and Agarwal, Daniel, and Naik (2008)). The portfolios are reformed on a monthly basis.

We compute equally-weighted returns for decile portfolios and readjust the portfolio weights if a fund disappears from our sample after ranking. Given our procedure to form the decile portfolios and to allow for the three-month waiting period for reforming portfolios, the out-of-sample returns of the portfolios are measured from April 1995 to December 2004. On average, 1,398 hedge funds are available in the cross-section at the beginning of each year, ranging from 650 funds in 1995 to 2,115 funds in 2004. We then estimate the alphas using the portfolios' out-of-sample returns.

Reported in Table 1 are the decile portfolios' pre-ranking exposures to ΔVOL, ΔSKEW, and ΔKURT from equation (12) as well as the post-ranking annualized alpha estimates, their t-statistics, and adjusted R-squared values (hereby $\overline{R}^2$) from the regressions using the FH-7 model in equation (11).

Table 1 shares the qualitative properties that the decile portfolios of hedge funds exhibit monotonically decreasing pattern in pre-ranking betas on ΔVOL, ΔSKEW, and ΔKURT, and almost monotonically increasing pattern in post-ranking FH-7 alphas. More specifically, the spread in alphas between the top and bottom deciles for sorts on ΔVOL is -13.48 percent per year (the difference between alpha of -2.66 percent for H portfolio in Panel A and 10.82 percent for L portfolio in the same panel) after controlling for the factors in the FH-7 model. The spreads in alphas for sorts performed on ΔSKEW and ΔKURT are respectively -14.85 percent per year and -14.59 percent per year with the FH-7 model. Further, results from the Gibbons, Ross, and Shanken (1989) test strongly reject that these alphas of the decile portfolios are jointly equal to zero.

Although the FH-7 model performs reasonably well, with $\overline{R}^2$ between 40 and 60 percent, it fails to eliminate the patterns in post-ranking alphas and the significant spreads in these alphas.

While the focus in Table 1 is on pre-ranking exposures (or betas) on higher-moment risks, it is imperative to note that the magnitudes of market betas, on average, take a value of 0.291 (strikingly similar to the 0.29 reported for an equally-weighted average of all TASS funds (TASSAVG) in Fung and Hsieh (2004b), see their Table 2 on page 74). Judging by the magnitudes of the pre-ranking betas on the higher-moments, hedge funds exhibit pronounced non-neutrality with respect to higher-moment risks but almost neutrality with respect to the equity market.

Since the FH-7 model does not include lookback straddles on equity and interest rates, in the ensuing analysis we also test the validity of our findings to the extended nine-factor model of Fung and Hsieh (2001). Even with the extended model, we continue to observe distinct patterns in alphas for hedge fund portfolios sorted on their higher–moment risk exposures.

The fact that we observe monotonically increasing alphas in hedge fund portfolios single-sorted on exposures to higher-moment risks provides initial evidence that higher-moment equity risks are useful in explaining the cross section of hedge fund returns. At the same time, an unappealing attribute of the single-sorting scheme is that it induces a large correlation between the post-formation returns spread of top and bottom deciles of funds sorted by their exposure to ΔVOL, ΔSKEW, and ΔKURT. For example, the D10 minus D1 portfolio return correlation is 0.60 for sorts done on ΔVOL and ΔSKEW; is 0.66 for sorts done on ΔVOL and ΔKURT; and is 0.91 for sorts done on ΔSKEW and ΔKURT. The next subsection argues that a three-way conditional sort on ΔVOL, ΔSKEW, and ΔKURT may be necessary to isolate the effects of higher-moment equity risks separately.

3.2. Conditional three-way sorts on higher-moment exposures bear considerably on fund returns

We adapt the two-way sorting procedure of Fama and French (1992) to perform three-way sorts of hedge funds based on their exposures to ΔVOL, ΔSKEW, and ΔKURT. To ensure enough funds in the sorted portfolios, we use terciles instead of decile portfolios. This approach provides 27 (3x3x3) portfolios sorted first on the hedge funds' exposures to ΔVOL, then to ΔSKEW, and finally to ΔKURT. Such a procedure allows us to achieve maximum dispersion in one higher–moment risk while keeping minimal dispersion in the remaining two higher-moment risks. The differences in portfolios' risk-adjusted returns can therefore be ascribed to one of the three higher-moment risks.

Table 2 presents results for the 27 portfolios (P1 to P27) resulting from the terciles - high (H), medium (M), low (L) - of conditional sorts on funds' exposures to the three higher-moment risks. Since P1 (P27) represents the portfolio with the highest (lowest) exposure to all three equity moments, the portfolio has the lowest (highest) post-ranking alphas from the FH-7 model. Furthermore, we observe an increasing pattern in alphas as we move down from P1 to P27. In particular, the alphas range between –5.59 to 14.95 percent after controlling for factors in the FH-7 model. Results from the Gibbons, Ross, and Shanken (1989) test suggest that these alphas together are statistically different from zero (the p-values are 0.00).

Observe the *significant spreads in the alphas* of the sets of three portfolios, i.e., P1 to P3, P4 to P6, and so on, that are designed to roughly have similar exposures to two out of the three higher-moment risks but to differ in their intensity of exposure to the remaining risk dimension. For example, the portfolios maintaining the highest exposure to ΔVOL and ΔSKEW but with exposures of varying severity to ΔKURT (i.e., P1 to P3) show FH-7 alphas ranging between –5.59 percent and –1.08 percent per year, which can be attributed distinctly to the kurtosis risk exposure.

One can similarly infer the range of alphas that arises from their exposures to volatility and skewness risks. That is, portfolios exhibiting the most negative exposure (i.e., the L portfolios) to ΔVOL and ΔKURT but with different exposures to ΔSKEW (i.e., P21, P24, and P27) generate

FH-7 alphas ranging from 6.35 percent to 14.95 percent per year which are due to skewness risk exposure.

Thus, based on the patterns in alphas and the magnitude of alpha spreads, the novelty of our findings is that higher-moment risk exposures bear considerably on hedge fund returns.

3.3. Bootstrap simulation shows that higher-moment risks are not statistical artifacts

To approach the analysis from a different angle, we investigate the possibility that spreads in alphas that we observe in our sample are spurious. The key question is: do we obtain the spreads in observed alphas purely by chance when hedge funds neither have higher-moment risks, nor have alphas, in their return generating processes? To address this question, we perform a bootstrap simulation comparable to the residual and factor resampling procedure outlined in Kosowski, Timmermann, Wermers, and White (2006).

First, we estimate all funds' alphas, factor loadings, and residual returns using the FH-7 model, and store the coefficient estimates $\{\hat{\beta}^{1,i}, \hat{\beta}^{2,i}, \hat{\beta}^{3,i}, \hat{\beta}^{4,i}, \hat{\beta}^{5,i}, \hat{\beta}^{6,i}, \hat{\beta}^{7,i}, i = 1,2,\ldots,N\}$, and the time series of estimated residuals $\{\hat{\varepsilon}^{i}_{t}, i = 1,2,\ldots,N,\, t = 1,2,\ldots,T\}$.

Next, for each bootstrap iteration b, we draw samples with replacement from the funds' stored residuals $\{\hat{\varepsilon}^{i,b}_{t_e}, t_e = s^b_1, s^b_2, \ldots, s^b_T\}$, and the factors $\{\text{SNPMRF}^b_{t_F}$, $\text{SCMLC}^b_{t_F}$, $\text{BD10RET}^b_{t_F}$, $\text{BAAMTSY}^b_{t_F}$, $\text{PTFSBD}^b_{t_F}$, $\text{PTFSFX}^b_{t_F}$, $\text{PTFSCOM}^b_{t_F}$, $t = u^b_1, u^b_2, \ldots, u^b_T\}$, where $s^b_1, s^b_2, \ldots, s^b_T$ and $u^b_1, u^b_2, \ldots, u^b_T$ are the time reorderings imposed by the bootstrap. We then construct the time series of simulated returns for all hedge funds subject to zero alphas:

$$\begin{aligned} r^{i,b}_t \;=\; & \hat{\beta}^{1,i}\text{SNPMRF}^b_{t_F} + \hat{\beta}^{2,i}\text{SCMLC}^b_{t_F} + \hat{\beta}^{3,i}\text{BD10RET}^b_{t_F} + \hat{\beta}^{4,i}\text{BAAMTSY}^b_{t_F} \\ & + \hat{\beta}^{5,i}\text{PTFSBD}^b_{t_F} + \hat{\beta}^{6,i}\text{PTFSFX}^b_{t_F} + \hat{\beta}^{7,i}\text{PTFSCOM}^b_{t_F} + \hat{\varepsilon}^{i,b}_{t_e}. \end{aligned} \tag{13}$$

The resulting simulated sample of fund returns has the same length, number of funds in the cross section, and number of return observations as dictated by the actual sample counterparts.

We then sort hedge funds into conditional three-way sorted portfolios based on their exposures to ΔVOL, ΔSKEW, and ΔKURT. Then, we compute out-of-sample returns of each of these sorted portfolios and allow for three months wait for reformation of the portfolios. Reconstituting the portfolios on a monthly basis, we compute equally-weighted returns for sorted portfolios and readjust the portfolio weights if a fund disappears from our sample after ranking. In the final step, the alphas are estimated from the out-of-sample returns of the difference between the top (i.e., P1) and the bottom (i.e., P27) portfolios. We run a total of 1,000 bootstrap iterations.

[Fig. 1 about here.]

Figure 1 shows that the 95 percent confidence interval of the bootstrapped spreads in alphas between the top and bottom hedge fund portfolios sorted on volatility, skewness, and kurtosis is between −8.5 percent and +8.5 percent. This implies that under the imposed condition of no higher-moment risks and zero alphas, the most extreme simulation outcomes are *not* of the order of 20 percent that we obtain from the actual sample. Thus, in conclusion, the bootstrap results provide a strong confirmation that the alpha spreads are not spurious.

3.4. There is concentration of extreme higher-moment exposures for funds pursuing certain styles

Given our finding that hedge funds are fundamentally exposed to higher-moment risks (albeit to varying degrees), it is tempting to ask: Are the findings in Tables 1 and 2 style-dependent? Do hedge funds disproportionately seek a particular type of higher-moment exposure (say, long or short) across styles? Fixing an investment style category from CSFB/Tremont, we focus on the hedge fund universe and design two statistical procedures to answer these questions. At the crux of Subsection 3.4.1 is a statistical test of differences in proportions. While the merit of this approach is that it permits the analysis of all ten hedge fund styles together and hence provides a broader foundation for our results, a possible disadvantage is that it does not account for the disparity in the number of funds across styles. The procedure adopted in Subsection 3.4.2 rectifies this limitation by picking the three styles with the most number of funds and then randomly selecting equal number of funds through resampling to implement the test of differences in proportions. The conclusions we draw here about the relative importance of higher-moment risks for different hedge fund styles hinge on triple-sorting of *all* hedge funds into 27 portfolios. Building on the above, a set of related, yet distinct, questions are addressed in Section 4, the thrust of which is to investigate the extent and sign of higher-moment exposures for individual funds *within* three major hedge fund styles.

3.4.1. Equity-oriented styles show greater proclivity towards extreme higher-moment exposures

Our statistical test essentially computes the frequency at which hedge funds that follow a given strategy (or style) end up in each of the 27 triple-sorted portfolios. At the same time, we calculate the unconditional average, which constitutes the average proportion of funds by that strategy in our sample. Then we test whether the observed frequencies in the cross section of exposure types are jointly different from the unconditional (grand) average (e.g., Agresti (1996)). Our end-objective is to tabulate information about 10 hedge fund styles for the 27 triple-sorted portfolios.

We focus on a chi-squared test for differences in proportions, as the fund universe is not uniformly distributed across investment styles. For example, Long/Short Equity funds comprise 37.48%, while Market Neutral funds comprise 5.31%, of the hedge fund universe (see the row titled "Grand average" in Table 3). That is, if you pick a fund randomly in a portfolio, the likelihood that it is a Long/Short fund is 37.48%.

Let us concentrate on Panel A of Table 3 which represents conditional frequencies across the type of exposures (across the three rows) as well as across styles (across the 10 style columns). Portfolios P1 (denoted H/H/H), P14 (denoted M/M/M), and P27 (denoted L/L/L) exhibit the most positive, near-zero, and most negative exposures to volatility, skewness, and kurtosis risks (as outlined in Table 2). The unconditional and conditional frequencies together with the p-values from the chi-squared test (with degrees of freedom equal to 2) of difference in proportions are informative about fund exposures for each of the ten fund styles. For example, the entry of 41.06% (44.42%) for Long/Short Equity reflects the conditional frequency of that style having the most positive (negative) exposure to higher-moment risks, P1 (P27).

If we observe a U-shaped pattern in the frequencies emerging for certain strategies, it implies that a greater fraction of funds show positive or negative exposures to the three higher-moment risks compared to near-zero exposures. Specifically for Long/Short, we observe a conditional frequency of 41.06% for P1 (H/H/H), 44.42% for P27 (L/L/L) and only 16.31% for P14 (M/M/M). The p-value of 0.00 corresponds to the null hypothesis that Frequency(P1)= Frequency(P14) = Frequency(P27) = 37.48%, which is the unconditional average frequency corresponding to the Long/Short style. This means that a higher fraction of Long/Short funds show positive and negative, i.e., long and short, exposures to volatility, skewness, and kurtosis risks. To reiterate, the idea is that if the conditional frequencies are statistically different from the unconditional frequency within a style, it validates the presence of differential exposures to higher-moments for that style.

Searching across styles reveals that in addition to Long/Short, Managed Futures, Emerging Markets, Global Macro, and Dedicated Short, also exhibit U-shaped frequency patterns. One point warrants emphasis here. These five styles together account for conditional frequencies of 90.89% and 87.93% of being in portfolios P1 and P27 versus the unconditional average of 68.42%, which indicates a greater disposition towards long and short exposures to higher-moment risks.

The remaining five hedge fund styles show hump-shaped pattern in frequencies. That is, lower frequencies for P1 and P27 portfolios that have extreme (positive or negative) exposures to higher-moment risks, but higher frequency for P14 portfolio that corresponds to near-zero exposure. Styles that fall in this category include Event Driven, Market Neutral, Convertible Arbitrage, Fixed Income Arbitrage, and Multi-Strategy. Overall, the lesson from this exercise is that compared to other styles, equity-oriented hedge fund styles are more likely to display extreme positive and negative higher-moment exposures.

Next, we investigate if our findings for the styles with extreme higher-moment exposures are driven by only one of the three higher-moment risks. To isolate the effect of each risk, we examine the variation *within* each higher-moment risk. For this purpose, we pool frequencies across the 27 portfolios to construct conditional likelihoods of showing High (H, i.e., long), Medium (M i.e., largely neutral), and Low (L, i.e., short) exposures to volatility, skewness, and kurtosis risks. The frequency for the portfolio with the most negative exposure to volatility risk (Vol-L) consequently corresponds to the average frequency across P19 to P27 portfolios. That is, we determine if the styles with greater sensitivity to these risks show extreme exposures to *each* of the three higher-moment risks *individually*.

Two further insights can be garnered from the results reported in Panels B, C, and D of Table 3. First, the styles that show U-shaped or hump-shaped frequency patterns for P1, P14, and P27 also exhibit similar patterns when frequencies are pooled to reflect volatility, skewness, and kurtosis risks. This suggests that our earlier results for the three higher-moment risks together were not attributable to exposures to one of them. Second, as we are isolating a particular risk exposure, the spreads in frequencies are much narrower compared to the counterparts in Panel A of Table 3. This is simply an artifact of the greater dispersion between the three portfolios P1, P14, and P27 as opposed to the dispersion in the averages of three portfolios (e.g., Vol-H, Vol-M, Vol-L), which are themselves averages of nine portfolios each. To summarize, these results suggest that equity-oriented hedge fund styles are more likely to exhibit extreme positive or negative higher-moment exposures by virtue of their primary exposure to the equity market.

3.4.2. Simulation-based resampling procedure accentuates the main findings for the biggest three styles

Since hedge fund style categories do not contain the same number of funds, we resort to a refinement that adjusts the results in Table 3 for the unequal number of funds across different hedge fund categories. We drop those styles which have too few funds and focus on three major style categories with the largest number of funds.

Of these three major styles, we start with the one containing the smallest number of funds, i.e., Event Driven that has 12.19% of the funds in our sample (see row labeled "Grand average" in Table 3). We then randomly select the same number of funds in the other two bigger styles, i.e., Managed Futures and Long/Short, to maintain equal numbers of funds across the three styles. Next, we repeat this exercise through resampling 1,000 times from the two styles to estimate the frequencies of funds into three portfolios with differential higher-moment risk exposures - P1 (H/H/H), P14 (M/M/M), and P27 (L/L/L). Finally, we test whether the observed frequencies are jointly different from the probability of randomly ending up in each of these three portfolios.

We report these results in Panel A of Table 4, where we continue to find the U-shaped pattern in the frequency distribution for Managed Futures and Long/Short, and a hump-shaped pattern for Event Driven. The frequencies in the three portfolios, P1, P14, and P27 in Table 4 are comparable to those in Table 3.

By decomposing the conditional frequency distribution for each of the three higher-moment risks individually, we also examine the variations within each higher-moment risk and report these results in Panels B, C, and D of Table 4. The results substantiate a U-shaped pattern in volatility, skewness, and kurtosis risks separately for the Managed Futures and Long/Short styles, and a hump-shaped pattern for the Event Driven style. Thus, our resampling methodology applied to the top three styles reiterate our earlier results that equity-oriented styles have a greater tendency to display extreme higher-moment exposures.

3.5. *Our results on the relevance of higher-moment exposures survive a host of validation checks*

The following empirical exercises reinforce the relevance of higher-moment risks for the cross-section of hedge fund returns from different perspectives.

3.5.1. *Adjustments for estimation error and backfilling bias fail to reduce the absolute spread in alphas*

Because of our choice of portfolio formation periods, the rankings for sorts on hedge funds' exposures to higher-moment risks might be affected by estimation error. The concern is that hedge funds that are not actually exposed to higher-moment risks might end up in the extreme portfolios. To probe such a concern, we employ a Bayesian framework to estimate pre-ranking betas in the formation period more efficiently, and present the out-of-sample alphas of the three-way sorted portfolios in Panel A of Table A-1 (in the Appendix after Table 9).[5] Given that Bayesian methodology usually leads to the shrinkage of alphas between best and worst performers (see Huij and Verbeek (2007) and Kosowski, Naik, and Teo (2007)), it is worth highlighting that the alpha dispersion of -22.25 percent for sorts based on Bayesian estimates of higher-moment betas does not depart from the OLS counterpart. Thus, our central findings are not materially affected by estimation error.

To address the backfilling bias, initial 24 months' return observations for all hedge funds are discarded. Results in Panel B of Table A-1 indicate that our conclusions regarding the spreads in alphas remain unchanged even though we lose 33 percent of our fund sample due to the removal of initial two years of data. The spread in alphas between the top and bottom portfolios is still -20.97 percent per year.

3.5.2. Inclusion of additional systematic risk factors also fails to reduce absolute spread in alphas

In addition to bond, currency, and commodity lookback straddles, Fung and Hsieh (2001) employ equity and interest rate lookback straddles as systematic factors to explain the returns of Managed Futures. We add these two lookback straddles to the FH-7 model to investigate if the spread in alphas for the three-way sorted portfolios disappear:

$$\begin{aligned} r_t^i &= \alpha_{FH9}^i + \beta^{1,i}\,\mathrm{SNPMRF}_t + \beta^{2,i}\,\mathrm{SCMLC}_t + \beta^{3,i}\,\mathrm{BD10RET}_t + \beta^{4,i}\,\mathrm{BAAMTSY}_t \\ &+ \beta^{5,i}\,\mathrm{PTFSBD}_t + \beta^{6,i}\,\mathrm{PTFSFX}_t + \beta^{7,i}\,\mathrm{PTFSCOM}_t + \beta^{8,i}\,\mathrm{PTFSIR}_t + \beta^{9,i}\,\mathrm{PTFSSTK}_t + \varepsilon_t^i, \quad (14) \end{aligned}$$

where PTFSIR_t and $\mathrm{PTFSSTK}_t$ are the returns of interest rate and equity lookback straddles in month t. Panel A in Table A-2 shows that there is still no flattening of the alphas. Hence our key findings on the role of higher-moment risks does not appear to be affected by the exclusion of lookback straddles on interest rate and equity in the FH-7 model.

Panel B of Table A-2 reports the annualized alphas obtained through our three-way sorted

[5] Bayesian approaches to estimate alphas and factor sensitivities based on a limited number of return observations have been employed by Baks, Metrick, and Wachter (2001), Jones and Shanken (2005), Busse and Irvine (2006), and Huij and Verbeek (2007) in the context of mutual funds, and by Kosowski, Naik, and Teo (2007) in the context of hedge funds.

portfolios based on augmenting the FH-7 model with the OTM put option factor of Agarwal and Naik (2004). We continue to observe significant spreads in alphas mirroring our earlier results from Table 2.

Finally, periods of high volatility coincide with periods of high market illiquidity. Guided by this logic, we consider the exposure of hedge funds to liquidity risk separate from volatility risk. Specifically, we include the Pastor and Stambaugh (2003) liquidity risk factor (LIQ) by augmenting the FH-7 model with the LIQ factor available from Wharton Research Data Services. Panel C of Table A-2 reveals significant spreads in alphas as in Table 2. In sum, liquidity effects are unlikely to explain spreads in alphas resulting from the sensitivity of hedge funds to higher-moment equity risks.

4. Investable higher-moment equity factors and hedge fund returns

This section analyzes the role of investable higher-moment factors and evaluates their ability to explain time series variations in individual hedge fund returns. In view of our empirical interests, we follow standard multifactor asset pricing theory and incorporate in the Fung and Hsieh (2004b) model, volatility, skewness, and kurtosis factors, defined as (r_t^f is riskfree return over month t):

$$F_t^{vo} \equiv z_t^{vo} - r_t^f, \qquad F_t^{sk} \equiv z_t^{sk} - r_t^f, \qquad F_t^{ku} \equiv z_t^{ku} - r_t^f. \tag{15}$$

z_t^{vo}, z_t^{sk}, and z_t^{ku} are returns of volatility, skewness, and kurtosis over month t respectively, the construction of which is detailed in equations (A1)-(A3) of Appendix A. It is imperative to recognize that our approach to calculating investable higher-moment factors, like in Fung and Hsieh (2001), relies on a portfolio of assets whose market prices are observable.

At the center of our analysis are three hedge fund styles, namely Managed Futures, Event Driven, and Long/Short Equity. These styles contain the largest concentration of funds, and are identified with a sufficiently diverse set of investment strategies to establish the generality of a multifactor model with higher-moment factors. Of particular interest is whether F_t^{vo}, F_t^{sk}, and F_t^{ku} are statistically relevant in the presence of the Fung and Hsieh (2004b) factors. Setting the stage, we first elaborate on the return behavior of higher-moments to learn whether it is linked to average fund returns.

4.1. Returns of higher-moments are linked to average return patterns of hedge funds

To tackle main tasks, we follow Fung and Hsieh (2001) and bin return observations for hedge funds and higher-moments based on how global equity markets have performed, as measured by MSCI World Index returns. In our analysis, State 1 (State 5), which comprise 13% of the observations, can be identified with MSCI return realizations in the left (right) tail, while the three intermediate states (respectively 26%, 22%, and 26% of the observations) roughly correspond to the neck of the MSCI return distribution. Table 5 (Panel A) reveals the linkages between returns of higher-moments and *equally-weighted* returns for hedge funds following Managed Futures, Event Driven, and Long/Short Equity styles.

What is worth emphasizing is that during months when global equity markets experienced crashes (on average, declining 6.91% in those months), the returns of volatility are huge, i.e., an average monthly return of 90.35%. Such a finding is consistent with the perception that declining equity markets are often associated with rising volatility, precisely when the long volatility position is expected to be profitable. Moreover, we note that the returns of volatility display an asymmetric U-shaped pattern with respect to equity returns: positive in the two extreme states and negative in the three intermediate states. The documented return patterns can be rationalized by the observation that the return of volatility involves a long position in both puts and calls, and do not deliver a sufficiently large payout in the intermediate states to offset the initial cost of the option positions.

The peculiar return pattern of skewness, which has positive returns during equity market crashes and negative otherwise, is indicative of a security that entitles investors to crash protection. Reflecting aversion to downside market moves, the return of skewness involves a long position in puts and a short position in calls, with the relatively more expensive puts dominating the calls. Return of skewness is large during left-tail events (i.e., 72.42% in State 1) and is monotonically declining with returns of equity.

Return of kurtosis may appear puzzling at first glance as it is negative in all states of the equity market. In general, long kurtosis reflects option positions that entitle the holder a large payout only when there is an extreme tail event. Such an event occurred once during our sample in August 1998 when the MSCI World Index fell by 13.78%. Associated with this month was a return of kurtosis of 242.12%. Given the absence of extreme events, the return of kurtosis was negative for the remaining 131 months in our sample.

Within the context of Rows 2 through 4 of Panel A of Table 5, we can make three additional points. First, it reinforces the results in Fung and Hsieh (2001) who have shown that Managed Futures generally do well in both up-markets and down-markets. Second, Event Driven funds are adversely impacted by left-tail extremes. Such a return profile could arise from an investor being short kurtosis as well as being short volatility. Finally, Long/Short Equity funds are different in the strategies they follow: they yield negative returns during declining equity markets (States 1 and 2), but have positive returns otherwise. Such a return pattern amounts to being short puts and long calls, virtually mimicking negative skewness exposure. Despite the considerable heterogeneity across the three styles, the common thread is the association of hedge fund returns with the returns of higher-moments in different states of the equity market.

These observations are the impetus for conducting a style-by-style analysis to address two essential economic questions. What are the predominant higher-moment exposures and how do they impact returns of hedge funds? Which higher-moment factors are statistically relevant beyond the Fung and Hsieh (2004b) factors? We explore these issues through individual fund regressions, as well as a panel estimation with style fixed effects and fund random effects.

4.2. *Results affirm that the equity volatility factor significantly affects returns of Managed Futures*

The regression analysis conducted here is inspired by two attributes of the data. The first motivation is that our style-by-style analysis shows that significant patterns and spreads in alphas remain after controlling for the Fung and Hsieh (2004b) factors. Our second motivation is prompted by the fact that the Fung and Hsieh (2001) paper could not detect a significant exposure of trend followers, most of which are in the Managed Futures category, to the equity lookback straddles.

Thus, a natural question that arises is whether any of the higher-moment factors, which are not directly captured within Fung and Hsieh (2004b), are helpful in explaining the time series behavior of hedge funds in the Managed Futures category. In light of the patterns observed in Panel A of Table 5, a possible prediction is that a strategy involving long volatility may exert significant influence on returns of Managed Futures. We investigate our prediction empirically by focusing on individual hedge funds, as they may allow us to measure the effect of higher-moment factors in a cleaner way, as positive and negative exposures may cancel in the construction of equally-weighted portfolios of hedge funds.

Our approach is to regress excess returns of hedge funds on ten factors, obtained by augmenting the Fung and Hsieh (2004b) factors with our higher-moment factors, as depicted below:

$$\begin{aligned} r_t^{mf,i} &= \alpha^i + \beta^{1,i}\,\mathrm{SNPMRF}_t + \beta^{2,i}\,\mathrm{SCMLC}_t + \beta^{3,i}\,\mathrm{BD10RET}_t + \beta^{4,i}\,\mathrm{BAAMTSY}_t \\ &+ \beta^{5,i}\,\mathrm{PTFSBD}_t + \beta^{6,i}\,\mathrm{PTFSFX}_t + \beta^{7,i}\,\mathrm{PTFSCOM}_t + \underbrace{\beta^{8,i}F_t^{vo} + \beta^{9,i}F_t^{sk} + \beta^{10,i}F_t^{ku}}_{\text{higher}-\text{moment factors}} + \varepsilon_t^i, \end{aligned} \tag{16}$$

where F_t^{vo}, F_t^{sk}, and F_t^{ku} are investable factors for volatility, skewness, and kurtosis (see equation (15)), and $r_t^{mf,i}$ represents the excess returns of hedge fund i in the Managed Futures category. The sensitivity coefficient, β, measures how returns of Managed Futures co-moves with each of the factors, e.g., a positive $\beta^{8,i}$ indicates a positive volatility exposure for hedge fund i. The null hypothesis is that $\beta^{\ell,i} = 0$, for $\ell = 8, \ldots, 10$. We estimate the model for those hedge funds that have a minimum of 3-year return history, which leaves us with a sample of 329 Managed Futures.

To get an initial understanding of return factors, consider Panel B of Table 5 which indicates low to moderate co-movement between higher-moment factors and lookback straddles on bonds, currencies, and commodities. Even though Panel A of Table 5 shows that the return patterns of volatility and kurtosis are distinct conditional on MSCI returns, the volatility and kurtosis factors are highly correlated in the time series with a correlation coefficient of 0.88, as seen in Panel B of Table 5. Hence, to cope with the reality of correlated higher-moment factors, we add each higher-moment factor one by one to determine its effect in isolation, and then together to capture combined effect after controlling for the Fung-Hsieh factors (see Panel A through D of Table 6).

Estimates reported in Table 6 share several features among the tested relations. At the outset, observe that Managed Futures exhibit a wide spectrum of exposures, both positive and negative, with respect to the higher-moment factors. Consider first the column "coef. >0, # funds," which reveals that the distribution of loadings on the higher-moments is far from symmetric: it is skewed towards *long volatility* (i.e., 229 funds out of 329; 70%), *long skewness* (i.e., 192 funds; 58%), and *long kurtosis* (i.e., 204 funds; 62%). This attribute of Managed Futures to have long exposures to all the three higher-moments is further affirmed by the average loadings of all funds reported under the column "coef. avg." The average loading is sensible and ranges between 0.004 and 0.012 (see Panel A, B, and C), and is in agreement with the kind of strategies associated with trend followers (see Fung and Hsieh (2001)).

Yet another way to determine the strength of the findings is to omit from consideration those funds that have statistically insignificant loadings at conventional levels, based on White's heteroskedastically-consistent estimator, which conveys several core results. What stands out is that, while still implying net positive volatility exposures for Managed Futures as a group, there are 81 funds (nearly 25%) that have statistically significant $\beta^{8,i} > 0$. This number compares favorably to 110 statistically significant loadings, $\beta^{6,i} > 0$, in the case of PTFSFX (the currency straddles) which Fung and Hsieh (2001) found crucial in explaining the returns of trend followers.

There are 95, 69, and 110 funds (i.e., 21% to 33%, see Table 6, Panels A to C) that have statistically significant positive or negative exposures to volatility, skewness, and kurtosis factors. Breaking it down into positive and negative exposures, 81, 44, and 79 funds exhibit positive exposure, while 14, 25, and 31 funds display negative exposure, respectively to volatility, skewness, and kurtosis factors. The implication being that when statistical significance is taken into account, again more funds show positive than negative exposures on each of the three higher-moment factors, especially volatility and kurtosis. Our results shed light on the somewhat elusive finding in Fung and Hsieh (2001), where none of the hedge funds had statistically significant exposure to the equity lookback straddle.

While the results from Panel D of Table 6 (i.e., all three factors together) generally agree with those from Panels A, B, and C, there is a reduction in the total number of funds with significant loadings, which is likely due to the fact that the volatility and kurtosis factors are correlated. Moreover, there is often a loss of degrees of freedom with the greater number of factors.

To aptly deal with these aspects of the factor data in our setting, we follow the suggestion of Cochrane and Piazzesi (2005) and consolidate the three higher-moment factors into a single-factor (see their equations (3) and (4)). Step A: Project *equally-weighted returns* of Managed Futures on a constant plus F_t^{vo}, F_t^{sk}, and F_t^{ku}, and compute the predicted value (F_t^{hm}) from the regression. The consolidated higher-moment factor computed this way is intrinsic to all Managed Futures. Step B: Include the consolidated higher-moment factor, F_t^{hm}, to the FH-7 model, and reestimate the 8-factor model for all the 329 Managed Futures:

	constant	snpmrf	scmlc	bd10ret	baamtsy	ptfsbd	ptfsfx	ptfscom	F^{hm}
avg. (all funds)	-0.002	0.054	0.037	0.362	0.324	0.029	0.036	0.049	0.66
coef.$> 0, p < 0.1$, #funds	11	63	18	138	38	93	113	82	84
avg.	0.009	0.579	0.488	0.803	2.086	0.097	0.088	0.16	2.046
coef.< 0, $p < 0.1$, #funds	45	34	9	17	7	17	11	12	16
avg.	-0.015	-0.616	-0.59	-0.912	-3.308	-0.119	-0.069	-0.111	-2.228

Our results imply that the number of hedge funds with significant loading on the consolidated higher-moment factor (i.e., F_t^{hm}) is now 100, comparable to many of the Fung-Hsieh factors.

Returning to Panel D of Table 6, we have also performed a χ^2 exclusion test to investigate whether the exposures are jointly equal to zero for a hedge fund. For example, for 101 out of 329 funds (i.e., 31%), we can reject the hypothesis that volatility and kurtosis exposures are jointly different from zero based on the $\chi^2(2)$ statistics. At the same time, the three higher-moment risk exposures are jointly different from zero for 129 Managed Futures (i.e., 39%) based on the $\chi^2(3)$ statistics. The results suggest that the three higher-moment factors belong to a multifactor model to explain fund returns.

Important to us, the takeaway is that higher-moment factors seem to be in the set of factors that explain time variation in returns of Managed Futures. This core finding can be justified by the positive and statistically significant loadings on higher-moment factors for a large number of individual Managed Futures. Although not yet shown, the same cohesive picture emerges when we implement a random coefficients model using a panel of hedge funds, for completeness, in Subsection 4.4.

4.3. Higher-moment factors help to characterize Event Driven and Long/Short returns

To provide broader underpinnings for the higher-moment factors, we investigate whether our results from Managed Futures generalize to Event Driven and Long/Short Equity hedge funds, and if so, which higher-moment factors receive relatively more weighting. The rationale to understand their return generating processes is rooted in the work of Mitchell and Pulvino (2001) and Fung and Hsieh (2004a), who provide a suggestive basis for Event Driven and Long/Short Equity returns to have option-like nonlinearities with heavier tails.

Two results stem from studying the Event Driven style, which contains 265 hedge funds with at least 36 monthly return observations. First, we observe from Panels A, B, and C of Table 7 that, as opposed to Managed Futures, a large proportion of Event Driven funds are *short skewness* and *short kurtosis*, and are also short volatility, but to a lesser extent. Specifically, 92 funds out of 265 (35%) show $\beta^{9,i} < 0$ i.e., statistically significant negative loading on skewness, while 91 funds show $\beta^{10,i} < 0$, i.e., statistically significant negative loading on kurtosis. Second, among the three lookback straddles, the bond market straddle is the most important followed by the commodity and the currency straddles. Consistent with the findings in Mitchell and Pulvino

(2001), Event Driven funds display pronounced exposures to the two traditional equity factors (i.e., SNPMRF and SCMLC) in the FH-7 model. On balance, the evidence that higher-moment factors characterize the returns of Event Driven funds suggests the wider applicability of higher-moment factors in assessing hedge fund risks.

How do higher-moment factors fare for Long/Short Equity, which is the largest style category with 1,040 hedge funds? The findings in Panels A, B, and C of Table 8 illustrate that SNPMRF and SCMLC continue to be prominent for Long/Short Equity as they were for Event Driven. However, a salient finding that emerges is that a large number of Long/Short funds are *long volatility*, *short skewness*, and *long kurtosis*. The Long/Short and Event Driven styles, however, differ in one key respect: while Event Driven funds are predominantly short kurtosis, the Long/Short Equity funds show marked long kurtosis exposures. The bottom line is that hedge funds are exposed to higher-moment factors, and the importance and direction/sign of these exposures varies with hedge fund styles to capture their diverse trading strategies.

Again performing a χ^2 test, as we did for Managed Futures, we find that for Event Driven (Long/Short equity) style, for 117 (233) funds out of 265 (317) one can reject the null hypothesis that all the three exposures are jointly equal to zero. Hence, the test suggests that omitting the three higher-moment factors can be expected to worsen the performance of the multifactor model in explaining the hedge fund returns.

4.4. *Estimation with style fixed effects and fund random effects points to significant average higher-moment exposures*

Building on the preceding analysis where a large number of individual hedge funds within a style were shown to have significant higher-moment loadings, this subsection presents an integrated methodology to study *average* higher-moment exposures for the three largest styles, using a joint estimation. Our aim is to incorporate the interaction of exposures across individual hedge funds within a style on the one hand, and across styles, on the other.

Suited for our purposes, we adopt the random coefficients model (see, among others, Verbeke and Molenberghs (2000) and Hsiao (2003)) and employ a panel of individual hedge funds differentiated by styles. The empirical specification for fund i in style group j takes the form:

$$\mathbf{y}_{ji} = \mathbf{X}_{ji}\beta_j + \mathbf{Z}_{ji}\upsilon_j + \varepsilon_{ji}, \tag{17}$$

where $\mathbf{y}_{ji}$ is the vector of monthly returns observed for fund i in style group j. Moreover, $\mathbf{X}_{ji}\beta_j$ is the fixed part of the model, which includes an intercept and p factors, $\mathbf{Z}_{ji}\upsilon_j$ is the random part of the model, which includes $p+1$ random effects, and ε_{ji} is the error term. Following a common practice, we assume that (i) the random effects are Normally distributed and uncorrelated, (ii) the variance of the random effect is the same across the three styles, and (iii) the error terms follow an first-order autoregressive process for hedge fund i. The model is estimated via maximum-likelihood, the details of which are provided in Appendix B. The standard errors have been corrected to deal with serial correlation and heteroskedasticity.

Table 9 reports the intercepts and the interaction of the ten factors (FH-7 factors and the three higher-moment factors) with the three style dummies (MF for Managed Futures, ED for Event Driven, and LS for Long/Short Equity). Consider first the results from adding each higher-moment factor incrementally to the FH-7 model, and then all the three higher-moment factors simultaneously.

Estimation results from the interaction terms of the factors and style dummies suggest one conclusion that emerges strongly: the average exposure to volatility is positive for Managed Futures, negative for Event Driven, and positive for Long/Short. The loadings on volatility varies between -0.002 to 0.005 and are highly significant with all p-values below 0.01. Clearly, the benefit of the estimation approach lies in greater statistical power: exploiting the entire panel for estimating the parameters simultaneously and focusing on style-level variation significantly reduces the number of unknown parameters, which makes inferences more trustworthy. The random coefficients model combines elements from individual hedge funds to obtain a consolidated average factor sensitivity, but is estimated jointly. We note that the two sets of results, one based on Table 9, and the other based on Tables 6, 7, and 8, complement one another.

What we find with respect to the skewness factor and the kurtosis factor is also in line with our earlier results. It bears repeating that the average skewness exposure is positive for Managed Futures, while it is negative for both Event Driven and Long/Short. Furthermore, the average kurtosis exposure is positive for Managed Futures and Long/Short, but negative for Event Driven. Overall, the results clarify that adding the factors one at a time versus putting them all together are generally consistent with each other, except that for Managed Futures (Event Driven) the loading on kurtosis (volatility) becomes negative (positive).

The estimation results for model (17) with style fixed effects and fund random effects can also provide the basis to examine whether the higher-moment exposures are jointly different across styles, as well as whether they are different from each other within a style. To articulate main ideas, four diagnostic tests are performed:

- Test 1: $F^{vo} * MF = F^{vo} * ED = F^{vo} * LS = 0$;
- Test 2: $F^{sk} * MF = F^{sk} * ED = F^{sk} * LS = 0$;
- Test 3: $F^{ku} * MF = F^{ku} * ED = F^{ku} * LS = 0$;
- Test 4: $F^{vo} * MF = F^{sk} * MF = F^{ku} * MF = 0$, and $F^{vo} * ED = F^{sk} * ED = F^{ku} * ED = 0$, and $F^{vo} * LS = F^{sk} * LS = F^{ku} * LS = 0$.

Drawing upon the results from the F-tests shows that the higher-moment exposures for the three styles are jointly different from zero (i) when we consider each style individually (F-values=25.92, 61.72, and 17.41, and all p-values=$<$0.0001), and (ii) when we account for all styles together (F-value=35.02, p-value=$<$0.0001). Evaluating the extent of the exposures using our methodology strengthens the presence of higher-moment risks. For one, it can overcome some of the limitations associated with the fund-by-fund time series regressions, and the model is amenable to estimating the fixed effects for each style jointly. At the same time, it accounts for random effects at the individual fund level around style average, within each style.

Collectively, these findings corroborate the cross-sectional variation in higher-moment exposures across styles while allowing for variations at the individual fund level within each style. The results also bear out in favor of higher-moment factors when economic significance is considered. For example, a one standard deviation change in the volatility factor can increase Managed Futures returns by 0.8% (i.e., 0.009×0.8885) on a monthly basis. In brief, the gist is that the average sensitivity to volatility, skewness, and kurtosis factors is statistically significant, both within a style and across styles in a manner that is compatible with their diverse trading strategies.

5. Conclusions

In this paper, we contribute by examining the role of higher-moment equity risks in explaining the cross section of hedge fund returns. Complementing this evidence, we construct investable higher-moment factors and judge their ability to describe the time series of hedge fund returns. The focal points of the latter exercise are the three biggest styles: Long/Short Equity, Managed Futures, and Event Driven.

Through our empirical investigation, the study accomplishes a number of objectives. First, we show that hedge funds are substantively exposed to higher-moment risks. Using a multi-factor model that does not account for higher-moment risks, we find significant dispersion and systematic patterns in alphas between the top and bottom portfolios of hedge funds, sorted on their exposures to volatility, skewness, and kurtosis risks. Second, the alpha spreads and patterns survive a host of validation checks, including a bootstrap simulation designed to assess whether the alpha spreads are spurious. Third, our style-by-style analysis reveals that higher-moment risks matter more for those fund styles that tend to apply their strategies to the equity markets and are less relevant for styles in which equity risk is not the primary exposure.

With a view to address the anomaly in Fung and Hsieh (2001) that equity lookback straddles are unimportant for Managed Futures in their sample, we examine the time series returns of individual Managed Futures to understand their generating processes. The key empirical finding is that the volatility factor is positive and statistically significant for a large number of Managed Futures.

To evaluate the broader applicability of the higher-moment factors, we furthermore analyze individual Event Driven funds. Here we observe a significantly negative sensitivity across individual funds to both the skewness factor and the kurtosis factor. Revealing the diverse set of trading strategies followed by hedge funds, our investigation uncovers a different pattern with respect to

Long/Short funds. A large number of individual Long/Short funds display a significantly negative sensitivity to the skewness factor and a significantly positive sensitivity to the kurtosis factor.

The big picture on the relevance of higher-moment factors is supported by the total number of funds that display statistically significant loadings on the higher-moment factors. Maximum-likelihood estimation with style fixed effects and fund random effects substantiate the relevance of higher-moment factors for the three big hedge fund styles, as we find strong evidence in favor of statistically significant average exposure sensitivities. Our empirical evidence on the ability of investable higher-moment factors to describe hedge fund returns can have implications for performance evaluation and risk management in the hedge fund industry.

Appendix A: Returns of higher-moments constructed from observable market prices

In order to construct investable higher-moment factors, we use option quotes on the S&P 500 index and exploit an explicit option positioning. Specifically, our sample consists of all out-of-the-money call and put options that are available nearest to the end of each month so as to align the return of higher-moment factors as closely as possible with the monthly hedge fund returns.

To understand the generating processes of hedge funds, the monthly return of volatility, denoted by z_t^{vo}, over month t, is calculated as:

$$\begin{aligned} 1+z_t^{vo} &\equiv \frac{\left(\ln\left(S_{t+\tau}/S_t\right)\right)^2}{\mathbb{M}_{2,t}} = \frac{\int_{K>S_t} \omega^{vo}[K]\ (S_{t+\tau}-K)^+\ dK + \int_{K<S_t} \omega^{vo}[K]\,(K-S_{t+\tau})^+\ dK}{\mathbb{M}_{2,t}}, \\ &\approx \frac{\sum_{K>S_t} \omega^{vo}[K]\ (S_{t+\tau}-K)^+\ \Delta K + \sum_{K<S_t} \omega^{vo}[K]\,(K-S_{t+\tau})^+\ \Delta K}{\mathbb{M}_{2,t}}, \end{aligned} \tag{A1}$$

where the option positioning $\omega^{vo}[K]$is presented in (4), $a^+ = \max(a,0)$, and τ is close to one-month. The denominator in (A1) reflects the cost of the payout $\left(\ln\left(S_{t+\tau}/S_t\right)\right)^2$.

In essence, we employ a static positioning in calls and puts to synthesize $\left(\ln\left(S_{t+\tau}/S_t\right)\right)^2$, which mirrors the Fung and Hsieh (2001) approach to roll over calls and puts so as to mimic the maximum or the minimum return payout. It furthermore accords with how gross returns of variance swaps can be measured, namely the sum of daily realized squared returns over the next one-month (say, $\sum_{j=0}^{T^m}(\ln S_{t+j+1}/S_{t+j})^2$) divided by the variance swap contract price determined at time t.

The method for constructing the return of negative skewness payout i.e., $-\left(\ln\left(S_{t+\tau}/S_t\right)\right)^3/(\mathbb{M}_{2,t})^{3/2}$ is analogously:

$$\begin{aligned} 1+z_t^{sk} &\equiv \frac{-\left(\ln\left(S_{t+\tau}/S_t\right)\right)^3/(\mathbb{M}_{2,t})^{3/2}}{(-\mathbb{M}_{3,t})/(\mathbb{M}_{2,t})^{3/2}}, \\ &\approx \frac{-\left(\sum_{K>S_t} \omega^{sk1}[K]\ (S_{t+\tau}-K)^+\ \Delta K\ \ -\ \ \sum_{K<S_t} \omega^{sk2}[K]\,(K-S_{t+\tau})^+\ \Delta K\right)}{(-\mathbb{M}_{3,t})}, \end{aligned} \tag{A2}$$

which involves taking a long position in puts and a short position in calls, where $\omega^{sk1}[K]$ and

$\omega^{sk2}[K]$ are respectively presented in (6).

Completing the description of return of higher-moments, we calculate the return of kurtosis as,

$$1+z_t^{ku} \equiv \frac{(\ln(S_{t+\tau}/S_t))^4/(\mathbb{M}_{2,t})^2}{(\mathbb{M}_{4,t})/(\mathbb{M}_{2,t})^2} \approx \frac{\sum_{K>S_t}\omega^{ku}[K]\,(S_{t+\tau}-K)^+\,\Delta K+\sum_{K<S_t}\omega^{ku}[K]\,(K-S_{t+\tau})^+\,\Delta K}{\mathbb{M}_{4,t}}, \tag{A3}$$

where the positions in calls and puts are shown in (7). We use z_t^{vo}, z_t^{sk}, and z_t^{ku} to construct investable higher-moment factors via (15).

Appendix B: Random coefficients model with fixed effects for styles and random effects for individual hedge funds

To fix the notation for the empirical model, we adopt the following convention:

$j=1,2,3,$ style groups (i.e., Managed Futures, Event Driven, and Long/Short Equity) ;

$i=1,\ldots,n_j,$ funds in style group j;

$t=1,\ldots,T_{ji},$ observations for fund i in style group j;

$p=1,2,\ldots,10,$ number of factors.

For every fund i in style group j, the estimated model is:

$$\underset{T_{ji}}{\mathbf{y}_{ji}} = \underset{T_{ji}\times(p+1)}{\mathbf{X}_{ji}} \underset{(p+1)\times 1}{\beta_j} + \underset{T_{ji}\times(p+1)}{\mathbf{Z}_{ji}} \underset{(p+1)\times 1}{\upsilon_j} + \underset{T_{ji}\times 1}{\varepsilon_{ji}}, \tag{A4}$$

where,

$\mathbf{y}_{ji}$ is the response vector of monthly returns observed for fund i in style group j;

$\mathbf{X}_{ji}\beta_j$ is the fixed part of the model, which includes one intercept and p factors;

$\mathbf{Z}_{ji}\upsilon_j$ is the random part of the model, which includes $p+1$ random effects;

ε_{ji} is the error term.

That is, for every style group,

$$\mathbf{y}_{ji} = \begin{bmatrix} y_{j1} \\ y_{j2} \\ \vdots \\ y_{jT_{ij}} \end{bmatrix}, \qquad \mathbf{X}_{ji} = \begin{bmatrix} 1 & x1_{j1} & \cdots & xp_{j1} \\ 1 & x1_{j2} & \cdots & xp_{j2} \\ \vdots & \vdots & & \vdots \\ 1 & x1_{jT_{ij}} & \cdots & xp_{jT_{ij}} \end{bmatrix}, \qquad \beta_j = \begin{bmatrix} \beta_{0j} \\ \beta_{1j} \\ \vdots \\ \beta_{pj} \end{bmatrix}, \quad \text{and,} \tag{A5}$$

$$\mathbf{Z}_{ji} = \begin{bmatrix} 1 & x1_{j1} & \cdots & xp_{j1} \\ 1 & x1_{j2} & \cdots & xp_{j2} \\ \vdots & \vdots & & \vdots \\ 1 & x1_{jT_{ij}} & \cdots & xp_{jT_{ij}} \end{bmatrix}, \qquad \upsilon_j = \begin{bmatrix} \upsilon_{0j} \\ \upsilon_{1j} \\ \vdots \\ \upsilon_{pj} \end{bmatrix}, \qquad \varepsilon_{ji} = \begin{bmatrix} \varepsilon_{j1} \\ \varepsilon_{j2} \\ \vdots \\ \varepsilon_{jT_{ij}} \end{bmatrix}. \tag{A6}$$

For the maximum-likelihood estimation, we assume that the random effects are Normally distributed and uncorrelated. Further, we posit that the variance of the random effects is the same across style groups. Finally, the error terms are assumed to be autocorrelated, and, for tractability reasons, modeled as an AR(1) process for each hedge fund.

$$\upsilon \sim \mathbf{N}(\mathbf{0}, \mathbf{G}), \qquad \mathbf{G} = \begin{bmatrix} \sigma^2_{\upsilon_0} & 0 & 0 & 0 \\ 0 & \sigma^2_{\upsilon_1} & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & \sigma^2_{\upsilon_p} \end{bmatrix}, \tag{A7}$$

$$\varepsilon_{ji} \sim \mathbf{N}(\mathbf{0}, \mathbf{R}_j), \qquad \mathbf{R}_j = \sigma^2_{\varepsilon_j} \begin{bmatrix} 1 & \rho_j & \cdots & \rho_j^{T_{ji}-1} \\ \rho_j & 1 & & \rho_j^{T_{ji}-2} \\ \vdots & & \ddots & \\ \rho_j^{T_{ji}-1} & \rho_j^{T_{ji}-2} & & 1 \end{bmatrix}. \tag{A8}$$

Note that even without introducing heterogeneity into the random part of the model, the variance-covariance matrix is $\mathbf{ZGZ}' + \mathbf{R}_j,\ \ j = 1, 2, 3$, and not $\sigma^2\mathbf{I}$.

Through our empirical specification we accommodate two levels of variation in fund returns for style group j:

(i) within the fund (time-series /longitudinal); and,

(ii) between funds in each style group (cross-sectional).

The within-funds model variation can be characterized as,

$$y_{jit} = b_{0ji} + b_{1ji}\, x1_{jit} + \ldots + b_{pji}\, xp_{jit} + \varepsilon_{jit}, \tag{A9}$$

where every fund $i = 1, \ldots, n_j$ in style group $j = 1,2,3$ has its own individual intercept b_{0ji} and slopes $b_{1ji}, \ldots, b_{pji}$. The error terms $\varepsilon_{ji1}, \ldots, \varepsilon_{jiT_{ji}}$ are assumed to be Normally distributed and autocorrelated. The variance and autocorrelation parameters ($\sigma^2_{\varepsilon_j}$ and ρ_j) vary across style groups $j = 1,2,3$.

Furthermore, the between-funds variation is modeled as:

$$\begin{aligned}
b_{0ji} &= \beta_{0j} + \upsilon_{0i}, \qquad \upsilon_{0i} \sim N(0, \sigma^2_{\upsilon_0}) \\
b_{1ji} &= \beta_{1j} + \upsilon_{1i}, \qquad \upsilon_{1i} \sim N(0, \sigma^2_{\upsilon_1}) \\
&\vdots \\
b_{pji} &= \beta_{pj} + \upsilon_{pi}, \qquad \upsilon_{pi} \sim N(0, \sigma^2_{\upsilon_p})
\end{aligned} \tag{A10}$$

where the intercept and slopes for style group $j = 1,2,3$ have an average level across all $i = 1, \ldots, n_j$ funds in the style group and random variation around that average, which is Normally distributed. Here, we assume that the fixed part is heterogeneous across styles but the variance of the random effect is the same for all styles. That is, $\beta_{p1} \neq \beta_{p2} \neq \beta_{p3}$, but $\sigma^2_{\upsilon_{p1}} = \sigma^2_{\upsilon_{p2}} = \sigma^2_{\upsilon_{p3}}$.

The model is estimated via maximum-likelihood using the SAS programming language. ■

References

Ackermann, C., R. McEnally, and D. Ravenscaft, 1999, "The Performance of Hedge Funds: Risk, Return, and Incentives," *Journal of Finance*, 54, 833–874.

Agarwal, V., N. Daniel, and N. Naik, 2008, "Role of Managerial Incentives and Discretion in Hedge Fund Performance," *Journal of Finance*, (forthcoming).

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

Agresti, A., 1996, *An Introduction to Categorical Data Analysis*. John Wiley, New York.

Amin, G., and H. Kat, 2003, "Hedge Fund Performance 1990-2000: Do the Money Machines Really Add Value?," *Journal of Financial and Quantitative Analysis*, 38, 251–274.

Ang, A., R. Hodrick, Y. Xing, and X. Zhang, 2006, "The Cross-Section of Volatility and Expected Returns," *Journal of Finance*, 61, 259–299.

Aragon, G., 2007, "Share restrictions and asset pricing: Evidence from the hedge fund industry," *Journal of Financial Economics*, 83, 33–58.

Avramov, D., R. Kosowski, N. Naik, and M. Teo, 2007, "Investing in hedge funds when returns are predictable," working paper, University of Maryland.

Baks, K., A. Metrick, and J. Wachter, 2001, "Should Investors Avoid All Actively Managed Mutual Funds? A Study in Bayesian Performance Evaluation," *Journal of Finance*, 56, 45–85.

Bakshi, G., and N. Kapadia, 2003, "Delta-Hedged Gains and the Negative Market Volatility Risk Premium," *Review of Financial Studies*, 16(2), 527–566.

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

Bakshi, G., and D. Madan, 2006, "A Theory of Volatility Spreads," *Management Science*, 52(12), 1950–1964.

Bollen, N., and R. Whaley, 2008, "Hedge Fund Risk Dynamics: Implications for Performance Appraisal," *Journal of Finance*, (forthcoming).

Bondarenko, O., 2004, "Market Price of Variance Risk and Performance of Hedge Funds," working paper, University of Illinois at Chicago.

Britten-Jones, M., and A. Neuberger, 2000, "Option Prices, Implied Price Processes, and Stochastic Volatility," *Journal of Finance*, 55, 839–866.

Brown, S., and W. Goetzmann, 1995, "Performance Persistence," *Journal of Finance*, 50, 679–698.

Brown, S., W. Goetzmann, R. Ibbotson, and S. Ross, 1992, "Survivorship-Bias in Performance Studies," *Review of Financial Studies*, 5, 553–580.

Busse, J., and P. Irvine, 2006, "Bayesian Alphas and Mutual Fund Persistence," *Journal of Finance*, 61, 2251–2288.

Carr, P., and D. Madan, 2001, "Optimal Positioning in Derivative Securities," *Quantitative Finance*, 1(1), 19–37.

Carr, P., and L. Wu, 2009, "Variance Risk Premia," *Review of Financial Studies*, 22(3), 1311–1341.

Cochrane, J., and M. Piazzesi, 2005, "Bond Risk Premia," *American Economic Review*, 95(1), 138–160.

Coval, J., and T. Shumway, 2001, "Expected Option Returns," *Journal of Finance*, 56(3), 983–1009.

Demeterfi, K., E. Derman, M. Kamal, and J. Zou, 1999, "A Guide to Volatility and Variance Swaps," *Journal of Derivatives*, 6(4), 9–32.

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

Diez, A., and R. Garcia, 2006, "Assessing and Valuing the Nonlinear Structure of Hedge Fund Returns," working paper, University of Montreal.

Fama, E., and K. French, 1992, "The Cross-Section of Expected Stock Returns," *Journal of Finance*, 47, 427–465.

Ferson, W., and R. Schadt, 1996, "Measuring fund strategy and performance in changing economic conditions," *Journal of Finance*, 51, 425–462.

Fung, W., and D. Hsieh, 1997, "Empirical characteristics of dynamic trading strategies: the case of hedge funds," *Review of Financial Studies*, 10, 275–302.

——— , 2000, "Performance Characteristics of Hedge Funds and CTA funds: Natural versus Spurious Biases," *Journal of Financial and Quantitative Analysis*, 35(2), 291–307.

——— , 2001, "The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers," *Review of Financial Studies*, 14(2), 313–341.

——— , 2004a, "Extracting portable alphas from Equity Long-Short Hedge Funds," *Journal of Investment Management*, 2, 57–75.

——— , 2004b, "Hedge Fund Benchmarks: A Risk-Based Approach," *Financial Analyst Journal*, 60, 65–81.

Fung, W., D. Hsieh, N. Naik, and T. Ramadorai, 2008, "Hedge Funds: Performance, Risk and Capital Formation," *Journal of Finance*, 63(4), 1777–1803.

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

Gibbons, M., S. Ross, and J. Shanken, 1989, "A Test of the Efficiency of a Given Portfolio," *Econometrica*, 57, 1121–1152.

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

Hasanhodzic, J., and A. Lo, 2007, "Can Hedge Fund Returns be Replicated? The Linear Case," *Journal of Investment Management*, 5, 5–45.

Hsiao, C., 2003, *Analysis of Panel Data*. Cambrige University Press, New York.

Huij, J., and M. Verbeek, 2007, "Cross-Sectional Learning and Short-Run Persistence in Mutual Fund Performance," *Journal of Banking and Finance*, 31, 973–997.

Jagannathan, R., A. Malakhov, and D. Novikov, 2006, "Do Hot Hands Exist Among Hedge Fund Managers? An Empirical Evaluation," working paper, NBER # 12015.

Jiang, G., and Y. Tian, 2005, "The Model-Free Implied Volatility and Its Information Content," *Review of Financial Studies*, 18, 1305–1342.

Jones, C., and J. Shanken, 2005, "Mutual Fund Performance with Learning Across Funds," *Journal of Financial Economics*, 78, 507–522.

Kosowski, R., N. Naik, and M. Teo, 2007, "Do Hedge Funds Deliver Alpha? A Bayesian and Bootstrap Analysis," *Journal of Financial Economics*, 84, 229–264.

Kosowski, R., A. Timmermann, R. Wermers, and H. White, 2006, "Can Mutual Fund Stars Really Pick Stocks? New Evidence from a Bootstrap Analysis," *Journal of Finance*, 61, 2551–2595.

Kraus, A., and R. Litzenberger, 1976, "Skewness Preference and the Valuation of Risk Assets," *Journal of Finance*, 31(4), 1085–1100.

Lewellen, J., and S. Nagel, 2006, "The conditional CAPM does not explain asset pricing anomalies," *Journal of Financial Economics*, 82, 289–314.

Liang, B., 2000, "Hedge Funds: the Living and the Dead," *Journal of Financial and Quantitative Analysis*, 35, 309–326.

Mitchell, M., and T. Pulvino, 2001, "Characteristics of Risk in Risk Arbitrage," *Journal of Finance*, 56, 2135–2175.

Pastor, L., and R. Stambaugh, 2003, "Liquidity Risk and Expected Stock Returns," *Journal of Political Economy*, 111, 642–685.

Patton, A., 2008, "Are "Market Neutral" Hedge Funds Really Market Neutral?," *Review of Financial Studies*, (forthcoming).

Verbeke, G., and G. Molenberghs, 2000, *Linear Mixed Models for Longitudinal Data*. Springer, New York.

Weisman, A., 2002, "Informationless investing and hedge fund performance measurement bias," *Journal of Portfolio Management*, 28, 80–91.

Table 1

Portfolios of hedge funds single-sorted by their exposures to volatility, skewness, and kurtosis risks (ΔVOL, ΔSKEW, and ΔKURT), and post-ranking regression results from the Fung-Hsieh seven-factor (FH-7) model

Reported are average pre-ranking higher-moment betas and post-ranking alphas, t-statistics, and adjusted R-squared values (denoted $\overline{R}^2$) from regressions using the Fung and Hsieh (2004b) seven-factor model (FH-7 model). Hedge funds are sorted each month into equally-weighted decile portfolios based on their higher-moment betas which are estimated using the following regression for rolling pre-ranking windows of 12 months: $r_t^i = \alpha_{4F}^i + \beta_{\mathrm{RMRF}}^i \mathrm{RMRF}_t + \beta_{\Delta\mathrm{VOL}}^i \Delta\mathrm{VOL}_t + \beta_{\Delta\mathrm{SKEW}}^i \Delta\mathrm{SKEW}_t + \beta_{\Delta\mathrm{KURT}}^i \Delta\mathrm{KURT}_t + \varepsilon_t^i$, where r_t^i represents excess return of hedge fund i, RMRF_t is excess return of the market portfolio in month t, and $\Delta\mathrm{VOL}_t$, $\Delta\mathrm{SKEW}_t$ and $\Delta\mathrm{KURT}_t$ are our proxies for equity volatility risk, skewness risk, and kurtosis risk, as defined in (8)-(10). Reported post-ranking alphas are annualized. Empirical tests use monthly net-of-fee returns of hedge funds from the 2004 Lipper TASS Hedge Fund Database over the period January 1994 to December 2004. The exclusionary criterion used to construct the hedge fund sample is described in Section 2. The row marked "GRS p-value" reports the p-value for the Gibbons, Ross, and Shanken (1989) test that all the post-ranking alphas are jointly equal to zero. In Panels A, B, and C, Portfolio H (L) represents the hedge fund decile with the most positive (negative) exposure to volatility, skewness and kurtosis risks, respectively. The sample covers 3,771 hedge funds.

		Pre-ranking exposures to market risk and higher-moment equity risks				FH-7 model (post-ranking)		
		β_{RMRF}	$\beta_{\Delta\mathrm{VOL}}$	$\beta_{\Delta\mathrm{SKEW}}$	$\beta_{\Delta\mathrm{KURT}}$	Alpha	Alpha-t	$\overline{R}^2$
		Panel A. Sorts on exposure to ΔVOL						
D1	H (positive)	0.70	5.96	8.14	1.55	-2.66%	-0.86	50%
D2		0.45	2.50	3.28	0.61	0.97%	0.62	65%
D3		0.35	1.38	1.73	0.32	1.80%	1.39	62%
D4		0.25	0.74	0.88	0.15	2.85%	2.73	60%
D5		0.19	0.28	0.40	0.05	4.24%	5.51	64%
D6		0.18	-0.11	0.10	-0.02	4.38%	5.20	66%
D7		0.18	-0.53	-0.40	-0.13	4.77%	4.64	62%
D8		0.20	-1.11	-0.92	-0.25	4.69%	4.00	61%
D9		0.23	-2.08	-1.93	-0.47	7.64%	5.32	60%
D10	L (negative)	0.18	-5.76	-5.26	-1.17	10.82%	4.65	53%
D1-D10						-13.48%	-3.82	12%
GRS p-value						0.00		

Table 1 continued

		Pre-ranking exposures to market risk and higher-moment equity risks				FH-7 model (post-ranking)		
		β_{RMRF}	$\beta_{\Delta VOL}$	$\beta_{\Delta SKEW}$	$\beta_{\Delta KURT}$	Alpha	Alpha-*t*	$\bar{R}^2$
		Panel B. Sorts on exposure to ΔSKEW						
D1	H (positive)	0.65	3.21	14.64	2.20	-4.58%	-1.49	53%
D2		0.44	1.42	5.96	0.88	2.72%	1.58	60%
D3		0.32	0.71	3.32	0.47	3.42%	2.68	67%
D4		0.26	0.40	1.77	0.24	2.74%	2.59	64%
D5		0.19	0.16	0.71	0.09	4.47%	4.83	64%
D6		0.18	-0.04	-0.14	-0.04	4.73%	5.81	65%
D7		0.19	-0.26	-1.05	-0.19	4.57%	4.36	61%
D8		0.23	-0.55	-2.34	-0.40	4.53%	3.71	61%
D9		0.26	-1.05	-4.59	-0.75	6.33%	4.52	60%
D10	L (negative)	0.20	-2.72	-12.32	-1.87	10.27%	4.65	42%
D1-D10						-14.85%	-4.10	14%
GRS *p*-value						0.00		
		Panel C. Sorts on exposure to ΔKURT						
D1	H (positive)	0.57	3.73	13.39	2.46	-3.72%	-1.25	55%
D2		0.39	1.52	5.51	0.98	0.96%	0.57	62%
D3		0.30	0.80	3.06	0.53	2.36%	1.96	67%
D4		0.23	0.43	1.61	0.27	3.48%	3.41	64%
D5		0.19	0.19	0.68	0.09	3.90%	4.27	60%
D6		0.18	-0.05	-0.09	-0.05	4.03%	4.64	65%
D7		0.22	-0.31	-0.94	-0.22	5.61%	5.39	62%
D8		0.25	-0.68	-2.11	-0.45	5.03%	3.87	58%
D9		0.28	-1.18	-4.09	-0.84	6.80%	4.59	56%
D10	L (negative)	0.29	-3.18	-11.05	-2.14	10.87%	4.78	40%
D1-D10						-14.59%	-4.04	10%
GRS *p*-value						0.00		

Table 2

Portfolios of hedge funds triple-sorted by their exposures to ΔVOL, ΔSKEW, and ΔKURT, and post-ranking regression results from the FH-7 model

Reported are average pre-ranking higher-moment betas and post-ranking alphas, *t*-statistics, and adjusted *R*-squared values ($\overline{R}^2$) of the 27 triple-sorted portfolios, and of the difference between the top and bottom portfolios (P1-P27), from regressions using the Fung and Hsieh (2004b) seven-factor model (FH-7 model). Each month hedge funds are sorted into equally-weighted triple-sorted portfolios based on their higher-moment betas, which are estimated using the following regression for rolling pre-ranking windows of 12 months: $r_t^i = \alpha_{4F}^i + \beta_{\text{RMRF}}^i \text{RMRF}_t + \beta_{\Delta\text{VOL}}^i \Delta\text{VOL}_t + \beta_{\Delta\text{SKEW}}^i \Delta\text{SKEW}_t + \beta_{\Delta\text{KURT}}^i \Delta\text{KURT}_t + \varepsilon_t^i$, where r_t^i represents excess return of hedge fund *i*, RMRF_t is excess return of the market portfolio in month *t*, and ΔVOL_t, ΔSKEW_t and ΔKURT_t are our proxies for volatility risk, skewness risk, and kurtosis risk. Reported post-ranking alphas are annualized. The sample is from 1994 to 2004 and covers 3,771 hedge funds. The row marked "GRS *p*-value" reports the *p*-value for the Gibbons, Ross, and Shanken (1989) test that all the post-ranking alphas are jointly equal to zero. Portfolio H/H/H (L/L/L) represents the hedge fund portfolio with the most positive (negative) exposures to volatility, skewness and kurtosis risks together.

		Pre-ranking exposures to market risk and higher-moment equity risks				FH-7 model (post-ranking)		
		β_{RMRF}	$\beta_{\Delta\text{VOL}}$	$\beta_{\Delta\text{SKEW}}$	$\beta_{\Delta\text{KURT}}$	Alpha	Alpha-*t*	$\overline{R}^2$
P1	H/H/H	0.78	6.68	18.80	3.34	-5.59%	-1.23	41%
P2	H/H/M	0.58	3.75	9.72	1.62	-2.54%	-1.08	56%
P3	H/H/L	0.63	3.02	7.39	0.83	-1.08%	-0.38	45%
P4	H/M/H	0.37	3.05	3.94	1.06	2.03%	0.98	49%
P5	H/M/M	0.37	2.04	3.12	0.55	1.60%	1.10	57%
P6	H/M/L	0.43	1.93	2.26	0.13	1.82%	1.10	52%
P7	H/L/H	0.31	2.49	-0.69	0.45	-0.23%	-0.13	49%
P8	H/L/M	0.37	1.92	-1.63	-0.11	2.12%	1.12	46%
P9	H/L/L	0.45	2.50	-6.62	-1.03	4.69%	1.64	28%
P10	M/H/H	0.25	0.21	6.32	1.04	-0.04%	-0.02	51%
P11	M/H/M	0.20	0.21	2.70	0.38	4.09%	3.55	52%
P12	M/H/L	0.26	0.11	2.00	0.05	2.95%	2.64	51%
P13	M/M/H	0.12	0.20	0.53	0.19	4.57%	4.99	54%
P14	M/M/M	0.09	0.09	0.20	0.02	4.16%	6.88	40%
P15	M/M/L	0.18	-0.02	-0.09	-0.17	4.52%	4.92	52%
P16	M/L/H	0.14	0.07	-1.46	-0.04	5.16%	4.87	51%
P17	M/L/M	0.20	-0.05	-2.16	-0.34	5.57%	5.40	50%
P18	M/L/L	0.30	0.00	-5.87	-1.03	6.07%	3.81	47%
P19	L/H/H	0.22	-2.60	7.49	1.13	3.15%	1.23	46%
P20	L/H/M	0.19	-1.82	2.52	0.19	5.38%	3.59	56%
P21	L/H/L	0.31	-2.40	1.58	-0.36	9.44%	4.22	38%
P22	L/M/H	0.10	-1.74	-1.00	-0.04	4.68%	3.09	53%
P23	L/M/M	0.17	-1.75	-1.77	-0.40	6.15%	4.84	59%
P24	L/M/L	0.30	-2.59	-2.46	-0.88	6.35%	3.68	55%
P25	L/L/H	0.11	-2.63	-5.59	-0.65	6.20%	3.43	57%
P26	L/L/M	0.23	-3.26	-7.50	-1.34	10.44%	5.39	48%
P27	L/L/L	0.20	-6.02	-15.93	-2.97	14.95%	4.78	27%
P1-P27						-20.54%	-3.85	11%
GRS *p*-value						0.00		

Table 3

Conditional frequencies of higher-moment exposures across fund styles

The style definitions adopted here are from CSFB/Tremont available at www.hedgeindex.com. "Grand average" reports the average frequency of hedge funds classified according to their investment styles as a fraction of the total hedge funds. Reported conditional frequencies are computed as the frequency each month for each style and then averaged across all months. The three portfolios – P1, P14, and P27, show the most positive (H/H/H), near-zero (M/M/M), and the most negative (L/L/L) exposures to the three higher-moment risks. Average frequencies across the 9 groups – H, M, L, for volatility, skewness, and kurtosis risks are presented in Panels B, C, and D. The reported frequency in Vol-H is pooled as $\frac{1}{9}(P1+P2+P3+P4+P5+P6+P7+P8+P9)$ and Vol-L as $\frac{1}{9}(P19+P20+P21+P22+P23+P24+P25+P26+P27)$. Likewise Skew-H = $1/9(P1+P2+P3+P10+P11+P12+P19+P20+P21)$ and Skew-L = $1/9(P7+P8+P9+P16+P17+P18+P25+P26+P27)$. Similarly, KURT-H = $1/9(P1+P4+P7+P10+P13+P16+P19+P22+P25)$ and KURT-L = $1/9(P3+P6+P9+P12+P15+P18+P21+P24+P27)$. The p-value is from a multivariate chi-squared test of difference in proportions with degrees of freedom equal to 2 (see Agresti (1996)).

	Long/ Short	**Managed Futures**	**Emerging Markets**	**Global Macro**	**Dedicated Short**	**Event Driven**	**Convert. Arbitrage**	**Market Neutral**	**Fixed Inc. Arbitrage**	**Multi Strategy**
Grand average	37.48%	15.04%	8.51%	6.14%	1.25%	12.19%	5.58%	5.31%	4.79%	4.01%
	Panel A: Portfolios with differential exposures to higher-moment risks									
P1 (H/H/H)	41.06%	30.79%	11.17%	6.01%	1.86%	2.88%	0.22%	2.29%	2.52%	1.21%
P14 (M/M/M)	16.31%	4.87%	4.80%	4.69%	0.61%	24.23%	15.94%	6.66%	14.23%	7.68%
P27 (L/L/L)	44.42%	22.06%	12.70%	6.91%	1.84%	3.95%	2.51%	1.65%	1.77%	2.19%
p-value	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
	Panel B: Portfolios with differential exposures to volatility risk									
Vol-H	43.37%	19.55%	8.18%	6.41%	1.46%	7.42%	3.01%	4.91%	3.15%	2.54%
Vol-M	30.55%	10.05%	6.49%	5.74%	0.96%	17.54%	9.40%	6.25%	7.52%	5.49%
Vol-L	38.52%	15.51%	10.86%	6.26%	1.31%	11.60%	4.34%	4.78%	3.69%	3.12%
p-value	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.67]	[0.00]	[0.00]
	Panel C: Portfolios with differential exposures to skewness risk									
Skew-H	40.09%	17.87%	9.09%	6.29%	1.25%	9.38%	4.05%	5.21%	3.80%	2.96%
Skew-M	33.31%	11.40%	6.75%	5.52%	1.08%	16.41%	8.23%	5.97%	6.60%	4.72%
Skew-L	39.03%	15.85%	9.69%	6.60%	1.41%	10.76%	4.46%	4.76%	3.97%	3.47%
p-value	[0.00]	[0.00]	[0.00]	[0.00]	[0.11]	[0.00]	[0.00]	[0.42]	[0.00]	[0.00]
	Panel D: Portfolios with differential exposures to kurtosis risk									
Kurt-H	36.51%	17.52%	9.24%	6.42%	1.48%	11.15%	4.30%	5.12%	4.70%	3.56%
Kurt-M	35.80%	13.00%	7.29%	5.92%	0.95%	14.40%	6.83%	5.93%	5.75%	4.14%
Kurt-L	40.13%	14.60%	9.00%	6.08%	1.31%	11.01%	5.62%	4.90%	3.91%	3.46%
p-value	[0.00]	[0.00]	[0.00]	[0.19]	[0.03]	[0.00]	[0.00]	[0.31]	[0.01]	[0.66]

Table 4

Conditional frequencies of higher-moment exposures after adjusting for differences in the number of funds through resampling

Reported are the conditional frequencies of higher-moment exposures for three hedge fund styles (i.e., Long/Short Equity, Managed Futures, and Event Driven) containing the most number of funds. Starting with the Event Driven style that has the least funds, we randomly select the same number of funds from Long/Short Equity and Managed Futures. We then repeat this exercise through re-sampling 1,000 times from three styles. The three portfolios – P1, P14, and P27, show the most positive (H/H/H), near-zero (M/M/M), and the most negative (L/L/L) exposures to the three higher-moment risks. Average frequencies across the 9 groups – H, M, L, for volatility, skewness, and kurtosis risks are presented in Panels B, C, and D. As before, the frequency in Vol-H is pooled as $\frac{1}{9}(P1+P2+P3+P4+P5+P6+P7+P8+P9)$, and Vol-L as $\frac{1}{9}(P19+P20+P21+P22+P23+P24+P25+P26+P27)$. Likewise Skew-H = $1/9(P1+P2+P3+P10+P11+P12+P19+P20+P21)$ and Skew-L = $1/9(P7+P8+P9+P16+P17+P18+P25+P26+P27)$. Similarly, Kurt-H = $1/9(P1+P4+P7+P10+P13+P16+P19+P22+P25)$ and Kurt-L = $1/9(P3+P6+P9+P12+P15+P18+P21+P24+P27)$. The p-value is from a multivariate chi-squared test of difference in proportions with degrees of freedom equal to 2 (see Agresti (1996)).

	Long/Short Equity	Managed Futures	Event Driven
Panel A: Exposures to higher-moment risks			
P1 (H/H/H)	40%	52%	8%
P14 (M/M/M)	23%	9%	68%
P27 (L/L/L)	47%	41%	12%
p-value	[0.00]	[0.00]	[0.00]
Panel B: Exposures to volatility risk			
Vol-H	46%	38%	16%
Vol-M	37%	19%	44%
Vol-L	43%	28%	29%
p-value	[0.00]	[0.00]	[0.00]
Panel C: Exposures to skewness risk			
Skew-H	44%	33%	24%
Skew-M	38%	21%	41%
Skew-L	44%	31%	26%
p-value	[0.00]	[0.00]	[0.00]
Panel D: Exposures to kurtosis risk			
Kurt-H	41%	32%	27%
Kurt-M	41%	24%	35%
Kurt-L	44%	28%	28%
p-value	[0.00]	[0.00]	[0.00]

Table 5

Returns of hedge funds and higher-moments, and the correlation between higher-moment factors and Fung and Hsieh (2004b) factors

MSCI World returns are rank-ordered from the most negative to the most positive and then classified into the 5 states as 13%, 26%, 22%, 26%, and 13% of the observations. Thus, State 1 (5) contains the 17 most negative (positive) monthly return realizations. Average returns in the states of the equity market are reported in Panel A for equally-weighted portfolios of Managed Futures, Event Driven, and Long/Short Equity, and the higher-moments. Reported in Panel B are the correlations between the higher-moment factors and the Fung-Hsieh factors. SNPMRF is return of the S&P 500 index minus the riskfree rate, SCMLC is Wilshire small cap minus large cap returns, BD10RET is return of the 10-year Treasury bond minus the riskfree rate, BAAMTSY is Baa bond return minus the 10-year Treasury bond return, and PTFSBD, PTFSFX, and PTFSCOM are returns of lookback straddles on bonds, currencies, and commodities. Total returns of the Barclays 1-3 month Treasury index is the proxy for the riskfree rate r_t^f. $F_t^{vo} \equiv z_t^{vo} - r_t^f$, $F_t^{sk} \equiv z_t^{sk} - r_t^f$, and $F_t^{ku} \equiv z_t^{ku} - r_t^f$ are respectively the higher-moment factors for volatility, skewness, and kurtosis. The sample period is January 1994 to December 2004 (132 observations).

Panel A: Returns in different states of the equity market

	State 1 (crashes)	State 2	State 3	State 4	State 5 (rallies)
MSCI returns	-0.0691	-0.0161	0.0111	0.0358	0.0639
Managed Futures	0.0183	-0.0045	0.0056	0.0140	-0.0069
Event Driven	-0.0085	0.0022	0.0085	0.0143	0.0142
Long/Short Equity	-0.0247	-0.0052	0.0139	0.0259	0.0333
Return of volatility	0.9035	-0.7209	-0.7098	-0.2857	0.2303
Return of skewness	0.7242	-0.9484	-1.1229	-1.4151	-2.0337
Return of kurtosis	-0.5143	-0.9862	-0.9793	-0.9203	-0.7890

Panel B: Correlation among the factors

	F^{vo}	F^{sk}	F^{ku}	snpmrf	scmlc	bd10ret	baamtsy	ptfsbd	ptfsfx
F^{sk}	0.34								
F^{ku}	0.88	0.51							
snpmrf	-0.22	-0.76	-0.32						
scmlc	-0.16	0.07	-0.16	-0.11					
bd10ret	0.26	0.05	0.25	-0.09	-0.13				
baamtsy	-0.35	-0.26	-0.34	0.30	0.19	-0.36			
ptfsbd	0.33	0.24	0.41	-0.15	-0.05	0.07	-0.13		
ptfsfx	0.13	0.08	0.10	-0.13	0.05	0.15	-0.11	0.17	
ptfscom	0.09	0.13	0.17	-0.14	-0.04	0.11	-0.18	0.16	0.28

Table 6
Higher-moment factors and individual Managed Futures

For each of the *329 hedge funds* in the Managed Futures category with at least 36 monthly observations, we perform the following regression and report the results in Panel D ($r_t^{mf,i}$ is excess returns of hedge fund i in the Managed Futures category):

$$\begin{aligned} r_t^{mf,i} &= \alpha^i + \beta^{1,i}\,\mathrm{SNPMRF}_t + \beta^{2,i}\,\mathrm{SCMLC}_t + \beta^{3,i}_{FH7}\,\mathrm{BD10RET}_t + \beta^{4,i}\,\mathrm{BAAMTSY}_t \\ &+ \beta^{5,i}\,\mathrm{PTFSBD}_t + \beta^{6,i}\,\mathrm{PTFSFX}_t + \beta^{7,i}\,\mathrm{PTFSCOM}_t + \underbrace{\beta^{8,i} F_t^{vo} + \beta^{9,i} F_t^{sk} + \beta^{10,i} F_t^{ku}}_{\text{higher}-\text{moment factors}} + \varepsilon_t^i \end{aligned}$$

where F_t^{vo}, F_t^{sk} and F_t^{ku} are volatility, skewness, and kurtosis factors (see equation (15)). Panels A, B, and C show the results from the restricted regressions omitting two of the three higher-moment factors. In other words, Panels A, B, and C report the results after including volatility, skewness, and kurtosis factors one at a time to the Fung-Hsieh seven-factor model. The sample period is January 1994 to December 2004 (132 observations). Reported are (i) the average exposure for each factor across all funds (under the column "coef. avg."), (ii) the number of funds exhibiting positive exposures (under the column "coef.>0 #funds"), (iii) the number of funds with positive or negative exposure with p-values less than 0.10 and the average of significant exposures (under the respective columns coef.>0 and $p < 0.10$, and coef.<0 and $p < 0.10$). The p-values are based on the White's heteroskedastically-consistent estimator. The final row in each panel displays the average adjusted R^2 across all hedge funds.

	Panel A: volatility factor						Panel B: skewness factor					
	coef. avg.	coef. >0 # funds	coef.>0 and $p<0.10$ # funds	avg.	coef.<0 and $p<0.10$ # funds	avg.	coef. avg.	coef. >0 # funds	coef.>0 and $p<0.10$ # funds	avg.	coef.<0 and $p<0.10$ # funds	avg.
Constant	0.001	170	45	0.018	46	-0.014	0.003	171	35	0.028	47	-0.016
snpmrf	0.040	164	61	0.574	40	-0.572	0.087	195	51	0.770	21	-0.581
scmlc	0.037	194	19	0.479	9	-0.590	0.029	183	18	0.464	12	-0.505
bd10ret	0.360	249	138	0.800	16	-0.896	0.400	248	148	0.842	14	-0.894
baamtsy	0.319	223	38	2.041	7	-3.403	0.275	210	33	1.892	7	-2.001
ptfsbd	0.030	224	95	0.098	17	-0.119	0.036	239	103	0.096	13	-0.107
ptfsfx	0.035	229	110	0.088	11	-0.070	0.038	239	114	0.092	10	-0.066
ptfscom	0.049	237	81	0.161	13	-0.106	0.047	234	78	0.160	10	-0.115
F^{vo}	0.006	229	81	0.020	14	-0.021						
F^{sk}							0.004	192	44	0.022	25	-0.016
$\overline{R}^2$	21.8%						21.3%					

	Panel C: kurtosis factor						Panel D: all three higher-moment factors together					
	coef. avg.	coef. >0 # funds	coef.>0 and $p<0.10$ # funds	avg.	coef.<0 and $p<0.10$ # funds	avg.	coef. avg.	coef. >0 # funds	coef.>0 and $p<0.10$ # funds	avg.	coef.<0 and $p<0.10$ # funds	avg.
Constant	0.010	201	74	0.050	44	-0.053	-0.023	129	15	0.106	51	-0.088
snpmrf	0.061	175	62	0.631	36	-0.581	0.050	176	46	0.809	28	-0.663
scmlc	0.035	192	19	0.479	8	-0.657	0.039	194	23	0.519	12	-0.527
bd10ret	0.359	250	139	0.799	17	-0.907	0.358	249	137	0.803	15	-0.894
baamtsy	0.315	213	38	1.970	6	-1.877	0.298	218	38	1.943	9	-1.838
ptfsbd	0.030	227	98	0.094	14	-0.124	0.030	229	97	0.094	14	-0.124
ptfsfx	0.037	237	117	0.089	8	-0.067	0.033	232	102	0.088	9	-0.068
ptfscom	0.046	234	80	0.156	12	-0.113	0.051	237	87	0.160	11	-0.107
F^{vo}							0.013	244	47	0.045	4	-0.027
F^{sk}							0.000	175	28	0.029	24	-0.036
F^{ku}	0.012	204	79	0.052	31	-0.063	-0.030	122	11	0.097	42	-0.112
$\overline{R}^2$	21.7%						22.2%					

Table 7

Higher-moment factors and individual Event Driven hedge funds

For each of the *265 hedge funds* in the Event Driven category with at least 36 monthly observations, we perform the following regression and report the results in Panel D ($r_t^{ed,i}$ is excess returns of hedge fund i in the Event Driven category):

$$\begin{aligned} r_t^{ed,i} &= \alpha^i + \beta^{1,i}\,\mathrm{SNPMRF}_t + \beta^{2,i}\,\mathrm{SCMLC}_t + \beta^{3,i}_{FH7}\,\mathrm{BD10RET}_t + \beta^{4,i}\,\mathrm{BAAMTSY}_t \\ &+ \beta^{5,i}\,\mathrm{PTFSBD}_t + \beta^{6,i}\,\mathrm{PTFSFX}_t + \beta^{7,i}\,\mathrm{PTFSCOM}_t + \underbrace{\beta^{8,i} F_t^{vo} + \beta^{9,i} F_t^{sk} + \beta^{10,i} F_t^{ku}}_{\text{higher-moment factors}} + \varepsilon_t^i \end{aligned}$$

where F_t^{vo}, F_t^{sk} and F_t^{ku} are volatility, skewness, and kurtosis factors (see equation (15)). Panels A, B, and C show the results from the restricted regressions omitting two of the three higher-moment factors. In other words, Panels A, B, and C report the results after including volatility, skewness, and kurtosis factors one at a time to the Fung-Hsieh seven-factor model. The sample period is January 1994 to December 2004 (132 observations). Reported are (i) the average exposure for each factor across all funds (under the column "coef. avg."), (ii) the number of funds exhibiting positive exposures (under the column "coef.>0 #funds"), (iii) the number of funds with positive or negative exposure with p-values less than 0.10 and the average of significant exposures (under the respective columns coef.>0 and $p < 0.10$, and coef.<0 and $p < 0.10$). The p-values are based on the White's heteroskedastically-consistent estimator. The final row in each panel displays the average adjusted R^2 across all hedge funds.

	Panel A: volatility factor						Panel B: skewness factor					
	coef. avg.	coef. >0 # funds	coef.>0 and $p<0.10$ # funds	avg.	coef.<0 and $p<0.10$ # funds	avg.	coef. avg.	coef. >0 # funds	coef.>0 and $p<0.10$ # funds	avg.	coef.<0 and $p<0.10$ # funds	avg.
Constant	0.002	153	72	0.007	40	-0.005	-0.002	101	24	0.009	55	-0.009
snpmrf	0.165	240	162	0.255	3	-0.140	0.094	185	67	0.300	12	-0.208
scmlc	0.139	241	135	0.210	1	-0.196	0.145	241	148	0.214	2	-0.218
bd10ret	0.046	192	31	0.196	1	-0.309	0.032	170	26	0.238	7	-0.214
baamtsy	0.224	182	73	0.709	5	-0.400	0.204	180	71	0.646	5	-0.430
ptfsbd	-0.009	83	7	0.076	64	-0.034	-0.008	76	7	0.109	73	-0.031
ptfsfx	0.006	198	39	0.021	4	-0.012	0.005	183	32	0.025	5	-0.014
ptfscom	-0.002	103	12	0.066	21	-0.023	-0.004	99	13	0.068	27	-0.026
F^{vo}	-0.001	78	2	0.009	58	-0.005						
F^{sk}							-0.005	36	3	0.015	92	-0.010
$\overline{R}^2$	22.8%						23.7%					

	Panel C: kurtosis factor						Panel D: all three higher-moment factors together					
	coef. avg.	coef. >0 # funds	coef.>0 and $p<0.10$ # funds	avg.	coef.<0 and $p<0.10$ # funds	avg.	coef. avg.	coef. >0 # funds	coef.>0 and $p<0.10$ # funds	avg.	coef.<0 and $p<0.10$ # funds	avg.
Constant	-0.005	79	15	0.016	89	-0.016	-0.009	89	10	0.061	61	-0.026
snpmrf	0.156	240	156	0.250	4	-0.132	0.088	187	77	0.283	10	-0.251
scmlc	0.137	240	121	0.220	1	-0.197	0.142	240	130	0.225	1	-0.202
bd10ret	0.054	200	35	0.206	1	-0.320	0.038	178	22	0.236	6	-0.255
baamtsy	0.211	181	71	0.705	7	-0.340	0.206	183	65	0.723	6	-0.372
ptfsbd	-0.007	94	7	0.096	49	-0.036	-0.006	88	6	0.073	49	-0.035
ptfsfx	0.006	197	36	0.024	5	-0.013	0.004	177	26	0.027	6	-0.021
ptfscom	-0.002	109	14	0.065	19	-0.023	-0.002	110	15	0.064	24	-0.028
F^{vo}							0.003	159	27	0.014	7	-0.019
F^{sk}							-0.005	68	6	0.015	56	-0.018
F^{ku}	-0.008	61	5	0.027	91	-0.017	-0.008	91	9	0.100	48	-0.034
$\overline{R}^2$	23.5%						24.6%					

Table 8

Higher-moment factors and individual Long/Short Equity hedge funds

For each of the *1040 hedge funds* in the Long/Short Equity category with at least 36 monthly observations, we perform the following regression and report the results in Panel D ($r_t^{ls,i}$ is excess returns of hedge fund i in the Long/Short category):

$$\begin{aligned} r_t^{ls,i} &= \alpha^i + \beta^{1,i}\,\text{SNPMRF}_t + \beta^{2,i}\,\text{SCMLC}_t + \beta_{FH7}^{3,i}\,\text{BD10RET}_t + \beta^{4,i}\,\text{BAAMTSY}_t \\ &+ \beta^{5,i}\,\text{PTFSBD}_t + \beta^{6,i}\,\text{PTFSFX}_t + \beta^{7,i}\,\text{PTFSCOM}_t + \underbrace{\beta^{8,i} F_t^{vo} + \beta^{9,i} F_t^{sk} + \beta^{10,i} F_t^{ku}}_{\text{higher-moment factors}} + \varepsilon_t^i \end{aligned}$$

where F_t^{vo}, F_t^{sk} and F_t^{ku} are volatility, skewness, and kurtosis factors (see equation (15)). Panels A, B, and C show the results from the restricted regressions omitting two of the three higher-moment factors. In other words, Panels A, B, and C report the results after including volatility, skewness, and kurtosis factors one at a time to the Fung-Hsieh seven-factor model. The sample period is January 1994 to December 2004 (132 observations). Reported are (i) the average exposure for each factor across all funds (under the column "coef. avg."), (ii) the number of funds exhibiting positive exposures (under the column "coef.>0 #funds"), (iii) the number of funds with positive or negative exposure with p-values less than 0.10 and the average of significant exposures (under the respective columns coef.>0 and $p < 0.10$, and coef.<0 and $p < 0.10$). The p-values are based on the White's heteroskedastically-consistent estimator. The final row of each panel displays the average adjusted R^2 across all hedge funds.

	Panel A: volatility factor						Panel B: skewness factor					
	coef. avg.	coef. > 0 # funds	coef.> 0 and $p < 0.10$ # funds	avg.	coef.< 0 and $p < 0.10$ # funds	avg.	coef. avg.	coef. > 0 # funds	coef.> 0 and $p < 0.10$ # funds	avg.	coef.< 0 and $p < 0.10$ # funds	avg.
Constant	0.004	727	239	0.012	60	-0.011	0.002	582	141	0.018	69	-0.018
snpmrf	0.446	924	732	0.635	36	-0.579	0.417	879	582	0.722	42	-0.703
scmlc	0.336	902	601	0.542	13	-0.451	0.337	902	605	0.540	13	-0.448
bd10ret	0.011	532	75	0.562	71	-0.465	0.009	534	73	0.591	72	-0.520
baamtsy	0.081	528	105	1.308	72	-1.166	0.056	500	104	1.309	89	-1.119
ptfsbd	-0.002	456	62	0.091	112	-0.060	-0.000	474	73	0.086	103	-0.059
ptfsfx	0.007	644	64	0.053	16	-0.040	0.007	638	78	0.055	20	-0.062
ptfscom	0.006	586	89	0.081	71	-0.064	0.005	578	87	0.081	69	-0.065
F^{vo}	0.001	572	110	0.014	50	-0.015						
F^{sk}							-0.002	409	70	0.019	132	-0.017
$\overline{R}^2$	29.2%						29.5%					

	Panel C: kurtosis factor						Panel D: all three higher-moment factors together					
	coef. avg.	coef. > 0 # funds	coef.> 0 and $p < 0.10$ # funds	avg.	coef.< 0 and $p < 0.10$ # funds	avg.	coef. avg.	coef. > 0 # funds	coef.> 0 and $p < 0.10$ # funds	avg.	coef.< 0 and $p < 0.10$ # funds	avg.
Constant	0.006	621	182	0.041	81	-0.043	0.007	564	136	0.094	98	-0.109
snpmrf	0.448	926	729	0.641	36	-0.617	0.396	841	530	0.752	52	-0.664
scmlc	0.336	899	599	0.543	14	-0.443	0.342	899	599	0.548	17	-0.388
bd10ret	0.010	530	77	0.551	68	-0.465	-0.004	490	64	0.658	79	-0.495
baamtsy	0.078	521	109	1.277	80	-1.137	0.083	532	102	1.346	71	-1.186
ptfsbd	-0.002	450	57	0.091	91	-0.063	-0.002	446	49	0.093	91	-0.065
ptfsfx	0.008	660	78	0.052	14	-0.069	0.006	613	58	0.059	25	-0.046
ptfscom	0.006	582	84	0.081	71	-0.062	0.004	569	74	0.086	80	-0.061
F^{vo}							0.001	553	80	0.033	61	-0.034
F^{sk}							-0.004	375	43	0.027	160	-0.022
F^{ku}	0.003	567	147	0.043	89	-0.046	0.008	557	120	0.133	85	-0.144
$\overline{R}^2$	29.4%						30.1%					

Table 9

Maximum-likelihood estimation results with style fixed effects and fund random effects

Maximum-likelihood estimation is performed on a panel of 1631 hedge funds across the three big styles. The empirical model for fund i in style group j is: $\mathbf{y}_{ji}$=$\mathbf{X}_{ji}\beta_j$+$\mathbf{Z}_{ji}\upsilon_j+\varepsilon_{ji}$, where $\mathbf{y}_{ji}$ is the response vector of monthly returns observed for fund i in style group j, $\mathbf{X}_{ji}\beta_j$ is the fixed part of the model, which includes an intercept and p factors, $\mathbf{Z}_{ji}\upsilon_j$ is the random part of the model, which includes $p+1$ random effects, and ε_{ji} is the error term. We assume that the random effects are Normally distributed and uncorrelated, the variances are the same across style groups, and the error terms follow an AR(1) process for hedge fund i. MF, ED, and LS are the dummies for Managed Futures, Event Driven, and Long/Short Equity styles.

	FH-7 plus volatility		FH-7 plus skewness		FH-7 plus kurtosis		FH-7 plus three higher-moments	
	coef.	*p*-value	coef.	*p*-value	coef.	*p*-value	coef.	*p*-value
MF intercept	0.002	0.001	0.003	0.000	0.009	<.0001	-0.007	0.006
ED intercept	0.001	0.000	-0.001	0.001	-0.005	<.0001	-0.010	<.0001
LS intercept	0.004	<.0001	0.003	<.0001	0.005	<.0001	0.004	0.000
snpmrf*MF	-0.014	0.564	0.026	0.343	-0.007	0.779	0.010	0.722
scmlc*MF	0.067	0.001	0.054	0.010	0.065	0.002	0.062	0.003
bd10ret*MF	0.472	<.0001	0.506	<.0001	0.478	<.0001	0.485	<.0001
baamtsy*MF	0.317	<.0001	0.252	<.0001	0.281	<.0001	0.325	<.0001
ptfsbd*MF	0.025	<.0001	0.032	<.0001	0.026	<.0001	0.028	<.0001
ptfsfx*MF	0.036	<.0001	0.038	<.0001	0.038	<.0001	0.036	<.0001
ptfscom*MF	0.053	<.0001	0.052	<.0001	0.051	<.0001	0.056	<.0001
F^{vo}*MF	0.005	<.0001					0.009	<.0001
F^{sk}*MF			0.003	<.0001			0.002	0.003
F^{ku}*MF					0.010	<.0001	-0.013	<.0001
snpmrf*ED	0.149	<.0001	0.093	0.000	0.141	<.0001	0.103	<.0001
scmlc*ED	0.136	<.0001	0.141	<.0001	0.133	<.0001	0.136	<.0001
bd10ret*ED	0.052	<.0001	0.038	0.000	0.059	<.0001	0.048	<.0001
baamtsy*ED	0.231	<.0001	0.235	<.0001	0.224	<.0001	0.235	<.0001
ptfsbd*ED	-0.011	<.0001	-0.010	<.0001	-0.008	0.001	-0.007	0.002
ptfsfx*ED	0.005	0.000	0.003	0.013	0.004	0.002	0.002	0.054
ptfscom*ED	-0.003	0.186	-0.003	0.118	-0.002	0.431	-0.001	0.506
F^{vo}*ED	-0.002	0.000					0.003	<.0001
F^{sk}*ED			-0.004	<.0001			-0.002	<.0001
F^{ku}*ED					-0.008	<.0001	-0.012	<.0001
snpmrf*LS	0.440	<.0001	0.417	<.0001	0.440	<.0001	0.407	<.0001
scmlc*LS	0.334	<.0001	0.334	<.0001	0.335	<.0001	0.338	<.0001
bd10ret*LS	0.038	<.0001	0.036	<.0001	0.037	<.0001	0.029	0.002
baamtsy*LS	0.047	0.038	0.028	0.215	0.040	0.072	0.046	0.039
ptfsbd*LS	-0.005	0.003	-0.003	0.090	-0.005	0.004	-0.005	0.004
ptfsfx*LS	0.006	<.0001	0.006	<.0001	0.006	<.0001	0.005	<.0001
ptfscom*LS	0.007	<.0001	0.007	<.0001	0.007	<.0001	0.006	0.000
F^{vo}*LS	0.001	0.004					0.001	0.054
F^{sk}*LS			-0.001	<.0001			-0.002	<.0001
F^{ku}*LS					0.002	0.014	0.002	0.098
-2 Log Lik.	-388457		-388340		-388326		-388606	

Table A-1

Post-ranking regression results for triple-sorted hedge fund portfolios using Bayesian estimation and after accounting for backfilling bias

Two types of empirical tests are conducted. Panel A reports results based on Bayesian estimation. Panel B reports results accounting for the backfiling bias that reduces the sample universe to 3,243 hedge funds. Reported throughout are post-ranking alphas, t-statistics and adjusted R-squared values ($\overline{R}^2$) of the 27 triple-sorted portfolios and the difference between the top and bottom portfolios (P1-P27) from regressions using the Fung and Hsieh (2004b) model. Each month hedge funds are first sorted into 27 equally-weighted triple-sorted portfolios based on their higher-moment betas, which are estimated using the following regression for rolling pre-ranking windows of 12 months and Bayesian estimation: $r_t^i = \alpha_{4F}^i + \beta_{\text{RMRF}}^i \text{RMRF}_t + \beta_{\Delta\text{VOL}}^i \Delta\text{VOL}_t + \beta_{\Delta\text{SKEW}}^i \Delta\text{SKEW}_t + \beta_{\Delta\text{KURT}}^i \Delta\text{KURT}_t + \varepsilon_t^i$, where RMRF_t is excess return of the market portfolio in month t, and ΔVOL_t, ΔSKEW_t and ΔKURT_t are our proxies for volatility risk, skewness risk, and kurtosis risk. All reported alphas are annualized. The row marked "GRS p-value" reports the p-value for the Gibbons, Ross, and Shanken (1989) test that all the post-ranking alphas are jointly equal to zero.

		FH-7 model Panel A: Bayesian estimation			FH-7 model Panel B: Backfilling bias		
		Alpha	Alpha-t	$\overline{R}^2$	Alpha	Alpha-t	$\overline{R}^2$
P1	H/H/H	-8.07%	-1.74	40%	-8.01%	-1.63	37%
P2	H/H/M	-3.47%	-1.35	51%	-3.33%	-1.40	56%
P3	H/H/L	-1.05%	-0.33	40%	-2.59%	-0.94	47%
P4	H/M/H	0.06%	0.03	39%	-0.20%	-0.08	46%
P5	H/M/M	1.68%	0.94	52%	1.02%	0.60	53%
P6	H/M/L	0.72%	0.28	42%	3.17%	1.85	47%
P7	H/L/H	2.26%	1.63	36%	-0.82%	-0.36	41%
P8	H/L/M	2.24%	1.32	37%	1.41%	0.63	36%
P9	H/L/L	2.27%	0.71	21%	1.91%	0.58	25%
P10	M/H/H	2.63%	1.16	47%	-0.58%	-0.24	36%
P11	M/H/M	4.17%	2.56	38%	3.89%	2.56	37%
P12	M/H/L	3.74%	2.95	33%	2.89%	2.12	44%
P13	M/M/H	5.29%	3.79	52%	4.00%	3.84	47%
P14	M/M/M	4.35%	4.45	44%	4.78%	6.42	34%
P15	M/M/L	5.26%	3.27	34%	4.51%	4.46	55%
P16	M/L/H	5.09%	4.52	45%	5.63%	4.07	43%
P17	M/L/M	5.10%	3.28	48%	4.39%	3.43	41%
P18	M/L/L	5.06%	2.59	44%	5.91%	3.07	36%
P19	L/H/H	4.26%	1.67	48%	1.59%	0.51	39%
P20	L/H/M	5.39%	3.36	45%	6.37%	3.12	38%
P21	L/H/L	7.78%	5.24	32%	8.28%	2.93	30%
P22	L/M/H	5.64%	2.56	41%	5.08%	2.43	42%
P23	L/M/M	6.18%	4.01	46%	4.76%	3.72	58%
P24	L/M/L	8.77%	3.65	35%	5.22%	2.43	44%
P25	L/L/H	6.13%	3.65	60%	6.27%	2.75	45%
P26	L/L/M	10.29%	5.07	53%	6.99%	2.97	40%
P27	L/L/L	14.18%	4.69	35%	12.96%	3.50	16%
P1-P27		-22.25%	-3.89	10%	-20.97%	-3.38	10%
GRS p-value		0.00			0.00		

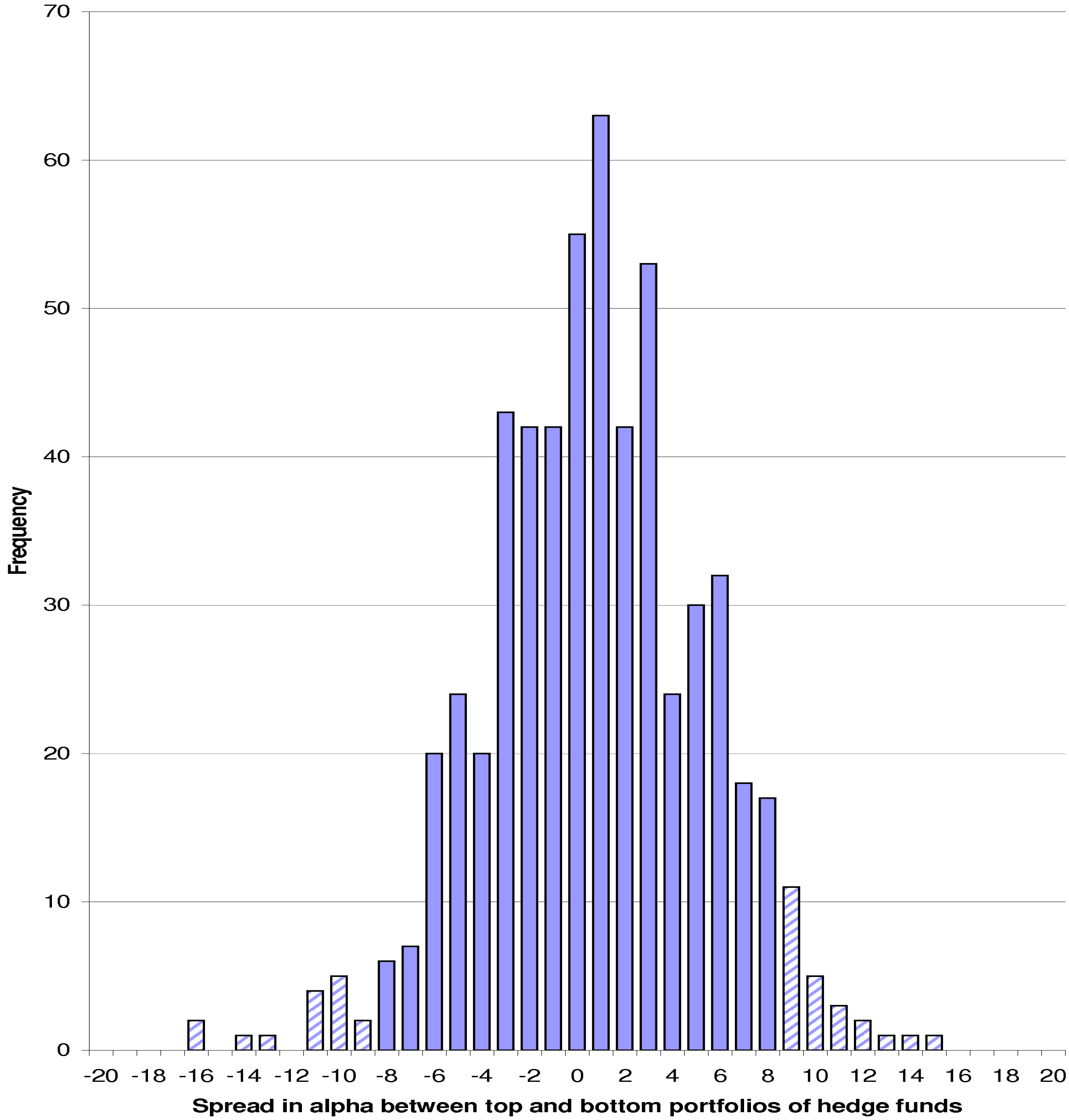
Table A-2

Post-ranking regression results for triple-sorted hedge fund portfolios using the FH-7 model augmented with alternative systematic risk factors

Reported in this table are post-ranking alphas, t-statistics and adjusted R-squared values ($\overline{R}^2$) of the 27 triple-sorted portfolios and the difference between the top and bottom portfolios (P1-P27) from regressions using Fung and Hsieh (2004b) model augmented with alternative risk factors. Panel A employs the extended FH-7 model with lookback straddles on interest rate and equity; Panel B employs the FH-7 model augmented with the out-of-the-money put (OTMPUT) factor of Agarwal and Naik (2004); Panel C employs the FH-7 model augmented with the the LIQ factor of Pastor and Stambaugh (2003) where LIQ is the liquidity risk factor from WRDS. As before, each month hedge funds are first sorted into 27 equally-weighted triple-sorted portfolios based on their higher-moment betas, which are estimated using the following regression for rolling pre-ranking windows of 12 months: $r_t^i = \alpha_{4F}^i + \beta_{\text{RMRF}}^i \text{RMRF}_t + \beta_{\Delta\text{VOL}}^i \Delta\text{VOL}_t + \beta_{\Delta\text{SKEW}}^i \Delta\text{SKEW}_t + \beta_{\Delta\text{KURT}}^i \Delta\text{KURT}_t + \varepsilon_t^i$, where RMRF_t is excess return of the market portfolio in month t, and ΔVOL_t, ΔSKEW_t and ΔKURT_t are our proxies for volatility risk, skewness risk, and kurtosis risk. All reported alphas are annualized. The row marked "GRS p-value" reports the p-value for the Gibbons, Ross, and Shanken (1989) test that all the post-ranking alphas are jointly equal to zero.

		Panel A: FH-7 augmented with lookback straddles on interest rate and equity			Panel B: FH-7 augmented with OTM put			Panel C: FH-7 augmented with liquidity factor		
		Alpha	Alpha-t	$\overline{R}^2$	Alpha	Alpha-t	$\overline{R}^2$	Alpha	Alpha-t	$\overline{R}^2$
P1	H/H/H	-5.64%	-1.12	40%	-6.16%	-1.33	40%	-6.13%	-1.52	53%
P2	H/H/M	-1.72%	-0.66	56%	-2.94%	-1.23	56%	-2.75%	-1.24	61%
P3	H/H/L	0.75%	0.24	45%	-2.00%	-0.70	46%	-1.16%	-0.41	45%
P4	H/M/H	3.01%	1.32	49%	1.85%	0.88	49%	1.85%	0.95	55%
P5	H/M/M	1.95%	1.21	57%	1.08%	0.74	59%	1.51%	1.07	60%
P6	H/M/L	3.73%	2.09	54%	1.34%	0.81	53%	1.79%	1.08	52%
P7	H/L/H	0.50%	0.24	49%	-0.22%	-0.12	49%	-0.32%	-0.18	51%
P8	H/L/M	3.03%	1.45	46%	1.41%	0.75	48%	2.04%	1.09	47%
P9	H/L/L	7.26%	2.34	30%	4.23%	1.45	28%	4.57%	1.61	29%
P10	M/H/H	-0.73%	-0.35	50%	-0.49%	-0.26	51%	-0.06%	-0.03	51%
P11	M/H/M	4.19%	3.28	52%	3.78%	3.25	53%	4.10%	3.54	52%
P12	M/H/L	3.55%	2.88	52%	2.68%	2.37	52%	2.97%	2.65	51%
P13	M/M/H	4.94%	4.87	54%	4.28%	4.65	55%	4.56%	4.96	54%
P14	M/M/M	4.62%	6.99	40%	4.06%	6.62	39%	4.15%	6.85	39%
P15	M/M/L	4.85%	4.77	52%	4.10%	4.51	55%	4.54%	4.92	52%
P16	M/L/H	6.50%	5.72	54%	5.03%	4.66	51%	5.12%	4.86	52%
P17	M/L/M	6.96%	6.30	53%	5.45%	5.18	50%	5.57%	5.37	50%
P18	M/L/L	7.00%	4.02	47%	5.64%	3.51	47%	6.05%	3.79	46%
P19	L/H/H	3.15%	1.11	46%	3.35%	1.28	46%	3.14%	1.22	46%
P20	L/H/M	5.45%	3.28	55%	5.33%	3.49	56%	5.39%	3.58	56%
P21	L/H/L	10.83%	4.42	39%	9.21%	4.04	38%	9.51%	4.27	38%
P22	L/M/H	3.83%	2.31	53%	4.37%	2.84	53%	4.66%	3.06	52%
P23	L/M/M	7.24%	5.32	61%	6.36%	4.92	59%	6.17%	4.84	59%
P24	L/M/L	7.45%	3.92	55%	5.97%	3.42	55%	6.48%	3.92	59%
P25	L/L/H	7.25%	3.65	57%	6.22%	3.37	56%	6.29%	3.51	58%
P26	L/L/M	13.20%	6.57	54%	10.84%	5.51	49%	10.43%	5.36	48%
P27	L/L/L	17.68%	5.23	30%	15.56%	4.90	27%	14.93%	4.75	26%
P1-P27		-23.33%	-3.96	11%	-21.72%	-4.01	12%	-21.05%	-4.24	23%
GRS p-value		0.00			0.00			0.00		

Fig. 1. Bootstrapped results on the frequency distribution of spreads in alphas between the top and bottom portfolios of hedge funds triple-sorted by their exposures to ΔVOL, ΔSKEW and ΔKURT



We generate a simulated sample of hedge fund returns by using the bootstrap procedure discussed in subsection 3.3. We then perform a three-way sort of all available hedge funds into portfolios based on their exposures to (i) volatility risk (ΔVOL), (ii) skewness risk (ΔSKEW), and (iii) kurtosis risk (ΔKURT). Then, we compute out-of-sample returns of each of these portfolios and allow for a three-month waiting period before reconstructing them on a monthly basis. We compute equally-weighted returns for the portfolios and readjust the portfolio weights if a fund disappears from our sample after ranking. Finally, we estimate the alphas using the out-of-sample returns of the long-short portfolios (i.e., the difference between the top and bottom portfolios). We run a total of 1,000 bootstrap iterations. The figure presents the frequency distribution of bootstrapped spreads in alphas between the top and bottom portfolios. The histogram shows how big of a spread in alphas is obtained by chance if a zero alpha is imposed in the FH-7 model specification. The 95 percent confidence interval for the bootstrapped spreads in alphas between the extreme portfolios is between -8.5 percent to $+8.5$ percent per annum, as marked.

cfr/working paper series

centre for financial research
cologne

CFR working papers are available for download from **www.cfr-cologne.de**.

Hardcopies can be ordered from: centre for financial research (CFR),
Albertus Magnus Platz, 50923 Koeln, Germany.

2010

No.	Author(s)	Title
10-08	V. Agarwal, V. Fos, W. Jiang	Inferring Reporting Biases in Hedge Fund Databases from Hedge Fund Equity Holdings
10-07	V. Agarwal, G. Bakshi, J. Huij	Do Higher-Moment Equity Risks Explain Hedge Fund Returns?
10-06	J. Grammig, F. J. Peter	Tell-Tale Tails
10-05	K. Drachter, A. Kempf	Höhe, Struktur und Determinanten der Managervergütung- Eine Analyse der Fondsbranche in Deutschland
10-04	J. Fang, A. Kempf, M. Trapp	Fund Manager Allocation
10-03	P. Finter, A. Niessen, S. Ruenzi	The Impact of Investor Sentiment on the German Stock Market
10-02	D. Hunter, E. Kandel, S. Kandel, R. Wermers	Endogenous Benchmarks
10-01	S. Artmann, P. Finter, A. Kempf	Determinants of Expected Stock Returns: Large Sample Evidence from the German Market

2009

No.	Author(s)	Title
09-17	E. Theissen	Price Discovery in Spot and Futures Markets: A Reconsideration
09-16	M. Trapp	Trading the Bond-CDS Basis – The Role of Credit Risk and Liquidity
09-15	A. Betzer, J. Gider, D. Metzger, E.Theissen	Strategic Trading and Trade Reporting by Corporate Insiders
09-14	A. Kempf, O. Korn, M. Uhrig-Homburg	The Term Structure of Illiquidity Premia
09-13	W. Bühler, M. Trapp	Time-Varying Credit Risk and Liquidity Premia in Bond and CDS Markets
09-12	W. Bühler, M. Trapp	Explaining the Bond-CDS Basis – The Role of Credit Risk and Liquidity
09-11	S. J. Taylor, P. K. Yadav, Y. Zhang	Cross-sectional analysis of risk-neutral skewness
09-10	A. Kempf, C. Merkle, A. Niessen	Low Risk and High Return - How Emotions Shape Expectations on the Stock Market

No.	Author(s)	Title
09-09	V. Fotak, V. Raman, P. K. Yadav	Naked Short Selling: The Emperor`s New Clothes?
09-08	F. Bardong, S.M. Bartram, P.K. Yadav	Informed Trading, Information Asymmetry and Pricing of Information Risk: Empirical Evidence from the NYSE
09-07	S. J. Taylor , P. K. Yadav, Y. Zhang	The information content of implied volatilities and model-free volatility expectations: Evidence from options written on individual stocks
09-06	S. Frey, P. Sandas	The Impact of Iceberg Orders in Limit Order Books
09-05	H. Beltran-Lopez, P. Giot, J. Grammig	Commonalities in the Order Book
09-04	J. Fang, S. Ruenzi	Rapid Trading bei deutschen Aktienfonds: Evidenz aus einer großen deutschen Fondsgesellschaft
09-03	A. Banegas, B. Gillen, A. Timmermann, R. Wermers	The Performance of European Equity Mutual Funds
09-02	J. Grammig, A. Schrimpf, M. Schuppli	Long-Horizon Consumption Risk and the Cross-Section of Returns: New Tests and International Evidence
09-01	O. Korn, P. Koziol	The Term Structure of Currency Hedge Ratios

2008

No.	Author(s)	Title
08-12	U. Bonenkamp, C. Homburg, A. Kempf	Fundamental Information in Technical Trading Strategies
08-11	O. Korn	Risk Management with Default-risky Forwards
08-10	J. Grammig, F.J. Peter	International Price Discovery in the Presence of Market Microstructure Effects
08-09	C. M. Kuhnen, A. Niessen	Is Executive Compensation Shaped by Public Attitudes?
08-08	A. Pütz, S. Ruenzi	Overconfidence among Professional Investors: Evidence from Mutual Fund Managers
08-07	P. Osthoff	What matters to SRI investors?
08-06	A. Betzer, E. Theissen	Sooner Or Later: Delays in Trade Reporting by Corporate Insiders
08-05	P. Linge, E. Theissen	Determinanten der Aktionärspräsenz auf Hauptversammlungen deutscher Aktiengesellschaften
08-04	N. Hautsch, D. Hess, C. Müller	Price Adjustment to News with Uncertain Precision
08-03	D. Hess, H. Huang, A. Niessen	How Do Commodity Futures Respond to Macroeconomic News?
08-02	R. Chakrabarti, W. Megginson, P. Yadav	Corporate Governance in India
08-01	C. Andres, E. Theissen	Setting a Fox to Keep the Geese - Does the Comply-or-Explain Principle Work?

2007

No.	Author(s)	Title
07-16	M. Bär, A. Niessen, S. Ruenzi	The Impact of Work Group Diversity on Performance: Large Sample Evidence from the Mutual Fund Industry

No.	Author(s)	Title
07-15	A. Niessen, S. Ruenzi	Political Connectedness and Firm Performance: Evidence From Germany
07-14	O. Korn	Hedging Price Risk when Payment Dates are Uncertain
07-13	A. Kempf, P. Osthoff	SRI Funds: Nomen est Omen
07-12	J. Grammig, E. Theissen, O. Wuensche	Time and Price Impact of a Trade: A Structural Approach
07-11	V. Agarwal, J. R. Kale	On the Relative Performance of Multi-Strategy and Funds of Hedge Funds
07-10	M. Kasch-Haroutounian, E. Theissen	Competition Between Exchanges: Euronext versus Xetra
07-09	V. Agarwal, N. D. Daniel, N. Y. Naik	Why is Santa so kind to hedge funds? The December return puzzle!
07-08	N. C. Brown, K. D. Wei, R. Wermers	Analyst Recommendations, Mutual Fund Herding, and Overreaction in Stock Prices
07-07	A. Betzer, E. Theissen	Insider Trading and Corporate Governance: The Case of Germany
07-06	V. Agarwal, L. Wang	Transaction Costs and Value Premium
07-05	J. Grammig, A. Schrimpf	Asset Pricing with a Reference Level of Consumption: New Evidence from the Cross-Section of Stock Returns
07-04	V. Agarwal, N.M. Boyson, N.Y. Naik	Hedge Funds for retail investors? An examination of hedged mutual funds
07-03	D. Hess, A. Niessen	The Early News Catches the Attention: On the Relative Price Impact of Similar Economic Indicators
07-02	A. Kempf, S. Ruenzi, T. Thiele	Employment Risk, Compensation Incentives and Managerial Risk Taking - Evidence from the Mutual Fund Industry -
07-01	M. Hagemeister, A. Kempf	CAPM und erwartete Renditen: Eine Untersuchung auf Basis der Erwartung von Marktteilnehmern

2006

No.	Author(s)	Title
06-13	S. Čeljo-Hörhager, A. Niessen	How do Self-fulfilling Prophecies affect Financial Ratings? - An experimental study –
06-12	R. Wermers, Y. Wu, J. Zechner	Portfolio Performance, Discount Dynamics, and the Turnover of Closed-End Fund Managers
06-11	U. v. Lilienfeld-Toal, S. Ruenzi	Why Managers Hold Shares of Their Firm: An Empirical Analysis
06-10	A. Kempf, P. Osthoff	The Effect of Socially Responsible Investing on Portfolio Performance
06-09	R. Wermers, T. Yao, J. Zhao	The Investment Value of Mutual Fund Portfolio Disclosure
06-08	M. Hoffmann, B. Kempa	The Poole Analysis in the New Open Economy Macroeconomic Framework
06-07	K. Drachter, A. Kempf, M. Wagner	Decision Processes in German Mutual Fund Companies: Evidence from a Telephone Survey
06-06	J.P. Krahnen, F.A. Schmid, E. Theissen	Investment Performance and Market Share: A Study of the German Mutual Fund Industry
06-05	S. Ber, S. Ruenzi	On the Usability of Synthetic Measures of Mutual Fund Net-Flows
06-04	A. Kempf, D. Mayston	Liquidity Commonality Beyond Best Prices

No.	Author(s)	Title
06-03	O. Korn, C. Koziol	Bond Portfolio Optimization: A Risk-Return Approach
06-02	O. Scaillet, L. Barras, R. Wermers	False Discoveries in Mutual Fund Performance: Measuring Luck in Estimated Alphas
06-01	A. Niessen, S. Ruenzi	Sex Matters: Gender Differences in a Professional Setting

2005

No.	Author(s)	Title
05-16	E. Theissen	An Analysis of Private Investors´ Stock Market Return Forecasts
05-15	T. Foucault, S. Moinas, E. Theissen	Does Anonymity Matter in Electronic Limit Order Markets
05-14	R. Kosowski, A. Timmermann, R. Wermers, H. White	Can Mutual Fund „Stars“ Really Pick Stocks? New Evidence from a Bootstrap Analysis
05-13	D. Avramov, R. Wermers	Investing in Mutual Funds when Returns are Predictable
05-12	K. Griese, A. Kempf	Liquiditätsdynamik am deutschen Aktienmarkt
05-11	S. Ber, A. Kempf, S. Ruenzi	Determinanten der Mittelzuflüsse bei deutschen Aktienfonds
05-10	M. Bär, A. Kempf, S. Ruenzi	Is a Team Different From the Sum of Its Parts? Evidence from Mutual Fund Managers
05-09	M. Hoffmann	Saving, Investment and the Net Foreign Asset Position
05-08	S. Ruenzi	Mutual Fund Growth in Standard and Specialist Market Segments
05-07	A. Kempf, S. Ruenzi	Status Quo Bias and the Number of Alternatives - An Empirical Illustration from the Mutual Fund Industry –
05-06	J. Grammig, E. Theissen	Is Best Really Better? Internalization in Xetra Best
05-05	H. Beltran, J. Grammig, A.J. Menkveld	Understanding the Limit Order Book: Conditioning on Trade Informativeness
05-04	M. Hoffmann	Compensating Wages under different Exchange rate Regimes
05-03	M. Hoffmann	Fixed versus Flexible Exchange Rates: Evidence from Developing Countries
05-02	A. Kempf, C. Memmel	On the Estimation of the Global Minimum Variance Portfolio
05-01	S. Frey, J. Grammig	Liquidity supply and adverse selection in a pure limit order book market

2004

No.	Author(s)	Title
04-10	N. Hautsch, D. Hess	Bayesian Learning in Financial Markets – Testing for the Relevance of Information Precision in Price Discovery
04-09	A. Kempf, K. Kreuzberg	Portfolio Disclosure, Portfolio Selection and Mutual Fund Performance Evaluation
04-08	N.F. Carline, S.C. Linn, P.K. Yadav	Operating performance changes associated with corporate mergers and the role of corporate governance
04-07	J.J. Merrick, Jr., N.Y. Naik, P.K. Yadav	Strategic Trading Behavior and Price Distortion in a Manipulated Market: Anatomy of a Squeeze

No.	Author(s)	Title
04-06	N.Y. Naik, P.K. Yadav	Trading Costs of Public Investors with Obligatory and Voluntary Market-Making: Evidence from Market Reforms
04-05	A. Kempf, S. Ruenzi	Family Matters: Rankings Within Fund Families and Fund Inflows
04-04	V. Agarwal, N.D. Daniel, N.Y. Naik	Role of Managerial Incentives and Discretion in Hedge Fund Performance
04-03	V. Agarwal, W.H. Fung, J.C. Loon, N.Y. Naik	Liquidity Provision in the Convertible Bond Market: Analysis of Convertible Arbitrage Hedge Funds
04-02	A. Kempf, S. Ruenzi	Tournaments in Mutual Fund Families
04-01	I. Chowdhury, M. Hoffmann, A. Schabert	Inflation Dynamics and the Cost Channel of Monetary Transmission

centre for financial research
cfr/university of cologne
Albertus-Magnus-Platz
D-50923 cologne
Fon +49(0)221-470-6995
Fax +49(0)221-470-3992
kempf@cfr-cologne.de
www.cfr-cologne.de