Dynamic Investment Opportunities and the Cross-Section of Hedge Fund Returns: Implications of Higher-Moment Risks for Performance

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, 3000 DR Rotterdam, The Netherlands*

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Abstract

In this paper, we examine higher-moment market risks in the cross-section of hedge fund returns to make several contributions. First, we show that hedge funds are substantially exposed to the three higher-moment risks - volatility, skewness, and kurtosis. In contrast, mutual funds do not display meaningful dispersions in their exposures to these risks. Further, funds of hedge funds when examined as a separate investment category do not show aggressive loading on higher-moment risks. Second, we provide evidence on economically significant premiums being embedded in hedge fund returns on account of their exposures to higher-moment risks. Third, we uncover a set of higher-moment factors that are not strongly associated with factors in benchmark models that are currently used for evaluating hedge fund performance. Finally, the addition of these higher-moment factors to benchmark models can better explain the variation in hedge fund returns. Bearing on issues of practical consequence, we find that benchmark models augmented with higher-moment factors can considerably alter the hedge funds' alpha-based rankings.

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

†Tel.: +1-301-405-2261. *E-mail address:* gbakshi@rhsmith.umd.edu

‡Tel.: +31 10 408 1358. *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, 2004), Mitchell and Pulvino (2001), Amin and Kat (2003), Agarwal and Naik (2004), Hasanhodzic and Lo (2007), and Fung et al. (2007)). For instance, Mitchell and Pulvino (2001) show that returns from risk arbitrage resemble the payoff from selling uncovered index put options. Fung and Hsieh (2001, 2004) articulate the view that hedge funds pursue dynamic trading strategies that enable them to generate positive returns during extreme market movements irrespective of its direction. They furthermore emphasize option-like traits of hedge fund returns and advocate the inclusion of lookback straddle returns as systematic factors in their model.[1]

While the observation that hedge fund returns can be characterized as a portfolio of options (for example, Fung and Hsieh (2001), Weisman (2002), Bondarenko (2004), Cochrane (2005), and Diez and Garcia (2006)) is intuitive, the related implication that hedge fund returns may be connected to the higher-order laws of the market return distribution has received little scrutiny. Specifically, a less than understood phenomena is whether hedge funds are compensated for bearing higher–moment risks, a hypothesis that can be rationalized within the multifactor modeling paradigms of Merton (1973) and Ross (1976). If so, are the rewards economically and statistically significant? What proportion of hedge fund returns stem from enduring higher–moment exposures? Hedge funds may be rewarded for taking higher-moment risks can be further motivated by two empirical findings:

- Investors generically require risk premiums for higher-moment market exposures as argued in the treatments of Rubinstein (1973), Kraus and Litzenberger (1976), and Vanden (2006). Harvey and Siddique (2000) show that expected return of assets with systematic skewness includes reward for this risk. Dittmar (2002) provides evidence in favor of kurtosis preferences.

- Ang et al. (2006) document that market volatility risk is priced in the cross-section of stock returns (see also Goyal and Santa-Clara (2003), Bali et al. (2005), Bali and Cakici (2007), and Ang et al. (2007a)). Moreover, there is mounting evidence of the pricing of higher–moments from the index option markets.[2] Given that hedge funds have option-like exposures due to their

[1] Studies that exploit the link of hedge fund returns to options are often inspired by the theoretical developments in Merton (1981), Henriksson and Merton (1981), and Glosten and Jagannathan (1994). A well-known result from Dybvig and Ingersoll (1982) states that the market factor is insufficient to price assets with non-linear payoffs such as options.

[2] An incomplete list includes Jackwerth and Rubinstein (1996), Bates (2000), Chernov and Ghysels (2000), Buraschi and Jackwerth (2001), Coval and Shumway (2001), Pan (2002), Bakshi and Kapadia (2003), Bakshi et al. (2003), Bollen and Whaley (2004), Jones (2006), Broadie et al. (2007), Doron et al. (2007), and Duan and Wei (2007).

use of dynamic trading strategies, they are potentially exposed to higher-moment market risks.

The purpose of this study is to investigate higher-moment exposures, alphas, and the pricing of higher-moment market risks in the cross-section of hedge fund returns. In the process, we bring a conceptual framework to the hedge fund literature by constructing model-free and forward-looking measures of higher-moment risks. Specifically, we compute the arbitrage-free value of the second, the third, and the fourth moment payoff of market returns from S&P 100 index options by spanning the relevant payoffs as shown in Bakshi et al. (2003).[3] Since it is not traditional to infer the arbitrage-free value of higher–moments beyond fourth–order, we focus on the exposures to central moments, namely volatility, skewness, and kurtosis.

There are several benefits of the use of option prices to extract the time-series of higher-moment risk measures. First, since option prices reflect future uncertainty, our higher-moment risk measures are inherently forward-looking. Recently, Christoffersen et al. (2006) and Conrad et al. (2007) have shown the relevance of using forward-looking measures of market betas and higher-moments, instead of historical and backward-looking measures, in explaining the cross-section of stock returns. One drawback of using historical time-series-based measures of skewness and kurtosis lies in the tradeoff between needing a long time-series data for precise estimation and a short estimation window to allow for variation in higher-moments over time (Jackwerth and Rubinstein (1996) and Engle (2004)). Our approach of using the arbitrage-free value of higher–moments extracted from a static positioning in options overcomes this limitation. Second, as Bates (2000), Pan (2002), Jones (2006), and Broadie et al. (2007) argue, index option prices reflect volatility and jump risk premiums that may be hard to infer directly from the equity index time–series.[4]

Our empirical investigation yields several findings that are supportive of our central themes. First, using benchmark multifactor models to control for systematic risk factors, we find significant dispersion in alphas between the top and bottom portfolios of hedge funds, sorted on their exposure to volatility, skewness, and kurtosis risks. Further, we favor conditional sorts based on exposures to

[3]There are number of researchers who have implemented methods for computing the forward-looking measures of variance. These include Bakshi and Madan (2000), Britten-Jones and Neuberger (2000), Carr and Madan (2001), Carr and Wu (2008), Bondarenko (2004), Demeterfi et al. (1999), Jiang and Tian (2005), and Conrad et al. (2007), among others.

[4]While our focus is on assessing the impact of market return higher–moments on the cross-section of hedge fund returns, it is plausible that higher–moments of commodity returns, currency returns, and interest rates are also potentially important sources of hedge fund returns. However, due to the lack of availability of matching options data in these markets, it is harder to construct higher-moment risk proxies in markets other than equity.

the three higher-moments risks, since the higher-moment risks are correlated with each other. Our findings are robust to the inclusion of additional systematic risk factors such as lookback straddles on equity and interest rates, out-of-the-money put option, and Pastor and Stambaugh (2003) liquidity risk factor. We also allow for potential estimation error through Bayesian analysis and test for the robustness of our results to any backfilling bias prevalent in hedge fund data. Finally, we also perform a bootstrap simulation (using the residual and factor resampling approach of Kosowski et al. (2006)) to rigorously show that the documented significance of higher-moment risks is not a consequence of data-driven spurious inferences.

Second, our results indicate a negative premium for market volatility and kurtosis risks, and a positive premium for the market skewness risk. Specifically, our findings imply average factor returns for volatility, skewness, and kurtosis of about -6.50 percent, 3.40 percent, and -2.40 percent per year.[5] Taking into account the exposure of hedge funds to the three higher-moment risks helps to quantify differences in hedge fund returns: they can potentially earn up to 3.7 percent, 2.9 percent, and 2.6 percent per year for exposure to volatility, skewness, and kurtosis risks, respectively.

Third, and importantly, when factor returns on higher-moments are incorporated in the model of Fung and Hsieh (2001, 2004), the dispersion in alphas of extreme portfolios of hedge funds effectively disappears. Furthermore, the systematic risk factors in Fung and Hsieh (2001, 2004) cannot explain the behaviors of factor returns on volatility, skewness, and kurtosis. Our higher moment risk factors reflect payoffs underlying the volatility, the cubic, and the quartic contracts (Bakshi et al. (2003)) and are therefore distinct from Fung and Hsieh's (2001, 2004) lookback straddle that is designed to capture the spread between the maximum and the minimum values attained by the underlying asset. Hence, our results convey the important message that higher-moment factors are not subsumed by commonly adopted risk factors in the empirical hedge fund literature.

Fourth, while there is conclusive evidence that hedge funds as a group show marked exposures to volatility, skewness, and kurtosis risks, it is *a priori* unclear which hedge fund strategies are most exposed to higher-moment risks. Given the growing interest in this segment of the hedge fund industry, we examine FOFs separately. In such an analysis, three possibilities can arise. One, if FOFs act opportunistically to boost their compensation and future fund flows, they may strategically load

[5] In particular, the sign of skewness and kurtosis risk premiums mirrors a finding from index options that supports a pronounced left skewness and fatter tails in the risk-neutral distribution compared to the physical counterparts.

up on higher-moment risks to increase returns. Two, if FOFs construct their portfolios to insulate investors from higher-moment risks, then they will actively seek to neutralize the underlying exposures. Finally, it is conceivable that FOFs do not aim to neutralize higher moment risks but achieve imperfect offsetting of these risks by virtue of their holding a large number of hedge funds following different trading strategies. We disentangle between these three hypotheses relating to the behavior of FOFs and their risk management practices. Based on a large cross-section of FOFs, our empirical investigation finds surprisingly that FOFs refrain from loading aggressively on higher-moment risks. But neither are the higher-moment exposures completely offset and neutralized to zero. Thus, the key lesson that emerges is that investors striving to achieve superior returns by leveraging higher-moment exposures are more likely to realize their objectives by investing in certain types of hedge funds rather than FOFs. Our analysis also reveals that strategies such as Long/Short Equity, Emerging Markets, and Managed Futures exhibit extreme positive and negative higher-moment exposures.

Finally, we do not find significant dispersion in exposures and alphas when we sort *mutual funds* based on their exposures to higher-moment risks. This crucial finding further supports our motivation to examine hedge funds which exhibit nonlinearities in market returns thereby making them more sensitive to the influence of higher-moment risks. Our findings accentuate the structural differences between mutual funds and hedge funds, and the relevance of using hedge funds as test assets to identify the presence of higher-moment risks and to quantify factor risk premiums.

Our evidence from hedge funds and mutual funds have broad implications for performance evaluation and diversification of risks in the money management industry. Overall, our study contributes to the body of theoretical and empirical research that suggests that higher-moment risk dimensions are important for a certain class of assets.

In what follows, Section 1 describes the data and the construction of variables. Section 2 relates higher-moment risk exposures to the cross-section of hedge fund returns. We also characterize factor risk premiums for volatility, skewness, and kurtosis risks, and study post-ranking alphas from the Fung and Hsieh (2001, 2004) model. Section 3 and Section 4 investigates exposures and alphas for funds of hedge funds and mutual funds respectively, while Section 5 conducts follow-up specification analysis. Finally, Section 6 concludes.

1 Fund Samples and Risk Factors

1.1 Proxies for higher-moment market risks and motivation for higher-moment exposures

Since our risk proxies for market volatility, skewness, and kurtosis are not directly traded, we extract them from S&P 100 index options traded on the Chicago Board Options Exchange (CBOE). This construction is based on the cost of reproducing the appropriate payoffs using out-of-the-money calls and puts (as shown in Theorem 1 of Bakshi et al. (2003), and in Britten-Jones and Neuberger (2000), Carr and Madan (2001), Demeterfi et al. (1999), Bakshi and Madan (2006), and Carr and Wu (2008)). Specifically, for equity index price S_t, the τ–period equity index return $R_{t,t+\tau} := \ln S_{t+\tau} - \ln S_t$ and interest rate r, we wish to characterize the value of the payoffs:

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

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

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

where $\mathbb{E}^{\mathbb{Q}}[.]$ is expectation under the risk-neutral valuation measure and $\mathbb{M}_{1,t}$ reflects intrinsic value of the claim to $(\ln S_{t+\tau} - \ln S_t)$. In our framework, $\mathbb{M}_{k,t}$, for $k = 2, \ldots, 4$, is the arbitrage-free value of the claim to the central moment payoff $(\ln S_{t+\tau} - \ln S_t - \mathbb{M}_{1,t})^k$. Furthermore, $\sqrt{\mathbb{M}_{2,t}}$, $\frac{\mathbb{M}_{3,t}}{(\mathbb{M}_{2,t})^{3/2}}$, and $\frac{\mathbb{M}_{4,t}}{(\mathbb{M}_{2,t})^2}$ are to be interpreted as the arbitrage-free value of the claim to market volatility, skewness, and kurtosis respectively.

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 equity market index, we fix notation and let $C[K]$ and $P[K]$ represent the market price of call option and put option with strike price K and τ-periods to expiration. Writing $R_{t,t+\tau}$ as R and tapping the model-free approach in Bakshi et al. (2003), Britten-Jones and Neuberger (2000), Carr and Madan (2001), and Carr and Wu (2008), we observe the following:

$$e^{r\tau}\mathbb{M}_{2,t} = \int_{-\infty}^{+\infty} R^2\, q[R]\, dR - \left(\int_{-\infty}^{+\infty} R\, q[R]\, dR\right)^2, \quad (4)$$

where we recognize that discounted expectation under the risk-neutral density, $q[R]$, gives the value of the underlying payoff. The cost of reproducing the volatility contract can be expressed as:

$$\int_{-\infty}^{+\infty} R^2 q[R] dR = e^{r\tau} \int_{S_t}^{+\infty} \frac{2\left(1 - \ln\left(\frac{K}{S_t}\right)\right)}{K^2} C[K]\, dK + e^{r\tau} \int_0^{S_t} \frac{2\left(1 + \ln\left(\frac{S_t}{K}\right)\right)}{K^2} P[K]\, dK, \quad (5)$$

$$e^{r\tau} \mathbb{M}_{1,t} = \int_{-\infty}^{+\infty} R\, q[R]\, dR = e^{r\tau} - 1 - e^{r\tau} \left(\int_0^{S_t} \frac{1}{K^2} P[K]\, dK + \int_{S_t}^{+\infty} \frac{1}{K^2} C[K]\, dK \right). \quad (6)$$

The current calculation of the VIX index by the CBOE is based on $\sqrt{\mathbb{M}_{2,t}}$ (Carr and Wu (2008)).

Proceeding to the cost of reproducing the cubic and quartic contracts, we have,

$$\int_{-\infty}^{+\infty} R^3 q[R] dR = \int_{S_t}^{+\infty} \frac{6 \ln\left(\frac{K}{S_t}\right) - 3(\ln\left(\frac{K}{S_t}\right))^2}{K^2} C[K] dK - \int_0^{S_t} \frac{6 \ln\left(\frac{S_t}{K}\right) + 3(\ln\left(\frac{S_t}{K}\right))^2}{K^2} P[K]\, dK, \quad (7)$$

$$\int_{-\infty}^{+\infty} R^4 q[R] dR = \int_{S_t}^{+\infty} \frac{12(\ln\left(\frac{K}{S_t}\right))^2 - 4(\ln\left(\frac{K}{S_t}\right))^3}{K^2} C[K] dK + \int_0^{S_t} \frac{12(\ln\left(\frac{S_t}{K}\right))^2 + 4(\ln\left(\frac{S_t}{K}\right))^3}{K^2} P[K] dK, \quad (8)$$

from which we construct $\mathbb{M}_{3,t}$ and $\mathbb{M}_{4,t}$ and hence $\frac{\mathbb{M}_{3,t}}{(\mathbb{M}_{2,t})^{3/2}}$, and $\frac{\mathbb{M}_{4,t}}{(\mathbb{M}_{2,t})^{2}}$. The computation of the intrinsic value of higher–moment payoffs requires options with constant maturity and we fix it to 28 days (see Bollen and Whaley (2004)). Details on the Riemann integral approximation of (5)-(8) 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)).

Consistent with the extant literature where first differences in index implied volatility (from CBOE) have been used to proxy market volatility risk (e.g., Ang et al. (2006)), we define,

$$\Delta \text{VOL}_t := \sqrt{\mathbb{M}_{2,t}} - \sqrt{\mathbb{M}_{2,t-1}}, \quad (9)$$

$$\Delta \text{SKEW}_t := \frac{\mathbb{M}_{3,t}}{(\mathbb{M}_{2,t})^{3/2}} - \frac{\mathbb{M}_{3,t-1}}{(\mathbb{M}_{2,t-1})^{3/2}}, \quad (10)$$

$$\Delta \text{KURT}_t := \frac{\mathbb{M}_{4,t}}{(\mathbb{M}_{2,t})^{2}} - \frac{\mathbb{M}_{4,t-1}}{(\mathbb{M}_{2,t-1})^{2}}. \quad (11)$$

ΔVOL_t, ΔSKEW_t and ΔKURT_t will be deployed as our proxies for higher-moment risks in the ensuing empirical investigation. 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 price.

Agreeing with prior evidence, the mean [standard deviation] of $\sqrt{12\,\mathbb{M}_{2,t}}$, SKEW_t and KURT_t is 18.83% [7.38%], -1.76 [0.72], and 10.34 [7.20]. Furthermore, as would be expected, $\sqrt{12\,\mathbb{M}_{2,t}}$ is highly correlated with the VIX_t index (the sample correlation coefficient is 0.91).

The negative market volatility risk premium is theoretically tenable as long equity investors dislike volatility (Coval and Shumway (2001), Bakshi and Kapadia (2003), Bondarenko (2004), and Carr and Wu (2008)), and hedge funds may be earning returns by being net sellers of index volatility. As skewness is synthesized through an option positioning involving a short position in index-puts and a long position in index-calls with puts dominating calls, the arbitrage-free value of market skewness is negative. Therefore, hedge funds with positive exposures to skewness risk can be expected to deliver positive returns. Analogously, hedge funds with negative exposures to kurtosis risk will experience positive returns as the risk premium for kurtosis risk is negative. Hedge funds may be exposed to kurtosis risk as they may be engaged in trading both deep out-of-money index calls and puts (the option positioning (8) is heavily weighted towards deep out-of-the-money options).

In sum, hedge funds have the expertise, and the risk appetite, to seek specific exposures to a factor with the hope of earning a risk premium.[6] The mechanism by which hedge funds sell tail risk to gain excess returns and how/whether it translates into higher-moment risk exposures remains an open question that can only be addressed empirically. Our investigation is not about higher–moments of hedge funds' returns but about the exposures of hedge fund returns to market higher–moments. Hence, one should not interpret the test of variance neutrality presented in Patton (2004) to mean hedge fund returns neutrality with respect to volatility exposures. As we shall see, our measures of shifts in tail movement, tail asymmetry, and tail size outlined in (9)-(11) can contribute to our understanding of how tail risks impact hedge funds (as in Patton (2004), Gupta and Liang (2005), Brown and Spitzer (2006), Boyson et al. (2006), and Cacho-Diaz (2007)).

[6] To generically interpret higher-moment risk premiums, suppose an investor holds the claim: $(R_{t,t+\tau} - \mathbb{M}_{1,t})^2$. The cost of reproducing this cash flow is precisely as shown in (4)-(6). For admissible stochastic discount factor, ξ, and covariance operator, $\text{Cov}_t(.,.)$, the reward for bearing volatility risk, μ_{VOL}, is then $\mu_{\text{VOL}} - r = -\text{Cov}_t(\xi_{t+1}/\xi_t, \Delta\text{VOL}_t)$. Once the stochastic discount factor has been identified, the volatility risk premium can be estimated (Cochrane (2004)).

1.2 Sample of individual hedge funds, funds of hedge funds, and mutual funds

We use monthly net-of-fee returns of hedge funds from the 2004 Lipper Hedge Fund (previously TASS) Database over the period January 1994 to December 2004. We exclude 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 et al. (1992) and Brown and Goetzmann (1995) since it includes dead/defunct funds. Hedge funds in the database could be missing due to reasons other than poor performance such as merger, restructuring, and voluntary stopping of reporting (Fung and Hsieh (2000), Liang (2000), and Getmansky et al. (2004)).[7]

To examine FOFs separately later in the paper, we also construct their sample for which we rely on the filters suggested in Fung et al. (2007) but we additionally require at least 12 consecutive return observations for a fund of fund to be included in the sample. The overall sample, which consists of 1062 FOFs, is comparable to Fung et al. (2007) who use merged database using HFR, CISDM, and TASS. The returns of both hedge funds and FOFs are net of all fees.

Data on mutual fund returns comes from 2004 CRSP Mutual Fund Survivorship-bias Free Database over the period January 1994 to December 2004. We follow established procedures (e.g., Carhart (1997), Pastor and Stambaugh (2002), Bollen and Busse (2005), Huij and Verbeek (2007), and Kosowski et al. (2006)) to select all equity mutual funds from CRSP with a minimum of 12 consecutive returns over the sample period. Since CRSP includes all funds that existed during this period, our data are free of the survivorship bias. There are 9,769 mutual funds in our sample. All mutual fund returns are reported net of operating expenses.

1.3 Factor data in excess return form

To measure risk-adjusted performance of both individual hedge funds and funds of hedge funds, and mutual funds, we employ two benchmark multifactor models: the Fung and Hsieh (2004) seven-factor model (henceforth, FH-7) and the Carhart (1997) four-factor model (henceforth, Carhart-4). Since the

[7] In our analysis, we also control for backfilling bias resulting from a hedge 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 et al. (1999), Fung and Hsieh (2000), and Malkiel and Saha (2005)). Accordingly, we remove the first 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 robustness checks.

Carhart-4 model is more appropriate for mutual funds and the FH-7 model is more suited for hedge funds, we respectively analyze mutual funds and hedge funds using these models to allow for broader comparison of our results across the two types of managed portfolios.

Drawing from the notation adopted in Fung et al. (2007), the FH-7 model can be represented as:

$$\begin{aligned} r_t^i \;=\; & \alpha_{FH7}^i + \beta_{FH7}^{1,i}\,\mathrm{SNPMRF}_t + \beta_{FH7}^{2,i}\,\mathrm{SCMLC}_t + \beta_{FH7}^{3,i}\,\mathrm{BD10RET}_t + \beta_{FH7}^{4,i}\,\mathrm{BAAMTSY}_t \\ & + \beta_{FH7}^{5,i}\,\mathrm{PTFSBD}_t + \beta_{FH7}^{6,i}\,\mathrm{PTFSFX}_t + \beta_{FH7}^{7,i}\,\mathrm{PTFSCOM}_t + \varepsilon_{t,FH7}^i, \end{aligned} \tag{12}$$

where r_t^i is the excess return of fund i over the riskfree rate in month t and $\varepsilon_{t,FH7}^i$ is fund i's residual return in month t. The systematic risk factors in the FH-7 model are,

- SNPMRF_t is S&P 500 return minus the riskfree rate in month t;
- SCMLC_t captures Wilshire small cap minus large cap return in month t;
- $\mathrm{BD10RET}_t$ reflects the yield spread between the 10-year Treasury bond and the three-month Treasury bill, adjusted for the duration of the 10-year bond;
- $\mathrm{BAAMTSY}_t$ measures monthly changes in the credit spread defined as Moody's Baa bond yield minus the 10-year Treasury bond yield, after adjusting for durations;
- PTFSBD_t, PTFSFX_t, and $\mathrm{PTFSCOM}_t$ are excess returns on portfolios of lookback straddles on bonds, currencies, and commodities respectively in month t.

David Hsieh graciously provided us with the updated factors, which are all expressed as return spreads. One-month Treasury rate taken from Ibbotson Associates is the proxy for the riskfree rate.

The Carhart-4 model takes the form:

$$r_t^i = \alpha_{C4}^i + \beta_{C4}^{1,i}\,\mathrm{RMRF}_t + \beta_{C4}^{2,i}\,\mathrm{SMB}_t + \beta_{C4}^{3,i}\,\mathrm{HML}_t + \beta_{C4}^{4,i}\,\mathrm{UMD}_t + \varepsilon_{t,C4}^i, \tag{13}$$

where RMRF_t is the value-weighted excess return of all NYSE, AMEX, and NASDAQ stocks in month t, SMB_t and HML_t are the returns on factor mimicking portfolios for size (Small Minus Big) and book-to-market-equity (High Minus Low) in month t as in Fama and French (1993), and UMD_t (Up Minus Down) is the proxy for the momentum effect in month t as documented by Jegadeesh and

Titman (1993), and $\varepsilon^i_{t,C4}$ is fund i's residual return in month t. The returns on RMRF, SMB, HML, and UMD are obtained from Kenneth French's data library.

2 Higher-Moment Risks and the Cross-Section of Hedge Fund Returns

For the main empirical tests conducted in this study, we use standard asset pricing tests using pooled time-series cross-sectional data where we estimate hedge funds' exposures to ΔVOL, ΔSKEW, and ΔKURT using time-series regressions to sort the funds into different portfolios based on their exposures. We start by performing independent sorts on each of these higher–moment risk exposures. Given the correlation between these exposures, we later suggest a three-way sort that may be more appropriate for separating the effect of ΔVOL, ΔSKEW, and ΔKURT.

We evaluate the sorted portfolios' out-of-sample performance and then estimate the spread between the portfolios' risk-adjusted returns after controlling for risk factors using the FH-7 model. Furthermore, we construct factor risk premiums for higher–moment risks in the tradition of Fama and French (1993), Liew and Vassalou (2000), and Cochrane (2004), and show that these factors capture risks distinct from those captured by the FH-7 model.

2.1 Independent sorts on exposures to ΔVOL, ΔSKEW, and ΔKURT

We first construct a set of base assets that display significant dispersion in the sensitivities to higher-moment risks. For this purpose, we form decile portfolios of hedge funds in the following way. Every 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). That is, we obtain the funds' exposures by estimating rolling CAPM-type regressions that are augmented by ΔVOL_t, ΔSKEW_t, and ΔKURT_t, over the past 12 months:

$$r^i_t = \alpha^i_{4F} + \beta^i_{\text{RMRF}}\text{RMRF}_t + \beta^i_{\Delta\text{VOL}}\Delta\text{VOL}_t + \beta^i_{\Delta\text{SKEW}}\Delta\text{SKEW}_t + \beta^i_{\Delta\text{KURT}}\Delta\text{KURT}_t + \varepsilon^i_t. \quad (14)$$

Proponents such as Ang et al. (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 use dynamic trading strategies often using leverage in response to changes in macroeconomic conditions and arbitrage opportunities (Bollen and Whaley (2007), Hasanhodzic and Lo (2007), Avramov et al. (2007), and Klebanov (2007)).

In fact, when we experimented with 24-month windows to estimate exposures it was assuring to find (i) only a small reduction in exposure magnitudes and (ii) minor narrowing of post-ranking alphas between the extreme portfolios. So, when we consider alpha spreads rather than the t-statistics of the estimated factor premiums, the results are not fundamentally different. Assuming the constancy of the exposures over longer windows breaks the link between exposures and future returns and results in greater empirical misspecification, a point made also by Ang et al. (2006). Later we address the possibility of estimation error in factor sensitivities induced through estimation windows by exploiting a Bayesian framework.

Given our approach to estimate factor loadings, it is crucial to keep the number of factors to a minimum in constructing the portfolios. Hence, to maintain parsimony, we employ the equity market factor along with the higher-moment risk factors in the formation period but we are careful to control for competing risk factors in the post-formation period using the model of Fung and Hsieh (2001, 2004).

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 hedge funds exhibiting the highest exposure to the relevant higher–moment risk and the bottom decile D10 comprises the collection of funds with the lowest exposure to that moment. Then, we compute out-of-sample returns of each of these deciles to account for any 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 decile portfolios to make our analysis consistent with frictions associated with hedge fund investing (Agarwal et al. (2006)). 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 rolling regression procedure to form the decile portfolios and 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. Table 1 reports the decile portfolios' pre-ranking exposures to ΔVOL, ΔSKEW, and ΔKURT from Equation (14) as well as the post-ranking annualized alpha estimates, their t-statistics, and adjusted R-squared values from the regressions based on Equations (12) and (13).

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 alphas. More specifically, the spread in alphas between the top and bottom deciles for sorts on ΔVOL is -13.47 percent per year (the difference between FH-7 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 -14.58 percent per year with the FH-7 model. Further, results from the Gibbons et al. (1989) test strongly reject that these alphas of the decile portfolios are jointly equal to zero. Finally, although the reported R-squared values indicate that the FH-7 model performs reasonably well in explaining the time-series variation in the decile portfolios' returns, it is unable to eliminate the distinct patterns in post-ranking alphas and significant spreads in these alphas.

While the focus in Table 1 is on pre-ranking exposures on higher-moment risks based on the empirical specification (14), another essential point to note are the magnitudes of market betas which, on average, take a value of 0.291 (similar to 0.29 reported for an equally-weighted average of all TASS funds (TASSAVG) in Fung and Hsieh (2004), see Table 2 on page 74). We reiterate later in Table 7 that, in contrast, the pre-ranking market betas for mutual funds are, on average, close to unity. Moreover judging by the magnitudes of the pre-ranking betas on higher-moments, hedge funds exhibit pronounced non-neutrality with respect to higher-moment risks.

Since the FH-7 model does not include lookback straddles on the equity index, we also test the robustness of our findings to the extended nine-factor model of Fung and Hsieh (2001, 2004) which incorporates lookback straddles on equities and interest rates. In a later robustness check with the extended model, we continue to observe pronounced spreads in alphas for hedge fund portfolios sorted on their exposure to higher–moment risks. The misspecification with the extended nine-factor model can be interpreted as implying that higher-moment risks contain information that is distinct from that embedded in the lookback straddles. Instrumental to the tasks at hand, the two sets of risks reflect diverse attributes of the return distribution with lookback straddle returns not subsuming the effect of our higher-moment risks.

The fact that we observe monotonically increasing alphas in hedge fund portfolios sorted on exposures to higher–moment risks provides initial confirmatory evidence that higher-moment equity risks are being priced in the cross-section of hedge fund returns. In this sense, our paper adds to the compelling list of studies that argues for the possible pricing of higher-moment risks, and preferences over higher-moments (see, for instance, Kraus and Litzenberger (1976), Bansal et al. (1993), Harvey and Siddique (2000), Dittmar (2002), Vanden (2006), Conrad et al. (2007), and Engle and Mistry (2007)).

However, an unappealing attribute of the single–sorting scheme that emerges is that it induces a rather large correlation between the post-formation returns spread of top and bottom deciles of hedge funds sorted by their exposure to ΔVOL, ΔSKEW, and ΔKURT. To be exact, the D10 minus D1 portfolio return correlation is 0.60 for sorts done on ΔVOL and ΔSKEW; it is 0.66 for sorts done on ΔVOL and ΔKURT; and it 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 circumvent the problem of high correlation. Otherwise, it is difficult to isolate the effect of higher-moment risks separately.

2.2 Conditional three-way sorts on exposures to ΔVOL, ΔSKEW, and ΔKURT

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 provides 27 (3x3x3) portfolios sorted first on the hedge funds' exposures to ΔVOL, then to ΔSKEW, and finally to ΔKURT. This approach 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 risk measures. Besides the stated difference in sorting, we follow the same exact procedure as in the previous subsection to estimate the quantile portfolios' pre-ranking betas, and post-ranking annualized alphas, their t-statistics and

R-squared values from the regressions in Equations (12) and (13).

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 multifactor model. Furthermore, we observe an increasing pattern in these alphas as we move down from P1 to P27. It is noteworthy that alphas range between –5.59 to 14.95 percent after controlling for factors in the FH-7 model. Finally, results from the Gibbons et al. (1989) test continue to suggest that these alphas together are statistically different from zero.

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 have similar intensity of exposure to two out of the three higher–moment risks but differ in their intensity of exposure to the remaining risks. 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 kurtosis risk exposure.

As intended, one can similarly infer the range of alphas that are sourced in their exposures to volatility and skewness risks. That is, portfolios exhibiting the most negative exposure to ΔVOL and ΔKURT but with different exposures to ΔSKEW (i.e., P21, P24, and P27) generate FH-7 alphas from 6.35 percent to 14.95 percent per year which can be credited to skewness risk exposure. Thus, based on results documented in Table 2, each higher-moment risk exposure bears considerably on hedge fund alphas.

2.3 Bootstrap Simulation

Proceeding further, we investigate the possibility that our empirical tests reject evidence of no premiums for high-moment risks when the premiums are actually absent. For this purpose, we perform a bootstrap simulation comparable to the residual and factor resampling procedure outlined in Kosowski et al. (2006). First, we estimate all funds' alphas, factor loadings, and residual returns using the FH-7 model, and store the coefficient estimates $\{\hat{\beta}^{1,i}_{FH7}, \hat{\beta}^{2,i}_{FH7}, \hat{\beta}^{3,i}_{FH7}, \hat{\beta}^{4,i}_{FH7}, \hat{\beta}^{5,i}_{FH7}, \hat{\beta}^{6,i}_{FH7}, \hat{\beta}^{7,i}_{FH7}, i = 1,2,\ldots,N\}$, 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 by using replacements from the funds' stored residuals $\{\hat{\varepsilon}_{t_e}^{i,b}, t_e = s_1^b, s_2^b, \ldots, s_T^b\}$, and the factors' $\{\text{SNPMRF}_{t_F}^b$, $\text{SCMLC}_{t_F}^b$, $\text{BD10RET}_{t_F}^b$, $\text{BAAMTSY}_{t_F}^b$, $\text{PTFSBD}_{t_F}^b$, $\text{PTFSFX}_{t_F}^b$, $\text{PTFSCOM}_{t_F}^b, t = u_1^b, u_2^b, \ldots, u_T^b\}$, where $s_1^b, s_2^b, \ldots, s_T^b$ and $u_1^b, u_2^b, \ldots, u_T^b$ are the time reorderings imposed by the bootstrap. We then construct time-series of simulated returns for all hedge funds subject to zero alphas:

$$\begin{aligned} r_t^{i,b} \quad = \quad & \hat{\beta}_{FH7}^{1,i}\text{SNPMRF}_{t_F}^b + \hat{\beta}_{FH7}^{2,i}\text{SCMLC}_{t_F}^b + \hat{\beta}_{FH7}^{3,i}\text{BD10RET}_{t_F}^b + \hat{\beta}_{FH7}^{4,i}\text{BAAMTSY}_{t_F}^b \\ & + \hat{\beta}_{FH7}^{5,i}\text{PTFSBD}_{t_F}^b + \hat{\beta}_{FH7}^{6,i}\text{PTFSFX}_{t_F}^b + \hat{\beta}_{FH7}^{7,i}\text{PTFSCOM}_{t_F}^b + \hat{\varepsilon}_{t_e}^{i,b}. \end{aligned} \tag{15}$$

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 empirical sample counterparts.

We then sort all available 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. The portfolios are reformed 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. Finally, we estimate the alphas using the out-of-sample returns of the long-short portfolios (i.e., the difference between the top and the bottom portfolios). We run a total of 1,000 bootstrap iterations.

If we find that only a few bootstrap iterations yield significant alpha estimates for the returns of the long-short portfolio, similar to those observed in our actual empirical analysis, such a finding would reinforce the idea that our results indicate higher-moment risks are being priced, and are not attributable to any distributional features of the hedge fund data.

The extreme tail values resulting from the bootstrap experiment displayed in Figure 1 shows that one could reject the hypothesis that our evidence of priced higher-moment risks is a statistical artifact. Under the imposed condition that higher-moment factor premiums are nonexistent, the most extreme simulation outcomes are not in the order of the empirical values of close to 20 percent we obtain from the empirical test. Specifically, the 95 percent confidence interval of the bootstrapped spreads in alphas between the top and bottom quantile of hedge funds sorted on volatility, skewness, and kurtosis is between -8.5 percent and +8.5 percent.

Thus, the bootstrap results provide a strong confirmation about the size of our tests, indicating there is little reason to suspect that our evidence with respect to the role of higher-moment risks is prone to data-driven spurious inferences.

2.4 Characterizing volatility, skewness, and kurtosis factor returns

Given the patterns in both alphas and higher-moment betas depicted in Table 2, the next step is to estimate the spread in the post-ranking returns of portfolios that are conditionally sorted on each of the three higher–moment risk exposures. Guided by Fama and French (1993), Liew and Vassalou (2000), and Cochrane (2004), one may estimate spreads by taking the return difference of portfolios with extreme exposure to one higher–moment risk after controlling for the effect of the other two higher-moment risks.

Specifically, the return spread between hedge fund portfolios with the highest and the lowest exposure to volatility risk is imputed as the average return differential between the first 9 portfolios (P1 to P9) and the last 9 portfolios (P19 to P27). We characterize this return spread as volatility premium, FVOL, and compute it as the return on a portfolio that long on hedge funds with high volatility risk exposure and short on hedge funds with low volatility risk exposure:

$$\begin{aligned} \text{FVOL} \quad := \quad & \frac{1}{9}\left(P1+P2+P3+P4+P5+P6+P7+P8+P9\right) \\ & - \frac{1}{9}\left(P19+P20+P21+P22+P23+P24+P25+P26+P27\right). \end{aligned} \tag{16}$$

The economic interpretation of the mean return spread computed through FVOL is that it reflects the zero cost portfolio that is long (short) on high (low) volatility risk exposures, but essentially neutral to skewness and kurtosis risk exposures.

Based on a parallel reasoning, we compute return spreads for portfolios with the highest and the lowest exposure to kurtosis risk. Specifically, we define the portfolio strategy FKURT via,

$$\begin{aligned} \text{FKURT} \quad := \quad & \frac{1}{9}\left(P1+P4+P7+P10+P13+P16+P19+P22+P25\right) \\ & - \frac{1}{9}\left(P3+P6+P9+P12+P15+P18+P21+P24+P27\right). \end{aligned} \tag{17}$$

Hence FKURT reflects the zero cost portfolio that is both neutral to volatility and skewness risk exposures.

We must emphasize that, by construction, the portfolio strategies underlying FVOL and FKURT are intended to capture the premium that is paid by hedge funds to have a *positive* return reaction to increases in equity volatility and kurtosis. If we were to compute the portfolio representing skewness risk, denoted FSKEW, in the same way as FVOL and FKURT, then FSKEW would capture the premium hedge funds pay for having a *negative* return reaction to increased equity skewness. This departure is caused by skewness having a negative intrinsic value due to the structure of the third moment payoff. To conform with the interpretation of volatility premium and kurtosis premium, we *reverse the order* of portfolios, and compute the return factor FSKEW as:

$$\begin{aligned} \text{FSKEW} \quad := \quad & \frac{1}{9}\left(P7+P8+P9+P16+P17+P18+P25+P26+P27\right) \\ & - \frac{1}{9}\left(P1+P2+P3+P10+P11+P12+P19+P20+P21\right). \end{aligned} \tag{18}$$

Analogous to size and book-to-market-equity factors of Fama and French constructed from 2x3 conditionally sorted portfolios of stocks, here FVOL, FSKEW, and FKURT proxy for the premiums on three higher-moment risk factors – volatility, skewness, and kurtosis, respectively.

The annualized time-series averages of returns on factor mimicking portfolios for higher-moment risks and their t-statistics reported in Table 3 suggest that not only are the underlying premiums statistically significant, they are also economically meaningful: -6.55 percent, 3.40 percent, and -2.39 percent per year for FVOL, FSKEW, and FKURT, respectively.

Given that higher-moment risks are strongly rewarded, a natural concern that arises is whether the risk premiums are economically plausible. In this regard, theory provides little guidance or bounds. However, based on individual stocks, Ang et al. (2006) report a volatility risk premium of -1 percent and Harvey and Siddique (2000) report a skewness risk premium of 3.60 percent. The discrepancy between the volatility risk premium here and in Ang et al. (2006) can be reconciled. As noted from Tables 1 and 2, the pre-ranking betas for volatility risk are substantial for hedge funds. For instance, in the quintile sorted portfolios of Ang et al. (2006, Table I on page 268) the volatility betas lie between -2.09 to 2.18, whereas they lie between -3.92 (i.e., (-2.08-5.76)/2) and 4.23 (i.e., (5.96+2.50)/2) for hedge funds (our Table 1). Thus, a plausible explanation is that hedge funds are intrinsically different in how they generate returns compared to passive stock portfolios. The reliance of hedge funds on dynamic strategies produces option-like payoffs, and imparts stronger higher-moment exposures that elevate risk premiums.

One methodological observation to be made is that the correlations between FVOL, FSKEW, and FKURT now range between -0.41 to 0.25, and are mitigated versions of the independent sort counterparts in Section 2.1. The reduction in cross-correlations suggest that our approach of conditionally sorting hedge fund portfolios to construct higher–moment risk factors offer greater flexibility than independent sorts where it is difficult to isolate the effect of each of the higher moment risks separately.

Estimated risk factors are not strongly associated with the classic risk factors of Fama and French (1993). To push the novelty of FVOL, FSKEW, and FKURT, we note that the contemporaneous correlation of FVOL with the size factor (i.e., SMB), the book-to-market factor (i.e., HML), and the momentum factor (i.e., UMD) is 0.39, −0.47, and 0.37, respectively. Furthermore, the correlation of FSKEW with SMB, HML, and UMD is -0.27, 0.38, and −0.25, and the correlation of FKURT with SMB, HML, and UMD is 0.11, −0.13, and −0.05. As a reference, the correlation between SMB and HML is −0.52, between SMB and UMD is 0.17, and HML and UMD are nearly uncorrelated.

Building on the above themes, we also perform time-series regressions of factor risk premiums on the FH-7 factors and report the findings in the final three columns of Table 3. The goal is to investigate whether higher-moment risks are empirically removed from the FH-7 risk factors. Several aspects of the regression results are worth highlighting. First, the alphas obtained from the FH-7 model are virtually indistinguishable from the average factor returns reported in column 2 of Table 3. This finding implies near-insensitivity of the risk premiums to the factors driving the FH-7 model. Second, the regressions produce low explanatory power as measured by the R-squared values (the maximum R-squared is 9%). Taken together, this evidence suggests that the risk factors in a class of prominent multifactor models do not encompass risks embedded in FVOL_t, FSKEW_t, and FKURT_t.

2.5 FH-7 model augmented with volatility, skewness, and kurtosis factor returns

Having established that hedge funds earn premiums for being exposed to higher–moment risks, we investigate to what extent the higher-moment risk factors FVOL, FSKEW, and FKURT are able to capture these premiums. Accordingly, we augment the FH-7 model specification in Equation (12) with the three higher-moment risk factors. The resulting ten factor model is:

$$\begin{aligned} r_t^i &= \alpha_{10F}^i + \beta_{10F}^{1,i}\,\text{SNPMRF}_t + \beta_{10F}^{2,i}\,\text{SCMLC}_t + \beta_{10F}^{3,i}\,\text{BD10RET}_t + \beta_{10F}^{4,i}\,\text{BAAMTSY}_t \\ &+ \beta_{10F}^{5,i}\,\text{PTFSBD}_t + \beta_{10F}^{6,i}\,\text{PTFSFX}_t + \beta_{10F}^{7,i}\,\text{PTFSCOM}_t \\ &+ \underbrace{\beta_{\text{FVOL}}^i\,\text{FVOL}_t + \beta_{\text{FSKEW}}^i\,\text{FSKEW}_t + \beta_{\text{FKURT}}^i\,\text{FKURT}_t}_{\text{FH}-7\text{ augmented with higher}-\text{moment factors}} + \varepsilon_{t,10F}^i. \end{aligned} \tag{19}$$

Essentially our approach is that if FVOL, FSKEW, and FKURT are able to capture the higher-moment premiums, the quantile portfolios should exhibit monotonically increasing or decreasing loadings on the higher-moment risk factors over the same period that is used to estimate alphas. We furthermore hypothesize that the augmented factor model should improve the explanatory power to describe both the cross-section and time-series of hedge fund returns. In particular, we should observe lower spreads in alphas for the cross-section of hedge fund portfolios sorted on exposures to higher–moment risks. Moreover, we should obtain higher R-squares from the time-series regressions using the augmented factor model that incorporates FVOL_t, FSKEW_t, and FKURT_t.

We report annualized alphas, post-ranking FVOL, FSKEW, and FKURT loadings, and the adjusted R-squares for the 27 conditionally sorted portfolios in Table 4. The strong patterns of post-ranking loadings on each of the three higher-moment risk factors using the augmented FH-7 model specification support a risk-based explanation for our findings (i.e., Fama and French (1992, 1993)). The majority of the t-statistics on the post-ranking higher-moment loadings are statistically significant.

Consider volatility, where the ex-post factor loadings, β_{FVOL}^i, on FVOL is between 0.37 to 1.24 for P1 to P9 (nine "H" portfolios corresponding to FVOL), between -0.03 to 0.25 for P10 to P18 (nine "M" portfolios corresponding to FVOL), and between -0.21 to -0.57 for P19 to P27 (nine "L" portfolios corresponding to FVOL). For the ex-post factor loadings on FSKEW and FKURT, we observe similar increasing and decreasing patterns.

Here a caveat is in order regarding the switch in sign for the loading on FSKEW for each of the P1 to 27 portfolios, compared to the pre-ranking skewness risk exposures in Table 2. Reported results are sensible as FSKEW is the premium paid by hedge funds to have a *positive* return reaction when skewness becomes less negative, as dictated by definition (18).

How do hedge fund generate excess returns? To isolate the fraction of hedge fund returns that can be attributed to their exposure to higher–moment risks, we take estimated higher-moment betas corresponding to hedge fund portfolios with the lowest exposure with respect to the second and the fourth moment, and the highest exposure with respect to the third moment in Table 4, and multiply them with the higher-moment risk factor premiums from Table 3.

- If we multiply the *lowest* volatility beta of -0.57 of P19 portfolio with the volatility premium of -6.55 percent, hedge funds can earn up to 3.73 percent excess return for volatility exposures;
- Likewise, taking the *highest* skewness beta of 0.85 for P9 portfolio and multiplying it by the skewness premium of 3.40 percent, we impute that hedge funds can potentially earn up to 2.89 percent excess return on account of their exposure to skewness;
- Finally, if we take the *lowest* kurtosis beta of -1.08 for P3 portfolio and multiply it by kurtosis premium of -2.39% percent we impute that hedge funds can potentially earn up to 2.58 percent excess return on account of their exposure to kurtosis.

Assuming the validity of the underlying multibeta representation (e.g., Cochrane (2004)), hedge funds can therefore earn excess return *up to* 3.73%, 2.89%, and 2.58% per year on account of their exposure to volatility, skewness, and kurtosis risks respectively.

Notice that (i) the patterns in alphas across the hedge fund portfolios are *now* not nearly as striking as the patterns in alphas resulting from FH-7 model in Table 2, and (ii) the alphas improve after accounting for higher-moment risks. For one, we find annualized alphas are all positive, and range between 2.31 percent to 9.45 percent per year for the augmented FH-7 model. In fact, the spread between the top and bottom portfolios is 1.36 percent per year and is not statistically significant with a t-statistics of 0.64. Overall, these results suggest that FVOL, FSKEW, and FKURT offer versatility in capturing cross-sectional spreads in hedge fund alphas by internalizing higher-moment risk exposures.

Additionally, we observe significant explanatory power with R-squares ranging from 40 percent to 80 percent for the augmented FH-7 model. For comparison, the R-squares for the FH-7 in Table 2 range from 27 percent to 59 percent. The general narrowing of spreads in alphas along with the enhanced explanatory ability both indicate that including the three higher-moment risk factors in addition to other risk factors in the FH-7 model can lead to a better performance attribution model for hedge fund returns.

To further corroborate the importance of higher-moment risk factors, we compare differences in hedge fund rankings based on the FH-7 model with and without including the higher-moment risk factors. For all the 2,499 hedge funds in our sample with more than 36 consecutive return observations over January 1994 to December 2004, we first estimate FH-7 model alphas relying on their entire return history. We then repeat the procedure to estimate alphas from the FH-7 model specification augmented with the three higher-moment risk factors as in equation(19).

Figure 2 provides a graphical representation of the percentage of hedge funds that are ranked into deciles based on their alphas both from the FH-7 model specification in (12) and the augmented FH-7 model specification in (19). The level of the bars along the diagonal (D1/D1, D2/D2,...,D10/D10) signify the percentage of funds that are ranked in the same deciles using the two models, and the off-diagonal bars represent the percentage of funds that have inconsistent decile rankings. For instance, the size of the off-diagonal bars in the first row of Figure 2 suggest that more than 30 percent of the funds that are ranked in the top decile based on alphas from the FH-7 model specification appear in a different decile once the funds exposures to FVOL, FSKEW, and FKURT are internalized. To further appreciate what is going on, consider the level of the second blue bar in the first row from the left. Now we see that 20 percent of the funds are ranked in the top decile using the FH-7 model but in the *second* decile using the augmented FH-7 model. Thus, the higher-moment risks wield a sizeable influence on hedge fund ranking. Realize that if we had not found any difference in the rankings of hedge funds with the inclusion of higher-moment factor returns, it would have been a cause for concern and would have casted doubt on the practical relevance of higher moment exposures. Putting it all together, this exercise provides additional supportive evidence that higher-moment risk dimensions can have a substantial impact on hedge fund returns and investors' selection of superior hedge funds.

2.6 Higher-moment exposures and distribution of investment style categories

Of possible interest here is to investigate whether certain hedge fund styles more actively seek higher-moment exposures. To describe such a test, fix an investment style category from CSFB/Tremont and compute the frequency at which hedge funds that follows that strategy end up in each of triple-sorted 27 portfolios. At the same time, we calculate the unconditional average which is the average proportion of funds by that strategy in our sample. Then we test whether the observed frequencies are jointly different from the unconditional average. We focus on a chi-squared test for differences in proportions, as hedge fund universe are not symmetrically distributed across investment styles. For example, long/short hedge funds comprise 37.48%, while market neutral funds comprise 5.31%, of the hedge fund universe (see Table 5).

Concentrate first on the triple-sorted portfolios P1 (denoted H/H/H), P14 (denoted M/M/M), and P27 (denoted L/L/L) that exhibit the most positive, near-zero, and most negative exposure to volatility, skewness, and kurtosis risks (as shown earlier in Table 2). The unconditional and conditional frequencies as well as the p-value from the chi-squared test of difference in proportions reported in Table 5 are informative about hedge fund exposures by investment strategy. In particular, the entry of 41.06% and 2.29%, respectively for Long/Short and Market Neutral strategy, reflects the conditional frequency of that style being in the most positively exposed portfolio P1. Our aim is to examine whether these proportions are different across the P1, P14, and P27 portfolios.

If we observe a U-shaped pattern in frequency emerging for certain strategies in Table 5, it implies that a greater fraction of funds showing positive or negative exposures to the three higher-moment risks compared to medium exposures. Specifically, we observe a conditional frequency of 41.06% for P1 (H/H/H), 44.42% for P27 (L/L/L) and 16.31% for P14 (M/M/M)) for the Long/Short Equity strategy. The p-value of 0.00 corresponds to the null hypothesis that Frequency(P1)= Frequency(P14) = Frequency(P27) = 37.48%, where the unconditional average frequency is 37.48%. The main idea is that if the conditional frequency is statistically different from the unconditional frequency for a hedge fund style, it validates the presence of extreme higher-moment exposures for that style.

Searching for such patterns in other strategies reveals that in addition to Long/Short Equity strategy, Emerging Markets,[8] Managed Futures, and Global Macro, also exhibit U-shaped patterns. Together, these strategies account for 62.28% of the hedge fund universe. Thus, the significance of this result is that a critical mass of hedge funds show heavy exposures (positive or negative) to higher-moment risks.

Other hedge fund styles show hump-shaped pattern in frequencies, i.e., lower frequencies for P1 and P27 portfolios that have extreme (high or low) exposures to higher-moment risks but higher

[8]The heavy concentration of Emerging Markets funds in extreme portfolios may seem surprising at first glance as we are using higher-moment risks of US equity market. However, this result can be explained by the fact that global equity markets are more strongly correlated with U.S. equities during periods of extreme returns (Longin and Solnik (2001)).

frequency for P14 portfolio that corresponds to medium higher-moment exposure. Styles that fall in this category include Event Driven, Market Neutral, Convertible Arbitrage, Fixed Income Arbitrage, and Multi-Strategy. Since, on average, the "M" portfolio corresponds to near-zero exposure, certain hedge fund styles are not geared towards exploiting higher-moment equity risks.

To examine the variation *within* each higher-moment risk, we also present the frequencies for the nine portfolios showing High (H), Medium (M), and Low (L) exposures to volatility, skewness, and kurtosis risks. For instance, the frequency for the portfolio with the most negative exposure to volatility risk (VOL-L) will correspond to average frequency for the portfolios P19 to P27. Notice that VOL-L portfolio is dominated by styles tilted towards Long/Short, Managed Futures, and Emerging Markets.

Now we determine if the styles with greater sensitivity to the these risks show extreme exposures to *each* of the three higher-moment risks *individually*. Five out of 9 strategies show a U-shape response with respect to frequencies. The p-value of 0.00 suggests that these frequencies are jointly different from the unconditional average frequency. With respect to portfolios sensitive to skewness and kurtosis risks, we observe a U-shaped frequency pattern for Long/Short Equity, Emerging Markets, Managed Futures, and to some extent, Global Macro styles. Further, we continue to find hump-shaped frequency pattern for Event Driven, Convertible Arbitrage, Fixed Income Arbitrage, and Multi-Strategy styles. In general, the frequency patterns are narrower compared to portfolios P1 and P27. Among various styles, Market Neutral Funds do not show any difference among each higher-moment risks, with p-values of at least 0.31.

Overall, our findings from P1 and P27 portfolios as well as from higher-moment portfolios confirm that only certain hedge fund styles such as Long/Short Equity, Emerging Markets, Managed Futures exhibit extreme higher-moment exposures. These extreme exposures are not concentrated in one-direction with a large proportion of funds showing both high and low exposures of opposite sign. This raises the possibility that one could neutralize higher-moment risks both across funds within an investment style and across different hedge fund styles. Such a finding has practical implications for investors and regulators searching for ways to manage their risks. Motivated by our findings, we now turn to an analysis of funds of hedge funds.

3 Higher-moment exposures and alphas from Funds of Hedge Funds

If the enormous popularity of FOFs among institutional investors is any indicator, the return on FOFs may more accurately represent returns earned by hedge fund investors (Brown et al. (2004), Ang et al. (2007b), and Fung et al. (2007)). Despite the additional layer of fees, FOFs are attractive as they have lower investment thresholds, offer due diligence services, and provide access to otherwise closed hedge funds. Indeed, FOFs now account for a predominant portion of inflows in the hedge fund industry. Equally germane is the fact that FOFs are less susceptible to data biases such as backfilling and survivorship. The principal argument put forth is that return histories of FOFs already incorporates the performance of hedge funds that have disappeared from the database (Fung and Hsieh (2000)).

To shed light on higher-moment risks from a different angle, we appeal to a sample of FOFs. Here we pose two substantive questions: First, what is the strength of volatility, skewness, and kurtosis risk exposures in the cross-section of FOFs? Second, do the exposures translate into large dispersion in alphas based on the FH-7 model?

Since FOFs have sufficient latitude to invest in hedge funds following different trading strategies, they could be conceived as having higher-moment risk exposures of varying intensity. First, if effective risk management for clients is the objective, then it could be argued that FOFs should be neutralizing higher-moment risk exposures. If this is indeed what FOFs do, one should observe little dispersion in the cross-section of higher-moment betas. To fix ideas, suppose a FOF invests 46% in portfolio P1 and 54% in portfolio P27, then it can effectively neutralize volatility, skewenss, and kurtosis risks simultaneously based on the higher-moment betas reported in Table 2.

On the other hand, FOFs could have incentives not to diversify higher-moment risks if it helps them in delivering greater returns. Drawing on the idea that compensation contracts hinge on total returns, and not risk-adjusted returns (or alphas), FOFs may actively seek to load on higher-moment risks in order to boost their compensation. Because the average risk premium for volatility and kurtosis risks is negative and is positive for skewness risk, it is desirable for FOFs to have negative exposures to volatility and kurtosis and positive exposures to skewness.

Finally, if FOFs choose hedge funds according to some internal model without knowing their higher-moment exposures, then we anticipate that FOF should exhibit narrower cross-sectional dispersion in exposures compared to hedge funds. Offsetting of higher-moment risk exposures may occur for a FOF by holding disparate hedge funds. From a general economic perspective, it is of interest to examine which of these three possibilities are borne out by the FOF data.

To answer the first question, we perform three-way sorts of FOFs based on their exposures to ΔVOL, ΔSKEW, and ΔKURT. Table 6 reports the pre-ranking loadings and the post-ranking alphas when FOFs are conditionally sorted into 27 portfolios. At the outset, we observe that the magnitudes of exposures are reduced by nearly 60 percent in comparison to Table 2 where we had included both individual hedge funds and FOFs in the sample. The cross-sectional standard deviation of $\beta_{\Delta VOL}$, $\beta_{\Delta SKEW}$, and $\beta_{\Delta KURT}$ across the 27 portfolios is 1.63, 4.02, 0.66 for FOFs compared to 2.66, 6.44, 1.13 with the combined sample of hedge funds and FOFs, implying a huge reduction in the dispersion of the loadings. Thus, FOFs may not be good candidates for extracting the premiums that are earned for taking higher-moment exposures. Finally, judging by the structure of $\beta_{\Delta VOL}$, $\beta_{\Delta SKEW}$, and $\beta_{\Delta KURT}$, it is is evident that FOFs do not completely neutralize exposure to higher-moment risks. At the same time, FOFs do not deliberately load up on such risks in order to earn higher returns and therefore to maximize their incentive fees.

Reflecting on the second question, an increasing pattern in post-ranking alphas is observed as one moves from FOF portfolio P1 to P27. There is also a significant dispersion in the alphas, ranging from -10.58% for P1 to 6.73% for P27. In other words, the portfolio of FOFs with the most positive (negative) exposures to volatility, skewness, and kurtosis risks experience the most negative (positive) alpha. Given the smaller dispersion in pre-ranking higher-moment betas for FOFs versus the combined sample of hedge funds and FOFs, it is difficult to visualize the commonality in alpha spreads between Table 6 and Table 2. One reason is that FH-7 model performs better for individual hedge funds than for FOFs, as seen by the lower R-squares for FOFs compared to those for the combined sample.

We conclude by emphasizing the main points. One, the sensitivities of FOFs to higher-moment risks are ameliorated across the board. Two, FOFs may be natural vehicles to offset higher-moment exposures, and therefore reduce the impact of higher-moment risks. As such, this may be an additional crucial benefit, unidentified in the extant literature, accruing to FOF investors. The reluctance in fully diversifying higher-moment risks has wider implications for understanding the tradeoffs faced by FOFs between their risk management practices and their incentives arising from performance-based compensation. Finally, investors vying to exploit higher-moment exposures to amplify their returns are better off investing in individual hedge funds rather than in FOFs.

4 Comparison with Equity Mutual Funds

In this section, we first compare and distinguish the results for hedge funds with another group of managed portfolios — equity mutual funds. Unlike hedge funds, mutual funds are relative-return managers. This implies that their performance can be benchmarked to returns on standard asset classes (Fung and Hsieh (1997)). In contrast to hedge funds, mutual funds seldom exploit short-selling, derivatives, and leverage (Koski and Pontiff (1999), Ackermann et al. (1999), Deli and Varma (2002), Almazan et al. (2004), and Griffin and Xu (2008)), which suggests that they do not follow dynamic trading strategies and therefore, are less likely to be exposed to higher-moment equity risks. This is the main testable prediction explored in this section.

Adopting a procedure similar to hedge funds, we place mutual funds into three-way sorted portfolios based on their exposure to ΔVOL, ΔSKEW, and ΔKURT. We then compute equally-weighted out-of-sample mutual fund returns using three months' wait for reformation of the portfolios to ensure a common basis for comparison with hedge funds.[9] Table 7 reports the pre-ranking betas on higher-moment risks and the spreads in post-ranking alphas of mutual fund portfolios conditionally sorted on their exposures to the three higher-moment risks. As mentioned before, the Carhart-4 model is a more appropriate benchmark for equity mutual funds and hence we refrain from a comparison with spreads in hedge fund alphas, which are based on the FH-7 model.

The dispersion in pre-ranking exposures vary between 3.47 to -2.47 for ΔVOL, 10.73 to -8.11 for ΔSKEW, and between -1.49 and 0.41 for ΔKURT. The cross-sectional standard deviation of $\beta_{\Delta VOL}$, $\beta_{\Delta SKEW}$, and $\beta_{\Delta KURT}$ across the 27 portfolios is 1.63, 4.03, 0.67 for mutual funds. These figures are smaller than the corresponding values of 2.66, 6.44, 1.13 for hedge funds, implying a huge reduction in the dispersion of the loadings. Moreover, the patterns in alphas across the sorted portfolios of mutual funds are far from pronounced: the spread in Carhart-4 alphas between the two extreme portfolios, P1 and P27, is 1.90 percent for mutual funds. Now the results from the Gibbons et al. (1989) test of all alphas being jointly equal to zero yields a p-value of 0.05. Comparing this result with that for hedge

[9] There are no explicit impediments to capital withdrawal such as lockup and notice periods for mutual fund investors. To carefully address this issue, we also examine mutual fund results without the waiting period. Since the two set of results are mutually consistent, the results without the waiting period are not reported.

funds earlier, there is stronger evidence of mutual fund alphas being not that different from zero. On balance, the documented results on the lower dispersion in exposures and the lower spreads in alphas support our claims of hedge funds being special in their being exposed to higher-moment risks.[10]

5 Follow-up Empirical Tests

Here we show that our findings on individual hedge funds are unlikely to be reversed by estimation error, backfilling bias, and to the inclusion of omitted systematic risk factors.

5.1 Robustness to estimation error and backfilling bias

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. One therefore faces the possibility that the factor risk premiums on higher-moments might actually be different from what we observe through our analysis.

To investigate this important concern, we employ a Bayesian framework to estimate pre-ranking betas in the formation period more efficiently. In doing so, we exploit empirical Bayes approach to estimate the regression in equation (14) in the formation period. Bayesian approaches to estimate alphas and factor sensitivities based on a limited number of return observations have been employed by Baks et al. (2001), Pastor and Stambaugh (2002), Jones and Shanken (2005), Busse and Irvine (2006) and Huij and Verbeek (2007) in the context of mutual funds, and by Kosowski et al. (2007) in the context of hedge funds.

To go to the heart of the issue, we present three-way sorted portfolios' out-of-sample risk-adjusted performance in Panel A of Table A-1 (in the Appendix). Considering that Bayesian methodology usually leads to the shrinkage of alphas between best and worst performers (i.e., Huij and Verbeek (2007) and Kosowski et al. (2007)), our finding that the alpha dispersion of -22.25 percent for sorts

[10]To strengthen this finding, we also conduct our analysis for mutual funds extending the sample from January 1984 to December 2004, the longest possible sample for which we can construct higher-moment risk measures from options market. Although we have restrictions for hedge funds in terms of using longer time series and using longer regression windows, the same does not apply to equity mutual funds. When we select all equity mutual funds from the CRSP database over January 1984 to December 2004 to construct triple-sorted portfolios and evaluate their post-ranking performance using the Carhart-4 model, we continue to observe the lack of significant spreads in alphas (results not reported).

based on Bayesian estimates of higher-moment betas does not depart from the OLS counterpart is worth highlighting. Thus, our key findings are not materially affected by estimation error.

To mitigate backfilling bias, we discard the first 24 return observations for all hedge funds. This sample has 2,541 hedge funds, and, on average, 847 funds are available in the cross-section at the beginning of each year (ranging from 289 funds in 1995 to 1,409 funds in 2004). Results in Panel B of Table A-1 (in the Appendix) indicate that our conclusions regarding the spreads in alphas remain unchanged even though we lose 33 percent of our fund sample due to removal of first two years' of data. The spread in alphas between the top and bottom portfolios is still –20.30 percent per year.

5.2 Robustness to omitted systematic risk factors

Our first task is to investigate the extent to which spreads in alphas for the three-way sorted portfolios are captured by the extended Fung and Hsieh (2001, 2004) nine-factor model (henceforth, FH-9):

$$\begin{aligned} r_t^i &= \alpha_{FH9}^i + \beta_{FH9}^{1,i}\,\mathrm{SNPMRF}_t + \beta_{FH9}^{2,i}\,\mathrm{SCMLC}_t + \beta_{FH9}^{3,i}\,\mathrm{BD10RET}_t + \beta_{FH9}^{4,i}\,\mathrm{BAAMTSY}_t \\ &+ \beta_{FH9}^{5,i}\,\mathrm{PTFSBD}_t + \beta_{FH9}^{6,i}\,\mathrm{PTFSFX}_t + \beta_{FH9}^{7,i}\,\mathrm{PTFSCOM}_t \\ &+ \beta_{FH9}^{8,i}\,\mathrm{PTFSSTK}_t + \beta_{FH9}^{9,i}\,\mathrm{PTFSIR}_t + \varepsilon_{t,FH9}^i, \end{aligned} \tag{20}$$

where $\mathrm{PTFSSTK}_t$ is the primitive trend following strategy in equity, and PTFSIR_t is the primitive trend following strategy in interest rates in month t. Panel A in Table A-2 (in the Appendix) reports the alphas resulting from the FH-9 model. 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 equity and interest rates.

The next task is to examine robustness to the OTM put option factor of Agarwal and Naik (2004) by augmenting the FH-7 model with OTMPUT. Panel B of Table A-2 reports the annualized alphas obtained through our three-way sorted portfolios. We continue to observe significant spreads in alphas for FH-7 mirroring our results from Table 2.

Finally, periods of high volatility coincide with periods of high market illiquidity (Pastor and Stambaugh (2003)). 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 LIQ factor available from Wharton Research Data Services. Panel C of Table A-2 reports the annualized alphas for our three-way sorted portfolios. Significant spreads in alphas is again observed as in Table 2. In sum, liquidity effects are unlikely to explain spreads in alphas resulting from sensitivity of hedge funds to higher–moment risks.

6 Concluding Remarks and Summary

In this paper, we examine the role of higher-moment risks in explaining the cross-section of hedge fund returns. We accomplish five objectives.

First, we show a significant dispersion in alphas of hedge fund portfolios obtained from both single-sorting and conditional three-way sorting of hedge funds based on their exposures to market volatility, skewness, and kurtosis risks.

Second, using three-way sorted portfolios of hedge funds based on their exposures to higher–moments, we show significant premiums for market volatility, skewness, and kurtosis risks of about –6.50 percent, 3.40 percent, and –2.40 percent per year. Furthermore, we find that hedge funds earn excess returns up to 3.7 percent, 2.9 percent, and 2.6 percent per year for exposure to volatility, skewness, and kurtosis risks, respectively.

Third, we show that the spreads in alphas are not subsumed by the seven factor model and the extended nine-factor model in Fung and Hsieh (2001, 2004). In particular, the factor returns on the higher–moments are not redundant in the presence of lookback straddles and not strongly associated with size and book-to-market factors.

Fourth, our empirical investigation finds that funds of hedge funds refrain from loading aggressively on higher-risks. Specifically, we observe dispersions in higher-moment betas that are 60 percent of those for the pooled sample of hedge funds and funds of hedge funds. These results indicate that funds of hedge funds do not completely neutralize higher-moment risks but do offset them partially while constructing their portfolios. Hence, investors vying to exploit higher-moment market exposures to enhance their returns are better off investing in hedge funds rather than in funds of hedge funds.

Fifth, our analysis reveals that equity mutual funds are not exposed in a substantial way to higher-moment risks, and spreads in alphas for extreme mutual fund portfolios are statistically insignificant based on the Carhart (1997) model.

Finally, ignoring higher-moment risk factors in multifactor models to estimate hedge fund alphas can potentially lead to the overestimation of alphas, thereby giving the appearance that hedge funds are delivering alphas when in fact they are significantly exposed to higher-moment risks. Thus, hedge fund managers may appear skilled if one fails to account for higher-moment risk exposures in the performance evaluation exercise. Moreover, it is shown that when a class of existing multifactor models for evaluating hedge fund performance are augmented with higher-moment factor returns, we can better explain the variation in hedge fund returns.

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Table 1: Portfolios of hedge funds single-sorted by their exposure to volatility, skewness, and kurtosis risks (ΔVOL, ΔSKEW and ΔKURT)

		Pre-ranking exposures for higher-moment risks				FH-7 Model (post-ranking)		
		β_{RMRF}	$\beta_{\Delta VOL}$	$\beta_{\Delta SKEW}$	$\beta_{\Delta KURT}$	Alpha	Alpha-*t*	Adj.Rsq.
		A. Sorts on exposure to ΔVOL						
D1	H	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	0.18	-5.76	-5.26	-1.17	10.82%	4.65	53%
D1-D10						-13.47%	-3.82	12%
Joint *p*-value						[0.00]		
		B. Sorts on exposure to ΔSKEW						
D1	H	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	0.20	-2.72	-12.32	-1.87	10.27%	4.65	42%
D1-D10						-14.85%	-4.10	14%
Joint *p*-value						[0.00]		

Table 1 continued

		Pre-ranking exposures for higher-moment risks				FH-7 Model (post-ranking)		
		β_{RMRF}	$\beta_{\Delta VOL}$	$\beta_{\Delta SKEW}$	$\beta_{\Delta KURT}$	Alpha	Alpha-*t*	Adj.Rsq.
		C. Sorts on exposure to ΔKURT						
D1	H	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	0.29	-3.18	-11.05	-2.14	10.87%	4.78	40%
D1-D10						-14.58%	-4.04	10%
Joint *p*-value						[0.00]		

Reported are average pre-ranking higher–moment betas and post-ranking alphas, *t*-statistics and adjusted *R*-squared values of the deciles from regressions with the Fung and Hsieh (2004) factors. Under our procedure, 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: $r_t^i = \alpha_{4F}^i + \beta_{RMRF}^i RMRF_t + \beta_{\Delta VOL}^i \Delta VOL_t + \beta_{\Delta SKEW}^i \Delta SKEW_t + \beta_{\Delta KURT}^i \Delta KURT_t + \varepsilon_t^i$, where $r_{i,t}$ represents excess return on the hedge fund, $RMRF_t$ is excess return on the market portfolio in month t, and ΔVOL_t, $\Delta SKEW_t$ and $\Delta KURT_t$ are our proxies for equity volatility risk, skewness risk, and kurtosis risk, as defined in (9)–(11). $\varepsilon_{4F}^{i,t}$ represents the residual return in month t. Reported post-ranking alphas are annualized. Throughout, our empirical tests use monthly net-of-fee returns of hedge funds from the 2004 Lipper Hedge Fund Database over the period January 1994 to December 2004. The exclusionary criterion used to construct the hedge fund sample is delineated in Section 1.2. In all, our sample covers 3,771 hedge funds and funds of funds. The row marked “Joint p-value” reports the p-value for the Gibbons et al. (1989) test that all the post-ranking alphas are jointly equal to zero.

Table 2: Portfolios of hedge funds triple-sorted by their exposure to ΔVOL, ΔSKEW and ΔKURT, and post-ranking regression results

		Pre-ranking exposures for higher-moments				FH-7 Model (post-ranking)		
		β_{RMRF}	$\beta_{\Delta\text{VOL}}$	$\beta_{\Delta\text{SKEW}}$	$\beta_{\Delta\text{KURT}}$	Alpha	Alpha-t	Adj.Rsq.
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%
Joint p-value						[0.00]		

Reported are average pre-ranking higher–moment betas and post-ranking alphas, t-statistics and adjusted R-squared values of the quantile portfolio from regressions with the Fung and Hsieh (2004) factors. Each month hedge funds are sorted into equally-weighted triple-sorted quantile 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 $r_{i,t}$ represents excess return on the hedge fund, RMRF_t is excess return on the market portfolio in month t, and ΔVOL_t, ΔSKEW_t and ΔKURT_t are our proxies for equity volatility risk, skewness risk, and kurtosis risk. $\varepsilon_{4F}^{i,t}$ represents the residual return in month t. Reported post-ranking alphas are annualized. The sample is from 1994 to 2004 and covers 3,771 hedge funds and funds of funds. The row marked "Joint p-value" reports the p-value for the Gibbons et al. (1989) test that all the post-ranking alphas are jointly equal to zero.

Table 3: Characteristics of factor risk premiums on volatility, skewness, and kurtosis risks, and alphas from the Fung and Hsieh (2001, 2004) 7-Factor model

	mean	t-stat	correlation matrix			FH-7 Model		
			FVOL	FSKEW	FKURT	Alpha	Alpha-t	Adj.Rsq
FVOL	-6.55%	-3.61	1.00			-7.10%	-3.91	9%
FSKEW	3.40%	2.25	-0.41	1.00		4.36%	2.85	8%
FKURT	-2.39%	-2.00	0.25	-0.32	1.00	-3.31%	-2.68	5%

Reported are annualized time-series averages and t-statistics of the three higher–moment risk factor premiums, and the correlation matrix between the higher-moment risk factor premiums. Following Fama and French (1993) and Liew and Vassalou (2000), the higher–moment return factors are computed as,

$$\begin{aligned} \text{FVOL} &= \frac{1}{9}(P1+P2+P3+P4+P5+P6+P7+P8+P9)-\frac{1}{9}(P19+P20+P21+P22+P23+P24+P25+P26+P27), \\ \text{FSKEW} &= \frac{1}{9}(P7+P8+P9+P16+P17+P18+P25+P26+P27)-\frac{1}{9}(P1+P2+P3+P10+P11+P12+P19+P20+P21), \\ \text{FKURT} &= \frac{1}{9}(P1+P4+P7+P10+P13+P16+P19+P22+P25)-\frac{1}{9}(P3+P6+P9+P12+P15+P18+P21+P24+P27), \end{aligned}$$

where $P1$ to $P27$ are the equally-weighted triple-sorted portfolios of hedge funds based on their higher-moment betas in Table 2. To get the alphas, each return factor is regressed on the Fung and Hsieh (2001, 2004) model specification, as in:

$$\begin{aligned} \text{FVOL}_t &= \alpha+\beta_1\,\text{SNPMRF}_t+\beta_2\,\text{SCMLC}_t+\beta_3\,\text{BD10RET}_t+\beta_4\,\text{BAAMTSY}_t+\beta_5\,\text{PTFSBD}_t+\beta_6\,\text{PTFSFX}_t+\beta_7\,\text{PTFSCOM}_t+\varepsilon_t, \\ \text{FSKEW}_t &= \alpha+\beta_1\,\text{SNPMRF}_t+\beta_2\,\text{SCMLC}_t+\beta_3\,\text{BD10RET}_t+\beta_4\,\text{BAAMTSY}_t+\beta_5\,\text{PTFSBD}_t+\beta_6\,\text{PTFSFX}_t+\beta_7\,\text{PTFSCOM}_t+\varepsilon_t, \\ \text{FKURT}_t &= \alpha+\beta_1\,\text{SNPMRF}_t+\beta_2\,\text{SCMLC}_t+\beta_3\,\text{BD10RET}_t+\beta_4\,\text{BAAMTSY}_t+\beta_5\,\text{PTFSBD}_t+\beta_6\,\text{PTFSFX}_t+\beta_7\,\text{PTFSCOM}_t+\varepsilon_t. \end{aligned}$$

Reported are the annualized alphas, t-statistics, and R-squared values.

Table 4: Portfolios of hedge funds triple-sorted by their exposure to ΔVOL, ΔSKEW and ΔKURT, and post-ranking regressions results using augmented Fung and Hsieh 7-factor model

		Augmented FH-7 Model Post-ranking exposures								
		Alpha	Alpha-t	β_{FVOL}	t	β_{FSKEW}	t	β_{FKURT}	t	Adj.Rsq
P1	H / H / H	9.45%	2.87	1.24	7.14	-0.59	-3.39	1.12	6.45	74%
P2	H / H / M	4.64%	2.68	0.68	7.43	-0.61	-6.69	-0.09	-0.96	80%
P3	H / H / L	4.30%	2.07	0.63	5.80	-1.02	-9.30	-1.08	-9.86	75%
P4	H / M / H	6.97%	3.77	0.51	5.26	0.09	0.89	0.51	5.23	66%
P5	H / M / M	5.10%	3.95	0.45	6.60	-0.09	-1.26	-0.02	-0.25	72%
P6	H / M / L	3.91%	2.81	0.39	5.34	-0.35	-4.71	-0.66	-9.04	71%
P7	H / L / H	2.31%	1.32	0.37	4.03	0.39	4.26	0.49	5.33	61%
P8	H / L / M	4.25%	2.36	0.57	5.99	0.31	3.31	-0.16	-1.70	59%
P9	H / L / L	5.03%	2.03	0.83	6.38	0.85	6.54	-0.56	-4.27	54%
P10	M / H / H	3.51%	2.08	0.01	0.07	-0.58	-6.59	0.29	3.26	66%
P11	M / H / M	5.11%	4.27	0.03	0.44	-0.25	-3.94	-0.08	-1.20	56%
P12	M / H / L	2.86%	2.64	-0.03	-0.47	-0.30	-5.35	-0.37	-6.49	61%
P13	M / M / H	5.53%	5.66	0.07	1.27	-0.04	-0.74	0.10	1.95	56%
P14	M / M / M	4.01%	6.13	0.03	0.93	0.03	0.87	-0.07	-2.16	40%
P15	M / M / L	4.18%	4.40	0.02	0.39	-0.10	-1.98	-0.28	-5.51	57%
P16	M / L / H	5.55%	5.12	0.08	1.44	0.23	4.07	0.25	4.33	57%
P17	M / L / M	4.77%	4.45	0.07	1.16	0.15	2.71	-0.18	-3.26	55%
P18	M / L / L	5.08%	3.31	0.25	3.09	0.34	4.15	-0.39	-4.86	58%
P19	L / H / H	3.63%	1.51	-0.57	-4.53	-0.66	-5.23	0.51	3.99	60%
P20	L / H / M	4.94%	3.63	-0.41	-5.70	-0.46	-6.39	0.14	1.97	69%
P21	L / H / L	7.16%	3.76	-0.38	-3.75	-0.76	-7.60	-0.89	-8.85	62%
P22	L / M / H	3.61%	2.44	-0.39	-4.99	-0.16	-2.07	0.30	3.80	62%
P23	L / M / M	4.39%	3.44	-0.30	-4.44	-0.12	-1.83	-0.06	-0.84	65%
P24	L / M / L	3.62%	2.26	-0.32	-3.83	-0.33	-3.91	-0.56	-6.69	67%
P25	L / L / H	3.68%	2.14	-0.33	-3.67	0.37	4.05	0.43	4.79	67%
P26	L / L / M	6.84%	3.61	-0.21	-2.10	0.41	4.12	-0.10	-0.95	58%
P27	L / L / L	8.09%	2.77	-0.42	-2.76	0.71	4.63	-0.23	-1.47	46%
P1-P27		1.36%	0.64	1.66	14.92	-1.30	-11.67	1.34	12.06	88%
Joint p-value		[0.00]		[0.00]		[0.00]		[0.00]		

Reported are post-ranking alphas, t-statistics and adjusted R-squared values of the quantile portfolios from regressions with the Fung and Hsieh (2001,2004) factors together with the FVOL, FSKEW, and FKURT as factors, where FVOL, FSKEW, and FKURT are the factor risk premiums for volatility, skewness, and kurtosis risks, respectively. The ten factor model is:

$$
\begin{aligned}
r_t^i &= \alpha_{10F}^i + \beta_{10F}^{1,i}\,\text{SNPMRF}_t + \beta_{10F}^{2,i}\,\text{SCMLC}_t + \beta_{10F}^{3,i}\,\text{BD10RET}_t + \beta_{10F}^{4,i}\,\text{BAAMTSY}_t \\
&\quad + \beta_{10F}^{5,i}\,\text{PTFSBD}_t + \beta_{10F}^{6,i}\,\text{PTFSFX}_t + \beta_{10F}^{7,i}\,\text{PTFSCOM}_t \\
&\quad + \beta_{\text{FVOL}}^i\,\text{FVOL}_t + \beta_{\text{FSKEW}}^i\,\text{FSKEW}_t \;+\; \beta_{\text{FKURT}}^i\,\text{FKURT}_t \;+\; \varepsilon_{t,10F}^i .
\end{aligned}
$$

Reported are the post-ranking factor loadings on FVOL, FSKEW, and FKURT and the annualized alphas. Each month hedge funds are sorted into equally-weighted triple-sorted quantile 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 RMFT_t is excess return on the market portfolio in month t, and ΔVOL_t, ΔSKEW_t and ΔKURT_t are our proxies for equity volatility risk, skewness risk, and kurtosis risk. The sample is from 1994 to 2004 and covers 3,771 hedge funds and funds of funds.

Table 5: Distribution of investment style categories for triple-sorted hedge fund portfolios

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

The first row of this table labeled "Average" reports the average frequency of hedge funds classified according to their investment styles as a fraction of the total number of funds. The style definitions are from CSFB/Tremont available at www.hedgeindex.com. For computing the average frequencies, we compute the frequency each month for each style and then the entries are averaged across all months. The next three rows report the frequency distribution of different hedge fund styles for 3 out of the 27 portfolios triple-sorted by their exposures to ΔVOL, ΔSKEW and ΔKURT. The three portfolios – P1, P14, and P27, show the highest (H/H/H), medium (M/M/M), and lowest (L/L/L) exposures to the three higher-moment risks. The next row reports the p-value from a multivariate chi-squared test of difference in proportions that compares if the frequencies in the P1, P14, and P27 portfolios are jointly different from the average (in the first row) for each of the investment styles. The table also reports the average frequencies across the 9 groups – H, M, L, for each of the higher-moment risks, VOL, SKEW, and KURT. As shown previously, the proportion in Volatility H are: $\frac{1}{9}(P1+P2+P3+P4+P5+P6+P7+P8+P9)$ and in Volatility L are: $\frac{1}{9}(P19+P20+P21+P22+P23+P24+P25+P26+P27)$, and similarly for others. The p-values reported for the three groups of VOL, SKEW, and KURT correspond to the multivariate chi-squared test for the frequencies across those three groups being jointly different from the average reported in the first row.

Table 6: Portfolios of funds of hedge funds (FOFs) triple-sorted by their exposure to ΔVOL, ΔSKEW and ΔKURT, and post-ranking regression results

		Pre-ranking exposures				FH-7 Model (post-ranking)		
		β_{RMRF}	$\beta_{\Delta\text{VOL}}$	$\beta_{\Delta\text{SKEW}}$	$\beta_{\Delta\text{KURT}}$	Alpha	Alpha-t	Adj.Rsq.
P1	H / H / H	0.44	3.87	10.78	1.91	-10.58%	-2.50	30%
P2	H / H / M	0.33	2.23	5.96	0.97	-5.59%	-1.87	34%
P3	H / H / L	0.33	1.67	4.40	0.54	-2.30%	-0.90	30%
P4	H / M / H	0.23	1.73	2.56	0.59	-1.11%	-0.62	32%
P5	H / M / M	0.24	1.22	2.09	0.34	-0.06%	-0.04	42%
P6	H / M / L	0.28	1.12	1.53	0.14	1.07%	0.60	39%
P7	H / L / H	0.14	1.54	-0.01	0.24	-0.31%	-0.15	23%
P8	H / L / M	0.20	1.15	-0.56	-0.01	0.13%	0.08	33%
P9	H / L / L	0.23	1.42	-3.32	-0.48	-1.83%	-0.54	15%
P10	M / H / H	0.18	0.13	4.13	0.63	1.75%	0.81	27%
P11	M / H / M	0.18	0.15	2.08	0.27	2.55%	1.88	37%
P12	M / H / L	0.24	0.09	1.64	0.09	3.63%	2.72	40%
P13	M / M / H	0.16	0.11	0.71	0.15	2.01%	1.70	42%
P14	M / M / M	0.18	0.04	0.47	0.04	3.17%	3.04	41%
P15	M / M / L	0.22	0.01	0.24	-0.09	3.57%	2.63	43%
P16	M / L / H	0.15	0.03	-0.59	-0.03	3.52%	2.80	40%
P17	M / L / M	0.18	-0.03	-1.01	-0.18	3.76%	3.27	42%
P18	M / L / L	0.21	-0.02	-2.57	-0.50	2.12%	1.22	27%
P19	L / H / H	0.15	-1.37	4.00	0.59	1.42%	0.52	25%
P20	L / H / M	0.16	-0.93	1.45	0.11	2.93%	1.62	33%
P21	L / H / L	0.20	-1.23	0.96	-0.14	2.67%	1.55	37%
P22	L / M / H	0.13	-1.02	-0.26	-0.03	4.44%	2.69	33%
P23	L / M / M	0.18	-1.02	-0.64	-0.19	5.73%	3.81	26%
P24	L / M / L	0.20	-1.35	-0.99	-0.39	5.62%	3.22	25%
P25	L / L / H	0.13	-1.49	-2.32	-0.36	4.52%	2.73	33%
P26	L / L / M	0.16	-1.89	-3.54	-0.70	4.15%	1.85	12%
P27	L / L / L	0.19	-3.29	-8.71	-1.73	6.73%	1.85	17%
P1-P27						-17.31%	-2.87	18%
Joint *p*-value						[0.00]		

Reported are post-ranking alphas, t-statistics and adjusted R-squared values of the quantile portfolio from regressions with the Fung and Hsieh (2004) factors. The sample is from 1994 to 2004 and covers 1,062 funds of hedge funds. We apply the same criterion as Fung et al. (2007) to construct the fund of funds sample. Each month funds of hedge funds are sorted into equally-weighted triple-sorted quantile 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 $r_{i,t}$ represents excess return on the hedge fund, RMRF_t is excess return on the market portfolio in month t, and ΔVOL_t, ΔSKEW_t and ΔKURT_t are our proxies for equity volatility risk, skewness risk, and kurtosis risk. ε_t^i represents the residual return in month t. Reported post-ranking alphas are annualized. The row marked "Joint p-value" reports the p-value for the Gibbons et al. (1989) test that all the post-ranking alphas are jointly equal to zero.

Table 7: Portfolios of mutual funds triple-sorted by exposure to higher-moment risks

		Pre-ranking Exposures for:				Carhart-4 Model (post-ranking)		
		β_{RMRF}	$\beta_{\Delta\text{VOL}}$	$\beta_{\Delta\text{SKEW}}$	$\beta_{\Delta\text{KURT}}$	Alpha	Alpha-t	Adj.Rsq.
P1	H / H / H	1.51	3.47	10.73	1.79	-1.49%	-0.52	89%
P2	H / H / M	1.31	2.62	7.00	1.06	-3.14%	-1.36	91%
P3	H / H / L	1.28	2.22	5.77	0.66	-3.88%	-1.97	93%
P4	H / M / H	1.18	2.18	3.60	0.82	-6.06%	-3.11	92%
P5	H / M / M	1.09	1.73	3.03	0.50	-5.24%	-3.56	95%
P6	H / M / L	1.05	1.55	2.40	0.21	-3.33%	-2.24	95%
P7	H / L / H	1.04	1.72	0.22	0.43	-5.59%	-2.02	84%
P8	H / L / M	0.93	1.45	-0.52	0.07	-4.76%	-2.55	91%
P9	H / L / L	0.91	1.47	-2.69	-0.41	-5.53%	-2.62	88%
P10	M / H / H	1.11	0.24	4.44	0.73	-2.36%	-1.16	89%
P11	M / H / M	1.00	0.17	2.40	0.31	-2.51%	-2.02	95%
P12	M / H / L	1.00	0.04	1.79	0.03	-0.66%	-0.45	94%
P13	M / M / H	0.94	0.10	0.33	0.20	-3.09%	-3.34	97%
P14	M / M / M	0.87	-0.03	0.02	-0.01	-1.51%	-2.38	98%
P15	M / M / L	0.89	-0.14	-0.32	-0.21	-2.11%	-1.77	95%
P16	M / L / H	0.87	-0.09	-1.79	-0.04	-3.22%	-2.36	93%
P17	M / L / M	0.81	-0.19	-2.39	-0.31	-1.79%	-1.37	93%
P18	M / L / L	0.81	-0.20	-4.22	-0.72	-1.41%	-0.70	85%
P19	L / H / H	1.03	-1.31	2.53	0.37	0.37%	0.17	86%
P20	L / H / M	0.96	-1.31	0.40	-0.06	-0.73%	-0.51	93%
P21	L / H / L	1.00	-1.58	-0.10	-0.38	1.11%	0.57	87%
P22	L / M / H	0.90	-1.36	-1.80	-0.18	-0.40%	-0.28	92%
P23	L / M / M	0.87	-1.47	-2.26	-0.41	1.20%	0.79	90%
P24	L / M / L	0.90	-1.86	-2.70	-0.69	1.82%	0.80	82%
P25	L / L / H	0.82	-1.70	-4.38	-0.53	0.24%	0.11	84%
P26	L / L / M	0.80	-2.05	-5.29	-0.88	1.25%	0.49	77%
P27	L / L / L	0.82	-2.74	-8.11	-1.51	0.41%	0.12	67%
P1-P27						-1.91%	-0.37	52%
Joint p-value						[0.05]		

Reported are the average pre-ranking higher moment betas and post-ranking alphas, and t-statistics and adjusted R-squared values of the quantile portfolios from regressions with the Carhart (1997) factors. Alphas are annualized. The sample is from 1994 to 2004 and covers 9,769 mutual funds. Each month mutual funds are sorted into equally-weighted triple-sorted quantile 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 on the market portfolio in month t, and ΔVOL_t, ΔSKEW_t and ΔKURT_t are our proxies for equity volatility risk, skewness risk, and kurtosis risk. The row marked "Joint p-value" reports the p-value for the Gibbons et al. (1989) test that all the post-ranking alphas are jointly equal to zero.

Appendix: Follow-up Empirical Tests

Table A-1: Portfolios of hedge funds triple-sorted by their exposure to ΔVOL, ΔSKEW and ΔKURT, with Bayesian estimation and accounting for backfiling bias

		FH-7 Model Panel A: Bayesian estimation			FH-7 Model Panel B: Backfilling Bias		
		Alpha	Alpha-t	Adj.Rsq	Alpha	Alpha-t	Adj.Rsq
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-P10		-22.25%	-3.89	10%	-20.97%	-3.38	10%
Joint p-value		[0.00]			[0.00]		

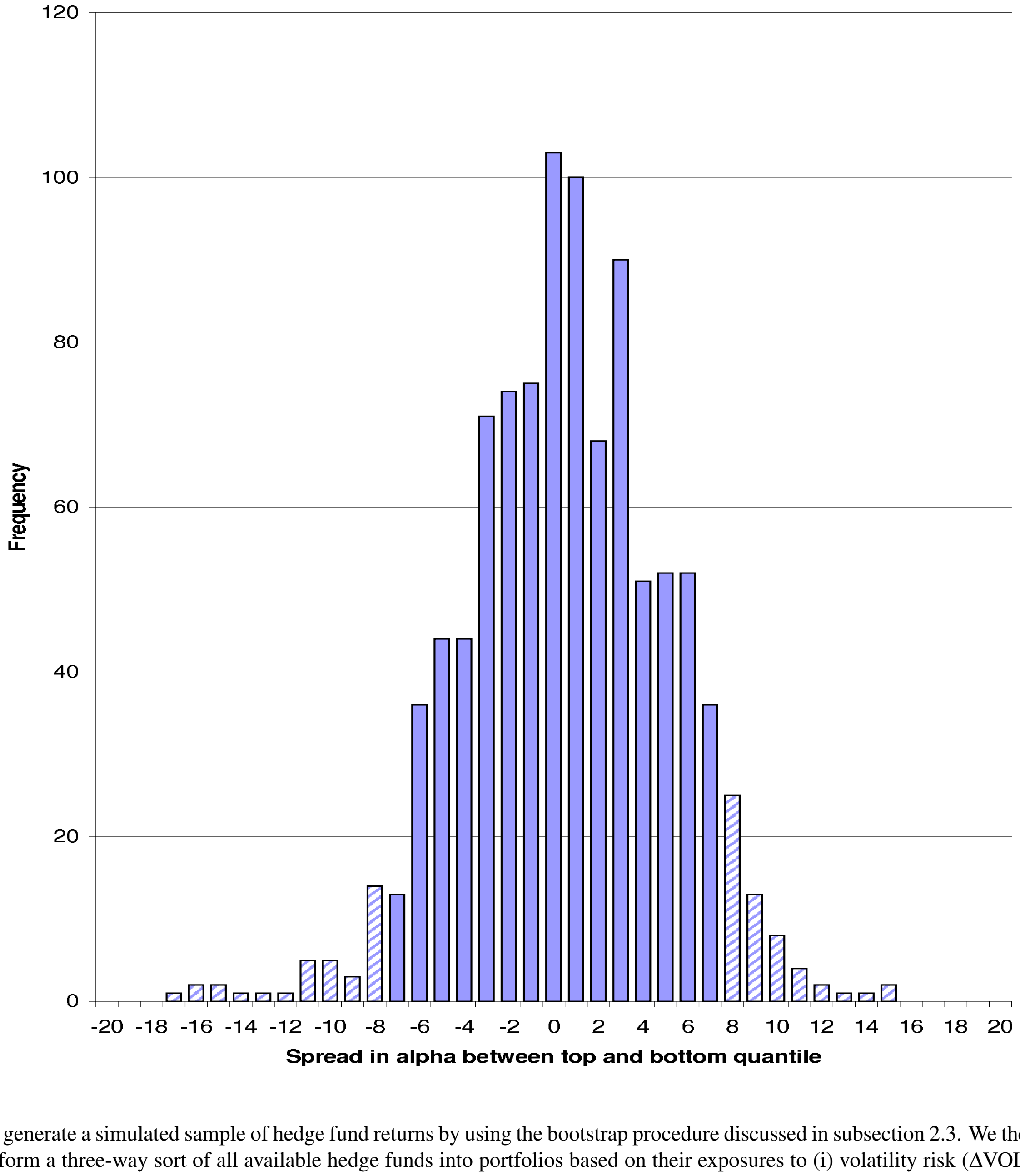
Two types of empirical tests are conducted. Panel A reports results based on Bayesian estimation. Panel B reports results accounting for the backfiling bias that reduces the sample universe to 3,243 hedge funds. Reported throughout are post-ranking alphas, t-statistics and adjusted R-squared values of the quantile portfolio from regressions using the Fung and Hsieh (2004) model. Each month hedge funds are first sorted into equally-weighted triple-sorted quantile 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 on the market portfolio in month t, and ΔVOL_t, ΔSKEW_t and ΔKURT_t are our proxies for equity volatility risk, skewness risk, and kurtosis risk. All reported alphas are annualized. The row marked "Joint p-value" reports the p-value for the Gibbons et al. (1989) test that all the post-ranking alphas are jointly equal to zero.

Table A-2: Portfolios of hedge funds triple-sorted by their exposure to ΔVOL, ΔSKEW and ΔKURT accounting for alternative systematic risk factors

		Panel A: Lookback Straddles on Equity and Interest rate			Panel B: FH-7 Augmented with OTM Put			Panel C: FH-7 Augmented with Liquidity factor		
		Alpha	Alpha-*t*	Adj.Rsq	Alpha	Alpha-*t*	Adj.Rsq	Alpha	Alpha-*t*	Adj.Rsq
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%	
Joint *p*-value	[0.00]			[0.00]			[0.00]			

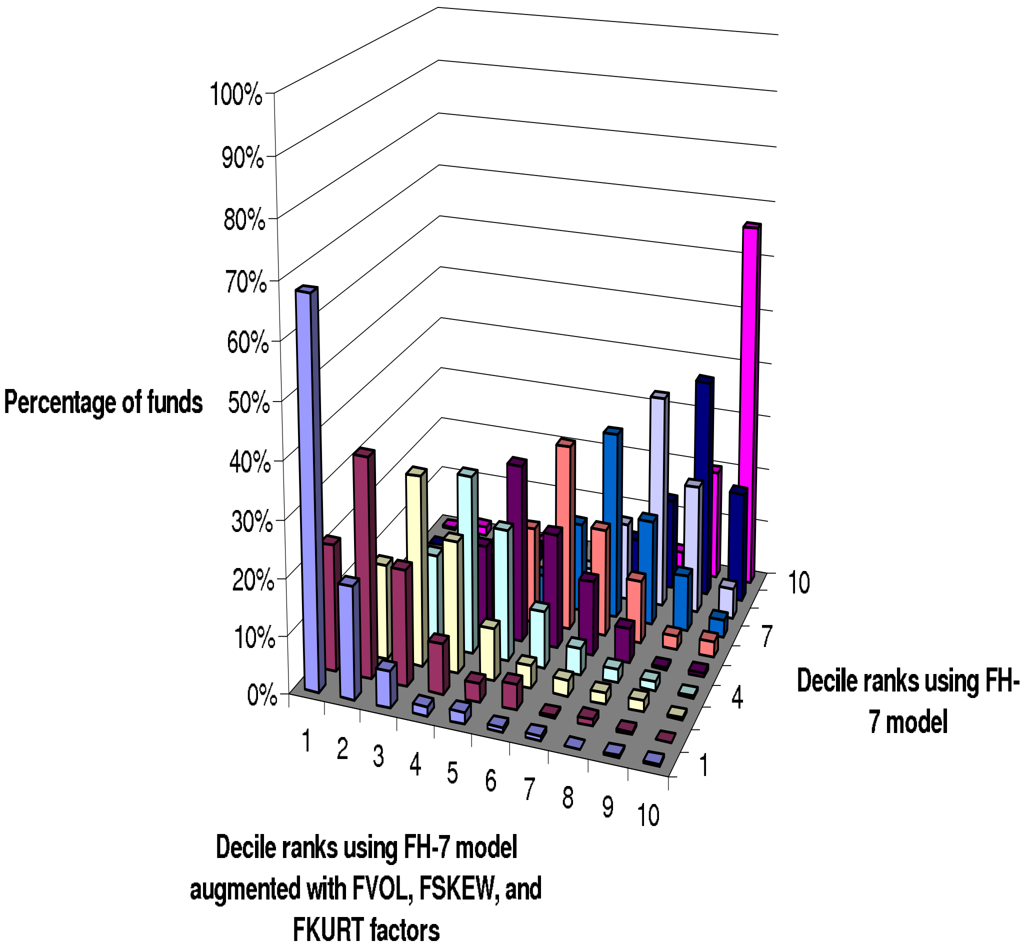
Reported in this table are post-ranking alphas, t-statistics and adjusted R-squared values of the quantile portfolio from regressions with alternative risk factors. Panel A employs the extended Fung and Hsieh (2001, 2004) model with lookback straddles on equity and interest rate; Panel B employs the FH-7 model augmented with the 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). Here LIQ is the liquidity risk factor from WRDS. As before, each month hedge funds are first sorted into equally-weighted triple-sorted quantile 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 on the market portfolio in month t, and ΔVOL_t, ΔSKEW_t and ΔKURT_t are our proxies for equity volatility risk, skewness risk, and kurtosis risk. All reported alphas are annualized. The row marked "Joint p-value" reports the p-value for the Gibbons et al. (1989) test that all the post-ranking alphas are jointly equal to zero.

Figure 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 2.3. 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.

Figure 2: Effect of including higher-moment risk factors in FH-7 model for hedge fund rankings



This figure shows the percentage of hedge funds that is ranked into deciles based on (i) the alphas from regressions with the Fung and Hsieh (2004) seven-factor model, and (ii) the alphas from the augmented Fung and Hsieh (2004) seven-factor model which includes higher–moment risk factors (FVOL, FSKEW, and FKURT). The bars on the diagonal (D1/D1, D2/D2, and so on) indicate the percentage of funds that are ranked in the same deciles using the two models. The off-diagonal bars represent the percentage of funds that have inconsistent decile rankings using the two models. For example, the second blue bar in the first row from the left represents shows that 20 percent of the funds are ranked in the *top* decile using the FH-7 model, but in the *second* decile using the augmented FH-7 model. The sample is from January 1994 to December 2004 and covers 3,193 hedge funds and funds of funds with at least 36 consecutive return observations.