# Higher-Moment Equity Risks and the Cross-Section of Hedge Fund Returns*

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**Abstract**

The reliance of hedge funds on state-contingent bets and derivatives may lead them to being exposed to higher-moment equity risks. In this paper, we examine higher-moment equity risks in the cross-section of hedge fund returns. We observe systematic patterns in the alphas of hedge funds sorted on their exposures to the three higher–moments of equity returns – volatility, skewness, and kurtosis. We also find significant premiums embedded in hedge fund returns on account of their exposures to higher-moment risks. Using three-way sorted portfolios of hedge funds based on their exposures to higher-moments, we find return premiums for volatility, skewness, and kurtosis of about –6.25 percent, 3 percent, and –2.5 percent per year with/without controlling for risk factors that have been shown to explain hedge fund returns. Our analysis using mutual fund returns does not yield significant patterns in alphas. These results indicate important differences between the nature of trading strategies used by the two types of managed portfolios. Our findings have implications for hedge fund portfolio construction and performance evaluation.

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), 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) 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), 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 less scrutiny. Specifically, a less than understood phenomena is whether hedge funds are compensated for bearing higher–moment risks, a hypothesis that can be potentially examined within the multifactor modeling paradigms of Merton (1973) and Ross (1976). If so, are the rewards economically and statistically significant? What part 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 equity volatility risk is priced in the cross-section of stock re-

[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).

turns (see also Goyal and Santa-Clara (2003), Bali et al. (2005), Bali and Cakici (2007), and Ang et al. (2007)). Hasanhodzic and Lo (2007) conduct time-series analysis of hedge fund returns and argue that volatility risk is a likely determinant of hedge fund returns. Granted that hedge funds have option-like market exposures due to their use of dynamic trading strategies, hedge funds are potentially exposed to higher-moment risks. 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. Moreover, there is mounting evidence of the pricing of higher–moments from the index option markets.[2]

The purpose of this study is to investigate the pricing of higher-moment equity 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 traded on the Chicago Board Options Exchange (CBOE) 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 exposure to the risks of three higher central moments, namely volatility, skewness, and kurtosis. While the lookback straddle in Fung and Hsieh (2001) is designed to capture the spread between the maximum and the minimum values attained by the underlying asset, our risk measures reflect higher–moment payoffs such as those underlying the volatility, the cubic, and the quartic contracts (Bakshi et al. (2003)).

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

[2] An incomplete list includes Jackwerth and Rubinstein (1996), Bates (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), and Duan and Wei (2007).

[3] There are number of researchers who have proposed 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), and Jiang and Tian (2005), among others.

are inherently forward-looking. Recently, Christoffersen et al. (2006) have shown the relevance of using forward-looking measures of market betas, 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 higher–moments such as 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. While our focus is on assessing the impact of equity 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.

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 quantile portfolios of hedge funds, sorted on their exposure to innovations in volatility, skewness, and kurtosis. Further, we favor conditional sorts based on exposures to the three higher-moments risks, since the higher-moment risk exposures are correlated with each other. These results are robust to the inclusion of additional systematic risk factors such as lookback straddles on equity and interest rates and out-of-the-money put option as well as 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 in hedge fund data.

Second, our results indicate a negative premium for equity index volatility and kurtosis risk factors, and a positive premium for the equity index skewness risk factor. Specifically, our findings imply average factor returns for volatility, skewness, and kurtosis of about -6.25 percent, 3 percent, and -2.5 percent per year. In particular, the sign of skewness and kurtosis 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 (the risk premium reflects expectation under the physical density minus the risk-neutral density). 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 3.38 percent, 2.22 percent, and 2.82 percent per year for exposure to volatility, skewness, and kurtosis risks, respectively. Appealing to the residual and factor resampling approach of Kosowski et al. (2006), we perform a bootstrap simulation to rigorously show that the documented significance of higher-moment risks is not a consequence of data-driven spurious inferences.

Third, and importantly, when higher–moment risk factors are incorporated in the models of Fung and Hsieh (2004) and Carhart (1997), the dispersion in alphas of extreme portfolios of hedge funds effectively disappears. Furthermore, the systematic risk factors in Fung and Hsieh (2001, 2004) and Agarwal and Naik (2004) cannot explain the behaviors of higher-moment risk factors. Hence, our results convey the important message that higher-moment risk factors are not subsumed by commonly adopted risk factors in the empirical hedge fund literature.

Finally, we do not find significant dispersion in alphas when we sort *mutual funds* into quantile portfolios 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 risk factor premiums.

Our findings have broad implications for performance evaluation and diversification in the hedge fund industry. For example, a funds of funds that wishes to hedge one of the higher-moment risks can benefit from such an analysis by simultaneously investing in hedge funds that allows it to offset higher-moment risks. Overall, our investigation contributes to the body of theoretical and empirical research that suggests that higher-moment risk dimensions are relevant to asset pricing and are priced.

The remainder of the paper is organized as follows. Section 1 describes the data and the construction of variables. Section 2 provides evidence on exposures of hedge funds' returns to higher-moment risks, and estimates the risk factor premiums for equity volatility, skewness, and kurtosis. Section 3 investigates the dispersion in alphas of mutual fund portfolios sorted on funds' exposures to higher-moment risks. Section 4 conducts follow-up specification analysis. Finally, Section 5 concludes.

# 1 Fund Samples and Risk Factors

## 1.1 Proxies for higher-moment equity risks

Since our risk proxies for equity 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 $\tau$–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:

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

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

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

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, we note that $\sqrt{\mathbb{M}_{2,t}}$, $\frac{\mathbb{M}_{3,t}}{(\mathbb{M}_{2,t})^{3/2}}$, and $\frac{\mathbb{M}_{4,t}}{(\mathbb{M}_{2,t})^2}$ are to be interpreted as the arbitrage-free value of the claim to equity return 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 $\tau$-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:

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

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:

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

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

Equation (5) is a consequence of spanning and pricing the payoff $(\ln S_{t+\tau} - \ln S_t)^2$. 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 equity volatility risk (e.g., Ang et al. (2006) and Coval and Shumway (2001)), we define,

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

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

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

$\Delta\text{VOL}_t$, $\Delta\text{SKEW}_t$ and $\Delta\text{KURT}_t$ will be deployed as our proxies for higher-moment equity risks in the ensuing empirical investigation. Risk proxies such as $\Delta\text{VOL}_t$ are not to be confused with powers of market returns used in market timing specifications (e.g., Ferson and Schadt (1996)). While $\Delta\text{VOL}_t$ reflects the change in the intrinsic value of the second central moment payoff on the market index over a fixed horizon, the market timing studies hinge on *realized* squared market return. 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.

Figure 1 shows the arbitrage-free value of equity return volatility, skewness, and kurtosis measured over January 1994 to December 2004. The mean [standard deviation] of $\sqrt{12\,\mathbb{M}_{2,t}}$, $\text{SKEW}_t$ and $\text{KURT}_t$ is 18.83% [7.38%], -1.76 [0.72], and 10.34 [7.20]. To facilitate comparisons, the $\text{VIX}_t$ index from the CBOE is plotted along with $\sqrt{12\,\mathbb{M}_{2,t}}$. Each moment varies stochastically through time with $\text{SKEW}_t$ and $\text{KURT}_t$ co-varying negatively.

The negative equity volatility risk premium is theoretically tenable as long equity investors dislike volatility (Bakshi and Kapadia (2003), Coval and Shumway (2001), 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 equity 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 market price of kurtosis risk is negative. Hedge funds may be exposed to kurtosis risk as they may be engaged in selling 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.[4] 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 equity return higher–moments.

[4]To see the generic interpretation of higher-moment risk premiums, suppose an investor holds the claim: $(R_{t,t+\tau} - \mathbb{M}_{1,t})^2$. The cost of reproducing this exposure is precisely given by equation (6). For any admissible stochastic discount factor, $\xi$, and covariance operator, $\text{Cov}_t(.,.)$, the reward for bearing volatility risk, $\mu_{\text{VOL}}$, is then $\mu_{\text{VOL}} - r = -\text{Cov}_t\,(\xi_{t+1}/\xi_t, \Delta\text{VOL}_t)$, which is, in principle, computable once the stochastic discount factor has been identified.

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), and Boyson et al. (2006).

### 1.2 Sample 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. Hedge funds classified as funds of hedge funds are omitted to maintain focus on the role of higher-moment risks on individual hedge funds. Our resulting sample covers 4,833 hedge funds. This sample universe is free from survivorship bias as documented by Brown and Goetzmann (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)).

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.

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

To measure risk-adjusted performance 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). Although Carhart-4 is more appropriate for mutual funds and FH-7 is more suited for hedge funds, we analyze hedge funds using both 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:

$$\begin{aligned} r_{i,t} &= \alpha^{i}_{FH7} + \beta^{1,i}_{FH7}\text{SNPMRF}_t + \beta^{2,i}_{FH7}\text{SCMLC}_t + \beta^{3,i}_{FH7}\text{BD10RET}_t + \beta^{4,i}_{FH7}\text{BAAMTSY}_t \\ &\quad + \beta^{5,i}_{FH7}\text{PTFSBD}_t + \beta^{6,i}_{FH7}\text{PTFSFX}_t + \beta^{7,i}_{FH7}\text{PTFSCOM}_t + \varepsilon^{i,t}_{FH7}, \end{aligned} \tag{12}$$

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

- $\text{SNPMRF}_t$ is S&P 500 return minus the riskfree rate in month $t$;
- $\text{SCMLC}_t$ captures Wilshire small cap minus large cap return in month $t$;
- $\text{BD10RET}_t$ 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;
- $\text{BAAMTSY}_t$ measures monthly changes in the credit spread defined as Moody's Baa bond yield

minus the 10-year Treasury bond yield, after adjusting for duration;

- $\text{PTFSBD}_t$, $\text{PTFSFX}_t$, and $\text{PTFSCOM}_t$ are excess returns on portfolios of lookback straddles on bonds, currencies, and commodities respectively in month $t$.

David Hsieh graciously provided us with the factor data. One-month Treasury bill rate is taken from Ibbotson Associates and is the proxy for the riskfree rate.

The Carhart-4 model takes the form:

$$r_{i,t} = \alpha^i_{C4} + \beta^{1,i}_{C4}\text{RMRF}_t + \beta^{2,i}_{C4}\text{SMB}_t + \beta^{3,i}_{C4}\text{HML}_t + \beta^{4,i}_{C4}\text{UMD}_t + \varepsilon^{i,t}_{C4}, \tag{13}$$

where $\text{RMRF}_t$ is the value-weighted excess return of all NYSE, AMEX, and NASDAQ stocks in month $t$, $\text{SMB}_t$ and $\text{HML}_t$ 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 $\text{UMD}_t$ (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 rank portfolios based on their exposures. We start by performing independent sorts on each of these higher–moment risk exposures. Given the correlation between funds' tail risk exposures, we suggest a three-way sort that may be more appropriate for separating the effect of ΔVOL, ΔSKEW, and ΔKURT.

We evaluate the rank portfolios' out-of-sample performance and then estimate the spread between the portfolios' risk-adjusted returns after controlling for risk factors using both FH-7 and Carhart-4 models. Furthermore, we construct risk factor premiums for higher–moment risks in the tradition of Fama and French (1993) and Liew and Vassalou (2000) and show that these factors capture risks distinct from those captured by the FH-7 and Carhart-4 models.

## 2.1 Independent sorts on ΔVOL, ΔSKEW, and ΔKURT

We first construct a set of base assets that display significant dispersion in the sensitivity to higher-moment equity 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 $\Delta\text{VOL}_t$, $\Delta\text{SKEW}_t$, and $\Delta\text{KURT}_t$, over the past 12 months:

$$r_{i,t} = \alpha^{i}_{4F} + \beta^{1,i}_{4F}\,\text{RMRF}_t + \beta^{2,i}_{4F}\,\Delta\text{VOL}_t + \beta^{3,i}_{4F}\,\Delta\text{SKEW}_t + \beta^{4,i}_{4F}\,\Delta\text{KURT}_t + \varepsilon^{i,t}_{4F}. \tag{14}$$

As argued by Ang et al. (2006), 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)). 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 models of Fung and Hsieh (2004) and Carhart (1997).

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 hedge 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 rank 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, 1,780 hedge funds are available in the cross-section at the beginning of each year, ranging from 830 funds in 1995 to 2,787 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 -12.95 percent per year (the difference between FH-7 alpha of -3.17 percent for H portfolio in Panel A and 9.78 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 KURT are respectively -13.87 percent per year and -14.21 percent per year with the FH-7 model. Corresponding magnitudes based on the Carhart-4 model show similarly strong relationships between post-ranking alphas. The reported *R*-squared values indicate that both the FH-7 model and the Carhart-4 model perform reasonably well in explaining the time-series variation in the decile portfolios' returns.

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 0.28 (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 5 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 and as hypothesized hedge funds exhibit a 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), Xu (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 -0.61 for sorts done on ΔVOL and ΔSKEW; it is 0.63 for sorts done on ΔVOL and ΔKURT; and it is -0.91 for sorts done on ΔSKEW and ΔKURT. Owing to the high correlations, independent sorts may not be sufficiently versatile to separately identify the contribution of ΔVOL, ΔSKEW, and ΔKURT. The next subsection argues that a three-way conditional sort on ΔVOL, ΔSKEW, and ΔKURT may circumvent this problem.

## 2.2 Conditional three-way sorts on 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 deciles 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 our results for the 27 portfolios (P1 to P27) resulting from the terciles – high (H), medium (M), low (L) – of conditional sorts on hedge 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 two multifactor models. Furthermore, we observe an increasing pattern in these alphas as we move down from P1 to P27.

It is noteworthy that alphas range between –6.33 to 13.79 percent after controlling for factors in the FH-7 model, and between –4.63 to 13.96 percent per year after controlling for factors in the Carhart-4 model.

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 –6.33 percent and –1.33 percent per year and Carhart-4 alphas ranging between -4.63 percent to -1.25 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 highest exposure to ΔVOL and ΔKURT but with different exposures to ΔSKEW (i.e., P1, P4, and P7) generate FH-7 alphas from –6.33 percent to 1.14 percent per year and Carhart-4 alphas from –4.63 percent to 1.26 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 Post-ranking return spreads of hedge fund portfolios conditionally sorted on higher-moment risks

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) and Liew and Vassalou (2000) one may estimate the 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 high volatility risk exposure and short on low volatility risk exposure:

$$\begin{aligned} \text{FVOL} \quad &:= \quad \frac{1}{9}\left(P1+P2+P3+P4+P5+P6+P7+P8+P9\right) \\ &\quad - \frac{1}{9}\left(P19+P20+P21+P22+P23+P24+P25+P26+P27\right). \end{aligned} \tag{15}$$

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, define the portfolio strategy FKURT via,

$$\begin{aligned}\text{FKURT} \;&:=\; \frac{1}{9}\left(P1+P4+P7+P10+P13+P16+P19+P22+P25\right)\\ &\quad -\;\frac{1}{9}\left(P3+P6+P9+P12+P15+P18+P21+P24+P27\right). \qquad (16)\end{aligned}$$

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 portfolios for volatility premium and kurtosis premium, we compute FSKEW as:

$$\begin{aligned}\text{FSKEW} \;&:=\; \frac{1}{9}\left(P7+P8+P9+P16+P17+P18+P25+P26+P27\right)\\ &\quad -\;\frac{1}{9}\left(P1+P2+P3+P10+P11+P12+P19+P20+P21\right). \qquad (17)\end{aligned}$$

Analogous to size and book-to-market-equity factors of Fama and French constructed from 2x3 conditionally sorted quantile 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 large: -6.27 percent, 2.96 percent, and -2.48 percent per year for FVOL, FSKEW, and FKURT, respectively. Higher-moment risks are strongly rewarded.

Further, the correlations between FVOL, FSKEW, and FKURT now lie between -0.41 to 0.26 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. The documented relevance of higher-moment factor premiums has implications for performance evaluation and for risk characterization of hedge funds.

Before closing this subsection, we perform time-series regressions of higher-moment premiums on the FH-7 and Carhart-4 factors and report the findings in the final six columns of Table 3. The goal is to investigate whether the estimated higher-moment risk factor premiums are related to risks captured by the FH-7 and Carhart-4 models. Several aspects of the regression results are worth highlighting. First, the alphas obtained from both FH-7 and Carhart-4 models are virtually indistinguishable from the average factor returns reported in column 2 of Table 3. This finding implies a near-zero sensitivity of the risk factor premiums to the factors driving FH-7 and Carhart-4 models. Second, the regressions produce modest to low explanatory power as measured by the $R$-squared values, especially for the FH-7 model. Taken together, this evidence suggests that the risk factors in a class of prominent multifactor models do not encompass risks embedded in FVOL, FSKEW, and FKURT.

## 2.4 Bootstrap Simulation

Proceeding, 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 $\{\hat{\varepsilon}^b_{i,t_e}, t_e = s^b_1, s^b_2, \ldots, s^b_T\}$, and the factors' $\{\text{SNPMRF}^b_{t_F}$, $\text{SCMLC}^b_{t_F}$, $\text{BD10RET}^b_{t_F}$, $\text{BAAMTSY}^b_{t_F}$, $\text{PTFSBD}^b_{t_F}$, $\text{PTFSFX}^b_{t_F}$, $\text{PTFSCOM}^b_{t_F}$, $t = u^b_1, u^b_2, \ldots, u^b_T\}$, where $s^b_1, s^b_2, \ldots, s^b_T$ and $u^b_1, u^b_2, \ldots, u^b_T$ are the time reorderings imposed by the bootstrap. We then construct time-series of simulated fund returns for all funds subject to zero alphas:

$$\begin{aligned} r^b_{i,t} &= \hat{\beta}^{1,i}_{FH7}\text{SNPMRF}^b_{t_F} + \hat{\beta}^{2,i}_{FH7}\text{SCMLC}^b_{t_F} + \hat{\beta}^{3,i}_{FH7}\text{BD10RET}^b_{t_F} + \hat{\beta}^{4,i}_{FH7}\text{BAAMTSY}^b_{t_F} \\ &+ \hat{\beta}^{5,i}_{FH7}\text{PTFSBD}^b_{t_F} + \hat{\beta}^{6,i}_{FH7}\text{PTFSFX}^b_{t_F} + \hat{\beta}^{7,i}_{FH7}\text{PTFSCOM}^b_{t_F} + \hat{\varepsilon}^b_{i,t_e}. \end{aligned} \tag{18}$$

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 quantile 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 rank portfolios and read-just 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 quantile 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 top minus bottom quantile portfolio returns 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 2 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 -7 percent and +7 percent.

Thus, the bootstrap results permit 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.

## 2.5 Results using Carhart-4 and FH-7 models augmented with FVOL, FSKEW, and FKURT

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:

$$\begin{aligned} r_{i,t} \;=\;& \alpha^{i}_{10F} + \beta^{1,i}_{10F}\,\mathrm{SNPMRF}_t + \beta^{2,i}_{10F}\,\mathrm{SCMLC}_t + \beta^{3,i}_{10F}\,\mathrm{BD10RET}_t + \beta^{4,i}_{10F}\,\mathrm{BAAMTSY}_t \\ &+ \beta^{5,i}_{10F}\,\mathrm{PTFSBD}_t + \beta^{6,i}_{10F}\,\mathrm{PTFSFX}_t + \beta^{7,i}_{10F}\,\mathrm{PTFSCOM}_t \\ &+ \underbrace{\beta^{8,i}_{10F}\,\mathrm{FVOL}_t + \beta^{9,i}_{10F}\,\mathrm{FSKEW}_t \;+\; \beta^{10,i}_{10F}\,\mathrm{FKURT}_t}_{\text{FH}-7\text{ augmented with return}-\text{based higher}-\text{moment factors}} + \varepsilon^{i,t}_{10F}. \end{aligned} \tag{19}$$

Likewise, we control for the risk factors suggested in Carhart (1997) by replacing the FH-7 factors by the Carhart-4 factors, producing a model driven by seven factors.

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 $\text{FVOL}_t$, $\text{FSKEW}_t$, and $\text{FKURT}_t$.

We report annualized alphas, FVOL, FSKEW, and FKURT factor loadings, and the adjusted-$R^2$'s for the 27 conditionally sorted portfolios in Table 4. We find strong patterns of post-ranking factor loadings on the higher-moment risk factors. Consider the return-based volatility factor, where the ex-post factor loadings on FVOL is between 0.41 to 1.17 using the FH-7 factors for P1 to P9 (nine ”H” portfolios corresponding to FVOL), between -0.03 to 0.21 for P10 to P18 (nine ”M” portfolios corresponding to FVOL), and between -0.20 to -0.54 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. The strong patterns of post-ranking factor loadings on each of the three higher-moment risk factors using augmented FH-7 and Carhart-4 model specifications support a risk-based explanation for our findings.

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 -0.54 of P19 portfolio using FH-7 with the volatility premium of -6.27 percent corresponding to the same model, it yields an excess return of 3.38 percent for volatility exposures;

- Likewise, taking the highest skewness beta of 0.75 for P9 portfolio and multiplying it by the skewness premium of 2.96 percent, we impute that hedge funds can potentially earn up to 2.22 percent excess return on account of their exposure to skewness;

- Finally, if we take the lowest kurtosis beta of -1.14 for P3 portfolio and multiply it by kurtosis premium of -2.48% percent we impute that hedge funds can potentially earn up to 2.82 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 3.38%, 2.22%, and 2.82% per year on account of their exposure to volatility, skewness, and kurtosis risks respectively.

Notice that the patterns in alphas across the hedge fund portfolios are *now* not nearly as striking as the patterns in alphas resulting from FH-7 and Carhart-4 models in Table 2. We find annualized alphas ranging from 2.14 percent to 7.87 percent (1.25 percent to 7.48 percent) per year for the augmented FH-7 (Carhart-4) model. In fact, the spread between the top and bottom quantile portfolios is less than one percent per year. Overall, these results suggest that FVOL, FSKEW, and FKURT are able to capture the cross-sectional spread in hedge fund alphas by internalizing higher-moment risk exposures.

Additionally, we observe significant explanatory power for both the models with *R*-squares ranging from 53 percent to 81 percent for the augmented FH-7 model, and from 53 percent to 79 percent for the augmented Carhart-4 model. For comparison, the *R*-squares for the FH-7 in Table 2 range from 26 percent to 57 percent, and from 23 percent to 61 percent for Carhart-4. The general narrowing of spreads in alphas along with the enhanced explanatory ability both indicate that including the three higher-moment equity risk factors in addition to other risk factors in FH-7 and Carhart-4 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 (the Carhart-4 model provides similar conclusions and omitted). For all the 3,193 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.

Figure 3 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. 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 3 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. Overall, this exercise provides additional supportive evidence that higher-moment risk dimensions can have a substantial impact on hedge fund returns.

## 3 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)). Further, 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), and Almazan et al. (2004)), which suggests that they do not follow dynamic trading strategies and therefore, are less likely to be exposed to higher-moment equity risks.

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.[5]

As mentioned before, the Carhart-4 model is a more appropriate benchmark for equity mutual funds. For this reason, we concentrate on this model and exclude the FH-7 model.

In Table 5, we report the spreads in alphas of mutual fund portfolios conditionally sorted on their exposure to the three higher-moment risks. While we do observe some patterns in alphas across the quantile portfolios of mutual funds, the patterns are not nearly as pronounced relative to hedge funds.

In particular, the return spread between the two extreme portfolios, P1 and P27, is a mere 1.90%, for mutual funds, compared to 18.59% with hedge funds (the difference of 13.96% and –4.63% in Table 2 for the Carhart-4 model).

Next, in Table 6, we present the annualized time-series averages of higher-moment risk factor premiums. These effectively are the premiums earned by mutual funds for their exposure to higher-

[5]There are no explicit impediments to capital withdrawal such as lockup and notice periods for mutual fund investors. To be cautious, 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.

moment risks. Although the average premiums are -4.31 percent, 1.82 percent, and -1.10 percent for volatility, skewness, and kurtosis, the equity mutual funds do not earn a statistically significant premium for their exposure to any of the higher-moment risks. The largest absolute t-statistic is 1.24. Recall for hedge funds, we obtained significant premiums of –6.27 percent, 2.96 percent and -2.48 percent for volatility, skewness and kurtosis risks (see Table 3). On balance, these results support our claims of hedge funds being somewhat unique in their being exposed to higher-moment risks.

To strengthen this finding, we also conduct our analysis for mutual funds using 24-month estimation window and 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 the length of time series and adopting regression windows, the same does not apply to equity mutual funds. If the same outcome results using a longer window and longer time-series for mutual funds, we can argue that if we had the same luxury for hedge funds, we would get similar conclusions. This would further convince readers about our main findings.

When we select all equity mutual funds from the CRSP database over January 1984 to December 2004 to construct triple-sorted portfolios using 24 month ranking periods and portfolios' post-ranking performance is evaluated using the Carhart-4 model, we continue to observe the lack of significant spreads in alphas (results not reported for the sake of brevity).

In short, these results provide further evidence in support of the existence of higher-moment risk factor premiums embedded in hedge fund returns but not for mutual funds.

# 4 Follow-up Empirical Tests

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

## 4.1 Robustness to estimation error and backfilling bias

Because of our choice of portfolio formation periods, the rankings for sorts on the 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 quantile portfolios. One therefore faces the possibility that the risk factor 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-rank betas in the formation period more efficiently. We exploit empirical Bayes approach to estimate the regression in equation (14) in the formation period.[6]

When evaluating the three-way sorted portfolios' out-of-sample risk-adjusted performance, we focus on the FH-7 model. The results in Panel A of Table 7 show that the dispersion in out-of-sample alphas for sorts on Bayesian estimates of the funds' higher-moment betas are not much different from those resulting from sorts on standard OLS estimates. More precisely, we observe a spread in alphas between the top and bottom quantile of 21.94 percent per year. We interpret these results as stating that our findings are not sensitive to an alternative methodology of using Bayesian beta estimates.

Moving to the role of backfilling, Fung and Hsieh (2000) document that hedge funds often initiate reporting their performance to a database after a few years since their inception date. Clearly, if the performance is unsatisfactory in those initial years, hedge funds are unlikely to report their perfor-

[6]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), and Busse and Irvine (2006) in the context of mutual funds, and by Kosowski et al. (2007) in the context of hedge funds.

mance between the inception date and the first performance reporting date. This leads to an upward bias in the hedge fund performance, labeled as backfilling bias by Fung and Hsieh (2000).

To mitigate backfilling, we discard the first 24 return observations for all hedge funds. The resulting sample covers 3,243 hedge funds, and, on average, 1,082 funds are available in the cross-section at the beginning of each year (ranging from 379 funds in 1995 to 1,793 funds in 2004). Results in Panel B of Table 7 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 quantile is still 20.30 percent per year.

### 4.2 Treatment of 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 Fund and Hsieh (2001, 2004) nine-factor model (henceforth, FH-9):

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

where $\mathrm{PTFSSTK}_t$ is the primitive trend following strategy in equity, and $\mathrm{PTFSIR}_t$ is the primitive trend following strategy in interest rates in month $t$. Panel A in Table 8 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 do 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 8 reports the annualized alphas obtained through our three-way sorted portfolios. We continue to observe significant spreads in alphas for FH-7 mirroring our Table 2.

Finally, a point has been made that 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 8 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.

Overall, the follow-up exercises presented in this section show that our empirical findings are robust.

## 5 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 conditionally three-way sorting of hedge funds based on their exposure to equity 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 volatility, skewness, and kurtosis risks of about –6.25 percent, 3 percent, and –2.5 percent per year. Furthermore, hedge funds earn up to 3.38 percent, 2.22 percent, and 2.82 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 in Fung and Hsieh (2004) and the nine-factor model in Fung and Hsieh (2001, 2004). In particular, the higher–moment risk factors are not redundant in the presence of lookback straddle returns.

Fourth, our analysis reveals that equity mutual funds are not exposed in a substantial way to higher-moment risks, and the premiums for higher-moment risks are statistically insignificant and substantially dampened versions of the hedge fund counterparts. In a stark contrast to hedge funds, the magnitude of spreads in alphas for extreme mutual fund portfolios are small (1.90 percent versus 18.59 precent).

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 measurement step. Moreover, it is shown that when a class of existing multifactor models for evaluating hedge fund performance are augmented with higher-moment risk factors, we can better explain hedge fund return variations.

When hedge fund returns reflect premiums for bearing higher-moment risks, issues concerning skill and capital formation in the hedge fund industry warrant reappraisals. Another relevant central question is whether funds of funds diversify, or do they amplify, higher-moment exposures? These questions are important in their own right and left to another time.

## References

C. Ackermann, R. McEnally, and D. Ravenscaft. The performance of hedge funds: Risk, return, and incentives. *Journal of Finance*, 54:833–874, 1999.

V. Agarwal and N. Naik. Risks and portfolio decisions involving hedge funds. *Review of Financial Studies*, 17(1):63–98, 2004.

V. Agarwal, N. Daniel, and N. Naik. Role of managerial incentives and discretion in hedge fund performance. Technical report, Georgia State University and London Business School, 2006.

A. Almazan, K. Brown, M. Carlson, and D. Chapman. Why constrain your mutual fund manager? *Journal of Financial Economics*, 73:289–321, 2004.

G. Amin and H. Kat. Hedge fund performance 1990-2000: Do the money machines really add value? *Journal of Financial and Quantitative Analysis*, 38:251–274, 2003.

A. Ang, R. Hodrick, Y. Xing, and X. Zhang. The cross-section of volatility and expected returns. *Journal of Finance*, 61:259–299, 2006.

A. Ang, R. Hodrick, Y. Xing, and X. Zhang. High idiosyncratic volatility and low returns: International and further U.S. evidence. Technical report, Columbia University, 2007.

K. Baks, A. Metrick, and J. Wachter. Should investors avoid all actively managed mutual funds? A study in Bayesian performance evaluation. *Journal of Finance*, 56:45–85, 2001.

G. Bakshi and N. Kapadia. Delta-hedged gains and the negative market volatility risk premium. *Review of Financial Studies*, 16(2):527–566, 2003.

G. Bakshi and D. Madan. Spanning and derivative security valuation. *Journal of Financial Economics*, 55:205–238, 2000.

G. Bakshi and D. Madan. A theory of volatility spreads. *Management Science*, December:1950–1964, 2006.

G. Bakshi, N. Kapadia, and D. Madan. Stock return characteristics, skew laws, and the differential pricing of individual equity options. *Review of Financial Studies*, 16(1):101–143, 2003.

T. Bali and N. Cakici. Idiosyncratic volatility and the cross-section of expected returns. *Journal of Financial and Quantitative Analysis*, forthcoming, 2007.

T. Bali, N. Cakici, X. Yan, and Z. Zhang. Does idiosyncratic risk really matter? *Journal of Finance*, 60:905–929, 2005.

R. Bansal, D. Hsieh, and S. Viswanathan. A new approach to international arbitrage pricing. *Journal of Finance*, 48:1719–1749, 1993.

D. Bates. Post-'87 crash fears in the S&P 500 futures option market. *Journal of Econometrics*, 94 (1/2):181–238, 2000.

N. Bollen and J. Busse. Short-run persistence in mutual fund performance. *Review of Financial Studies*, 18:569–597, 2005.

N. Bollen and R. Whaley. Hedge fund risk dynamics: Implications for performance appraisal. Technical report, Vanderbilt University, 2007.

N. Bollen and R. Whaley. Does net buying pressure affect the shape of implied volatility functions? *Journal of Finance*, 59:711–753, 2004.

O. Bondarenko. Market price of variance risk and performance of hedge funds. Technical report, University of Illinois at Chicago, 2004.

N. Boyson, C. Stehel, and R. Stulz. Is there a hedge fund contagion? Technical report, NBER #12090, 2006.

M. Britten-Jones and A. Neuberger. Option prices, implied price processes, and stochastic volatility. *Journal of Finance*, 55:839–866, 2000.

M. Broadie, M. Chernov, and M. Johannes. Specification and risk premiums: The information in S&P 500 futures options. *Journal of Finance*, 62:1453–1490, 2007.

S. Brown and W. Goetzmann. Survivorship-bias in performance studies. *Review of Financial Studies*, 5:553–580, 1992.

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

S. Brown and J. Spitzer. Caught by the tail: Tail risk neutrality and hedge fund returns. Technical report, New York University, 2006.

A. Buraschi and J. Jackwerth. The price of a smile: Hedging and spanning in option markets. *Review of Financial Studies*, 14(2):495–527, 2001.

J. Busse and P. Irvine. Bayesian alphas and mutual fund persistence. *Journal of Finance*, 61:2251–2288, 2006.

M. Carhart. On persistence in mutual fund performance. *Journal of Finance*, 52:57–82, 1997.

P. Carr and D. Madan. Optimal positioning in derivative securities. *Quantitative Finance*, 1(1):19–37, 2001.

P. Carr and L. Wu. Variance risk premia. *Review of Financial Studies (forthcoming)*, 2008.

P. Christoffersen, K. Jacobs, and G. Vainberg. Forward-looking betas. Technical report, McGill University, 2006.

J. Cochrane. *Asset Pricing*. Princeton University Press, Princeton, NJ, 2004.

J. Cochrane. Betas, options, and portfolios of hedge funds. Technical report, University of Chicago, 2005.

J. Coval and T. Shumway. Expected option returns. *Journal of Finance*, 56(3):983–1009, 2001.

D. Deli and R. Varma. Contracting in the investment management industry: evidence from mutual funds. *Journal of Financial Economics*, 63:79–98, 2002.

K. Demeterfi, E. Derman, M. Kamal, and J. Zou. A guide to volatility and variance swaps. *Journal of Derivatives*, 6(4):9–32, 1999.

P. Dennis and S. Mayhew. Risk-neutral skewness: Evidence from stock options. *Journal of Financial and Quantitative Analysis*, 37:471–493, 2002.

A. Diez and R. Garcia. Assessing and valuing the nonlinear structure of hedge fund returns. Technical report, University of Montreal, 2006.

R. Dittmar. Nonlinear pricing kernels, kurtosis preferences, and evidence from the cross-section of equity returns. *Journal of Finance*, 57(1):369–403, 2002.

J.-C. Duan and J. Wei. Systematic risk and the price structure of individual equity options. *Review of Financial Studies (forthcoming)*, 2007.

P. Dybvig and J. Ingersoll. Mean-variance theory in complete markets. *Journal of Business*, 55 (2): 233–251, 1982.

R. Engle. Risk and volatility: econometric models and financial practice. *American Economic Review*, 94:405–420, 2004.

R. Engle and A. Mistry. Priced risk and asymmetric volatility in the cross-section of skewness. Technical report, New York University, 2007.

E. Fama and K. French. The cross-section of expected stock returns. *Journal of Finance*, 47:427–465, 1992.

E. Fama and K. French. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33:3–56, 1993.

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

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

W. Fung and D. Hsieh. Performance characteristics of hedge funds and CTA funds: Natural versus spurious biases. *Journal of Financial and Quantitative Analysis*, 35(2):291–307, 2000.

W. Fung and D. Hsieh. The risk in hedge fund strategies: Theory and evidence from trend followers. *Review of Financial Studies*, 14(2):313–341, 2001.

W. Fung and D. Hsieh. Hedge fund benchmarks: A risk-based approach. *Financial Analyst Journal*, 60:65–81, 2004.

W. Fung, D. Hsieh, N. Naik, and T. Ramadorai. Hedge funds: Performance, risk and capital formation. *Journal of Finance (forthcoming)*, 2007.

M. Getmansky, A. Lo, and I. Makarov. An econometric model of serial correlation and illiquidity in hedge fund returns. *Journal of Financial Economics*, 74:529–609, 2004.

L. Glosten and R. Jagannathan. A contingent claims approach to performance evaluation. *Journal of Empirical Finance*, 1:133–160, 1994.

A. Goyal and P. Santa-Clara. Idiosyncratic risk matters! *Journal of Finance*, 58:975–1007, 2003.

A. Gupta and B. Liang. Do hedge funds have enough capital: A value–at–risk approach. *Journal of Financial Economics*, 77:219–253, 2005.

C. Harvey and A. Siddique. Conditional skewness in asset pricing tests. *Journal of Finance*, 55(3): 1263–1295, 2000.

J. Hasanhodzic and A. Lo. Can hedge fund returns be replicated? the linear case. *Journal of Investment Management*, 5:5–45, 2007.

R. Henriksson and R. Merton. On market timing and investment performance II: Statistical procedures for evaluating forecasting skill. *Journal of Business*, 41:867–887, 1981.

J. Huij and M. Verbeek. Cross-sectional learning and short-run persistence in mutual fund performance. *Journal of Banking and Finance*, 31:973–997, 2007.

J. Jackwerth and M. Rubinstein. Recovering probability distributions from contemparaneous security prices. *Journal of Finance*, 51:1611–1631, 1996.

N. Jegadeesh and S. Titman. Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, 48:65–91, 1993.

G. Jiang and Y. Tian. The model-free implied volatility and its information content. *Review of Financial Studies*, 18:1305–1342, 2005.

C. Jones. A nonlinear factor analysis of S&P 500 index option returns. *Journal of Finance*, 61: 2325–2363, 2006.

C. Jones and J. Shanken. Mutual fund performance with learning across funds. *Journal of Financial Economics*, 78:507–522, 2005.

J. Koski and J. Pontiff. How are derivatives used? evidence from the mutual fund industry. *Journal of Finance*, 54:791–816, 1999.

R. Kosowski, A. Timmermann, R. Wermers, and H. White. Can mutual fund stars really pick stocks? new evidence from a bootstrap analysis. *Journal of Finance*, 66:341–360, 2006.

R. Kosowski, N. Naik, and M. Teo. Do hedge funds deliver alpha? A Bayesian and bootstrap analysis. *Journal of Financial Economics*, 84:10–20, 2007.

A. Kraus and R. Litzenberger. Skewness preference and the valuation of risk assets. *Journal of Finance*, 31(4):1085–1100, 1976.

B. Liang. Hedge funds: the living and the dead. *Journal of Financial and Quantitative Analysis*, 35: 309–326, 2000.

J. Liew and M. Vassalou. Can book-to-market, size and momentum be risk factors that predict economic growth? *Journal of Financial Economics*, 57:221–245, 2000.

B. Malkiel and A. Saha. Hedge funds: Risk and return. *Journal of Portfolio Management*, 61(6): 80–88, 2005.

R. Merton. On market time and investment performance I: An equilibrium theory for market forecasts. *Journal of Business*, 54:363–407, 1981.

R. Merton. An intertemporal asset pricing model. *Econometrica*, 41:867–887, 1973.

M. Mitchell and T. Pulvino. Characteristics of risk in risk arbitrage. *Journal of Finance*, 56:2135–2175, 2001.

J. Pan. The jump-risk premia implicit in options: evidence from an integrated time-series study. *Journal of Financial Economics*, 63:3–50, 2002.

L. Pastor and R. Stambaugh. Liquidity risk and expected stock returns. *Journal of Political Economy*, 111:642–685, 2003.

L. Pastor and R. Stambaugh. Mutual fund performance and seemingly unrelated assets. *Journal of Financial Economics*, 63:315–349, 2002.

A. Patton. Are "market neutral" hedge funds really market neutral? Technical report, University of Oxford, 2004.

S. Ross. The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, 13:341–360, 1976.

M. Rubinstein. The fundamental theorem of parameter-preference security valuation. *Journal of Financial and Quantitative Analysis*, 8(1):61–69, 1973.

J. Vanden. Option coskewness and capital asset pricing. *Review of Financial Studies*, 19:1279–1320, 2006.

J. Xu. Price convexity and skewness. *Journal of Finance*, 62:2521–2552, 2007.

# Tables and Figures

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: | | | | FH-7 Model (post-ranking) | | | Carhart-4 Model (post-ranking) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | RMRF | ΔVOL | ΔSKEW | ΔKURT | Alpha | Alpha-$t$ | Adj.Rsq. | Alpha | Alpha-$t$ | Adj.Rsq |
| | | A. Sorts on exposure to ΔVOL | | | | | | | | | |
| D1 | H | 0.65 | 5.54 | 7.57 | 1.45 | -3.17% | -1.08 | 50% | -2.42% | -0.88 | 59% |
| D2 | | 0.41 | 2.24 | 2.98 | 0.55 | 0.04% | 0.03 | 61% | -0.18% | -0.12 | 65% |
| D3 | | 0.31 | 1.24 | 1.64 | 0.30 | 1.58% | 1.22 | 58% | 0.99% | 0.79 | 63% |
| D4 | | 0.23 | 0.67 | 0.91 | 0.15 | 2.63% | 2.63 | 59% | 2.19% | 2.21 | 62% |
| D5 | | 0.19 | 0.25 | 0.49 | 0.06 | 3.77% | 4.40 | 62% | 3.37% | 3.88 | 62% |
| D6 | | 0.17 | -0.11 | 0.18 | -0.01 | 4.30% | 5.08 | 61% | 3.71% | 4.30 | 61% |
| D7 | | 0.17 | -0.48 | -0.22 | -0.10 | 4.23% | 3.97 | 58% | 3.45% | 3.19 | 58% |
| D8 | | 0.19 | -0.98 | -0.72 | -0.21 | 4.70% | 4.37 | 62% | 4.21% | 3.83 | 62% |
| D9 | | 0.22 | -1.86 | -1.63 | -0.41 | 6.44% | 4.57 | 56% | 5.84% | 3.94 | 54% |
| D10 | L | 0.19 | -5.28 | -4.87 | -1.10 | 9.78% | 4.44 | 52% | 9.11% | 3.96 | 50% |
| | | B. Sorts on exposure to ΔSKEW | | | | | | | | | |
| D1 | H | 0.62 | 3.02 | 13.62 | 2.05 | -4.68% | -1.59 | 53% | -3.87% | -1.35 | 57% |
| D2 | | 0.40 | 1.25 | 5.43 | 0.80 | 1.90% | 1.10 | 57% | 1.41% | 0.83 | 61% |
| D3 | | 0.30 | 0.68 | 3.03 | 0.43 | 2.60% | 2.13 | 65% | 1.94% | 1.59 | 67% |
| D4 | | 0.24 | 0.36 | 1.67 | 0.23 | 2.95% | 2.80 | 61% | 2.13% | 2.12 | 66% |
| D5 | | 0.19 | 0.14 | 0.73 | 0.08 | 3.78% | 4.10 | 62% | 3.24% | 3.57 | 65% |
| D6 | | 0.18 | -0.04 | -0.04 | -0.03 | 4.44% | 5.03 | 60% | 3.84% | 4.37 | 62% |
| D7 | | 0.18 | -0.23 | -0.85 | -0.16 | 4.08% | 3.93 | 58% | 3.48% | 3.35 | 60% |
| D8 | | 0.20 | -0.49 | -1.96 | -0.34 | 4.08% | 3.31 | 57% | 3.11% | 2.50 | 58% |
| D9 | | 0.24 | -0.94 | -4.00 | -0.66 | 5.65% | 4.35 | 58% | 5.22% | 3.81 | 55% |
| D10 | L | 0.19 | -2.50 | -11.36 | -1.74 | 9.19% | 4.30 | 41% | 9.54% | 4.08 | 33% |

*Table 1 continued*

| | | Pre-ranking exposures for: | | | | FH-7 Model (post-ranking) | | | Carhart-4 Model (post-ranking) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | RMRF | ΔVOL | ΔSKEW | ΔKURT | Alpha | Alpha-*t* | Adj.Rsq. | Alpha | Alpha-*t* | Adj.Rsq. |
| | | C. Sorts on exposure to ΔKURT | | | | | | | | | |
| D1 | H | 0.54 | 3.47 | 12.50 | 2.28 | -4.37% | -1.53 | 54% | -3.27% | -1.16 | 57% |
| D2 | | 0.36 | 1.36 | 5.04 | 0.88 | 0.58% | 0.35 | 60% | 0.41% | 0.24 | 62% |
| D3 | | 0.28 | 0.74 | 2.78 | 0.48 | 2.50% | 2.12 | 63% | 2.00% | 1.70 | 65% |
| D4 | | 0.22 | 0.40 | 1.53 | 0.25 | 3.03% | 2.94 | 61% | 2.19% | 2.27 | 68% |
| D5 | | 0.19 | 0.19 | 0.71 | 0.09 | 3.45% | 3.69 | 56% | 2.89% | 3.17 | 60% |
| D6 | | 0.18 | -0.04 | 0.00 | -0.04 | 3.49% | 3.90 | 61% | 2.98% | 3.33 | 63% |
| D7 | | 0.20 | -0.27 | -0.74 | -0.18 | 4.47% | 4.20 | 60% | 3.72% | 3.45 | 60% |
| D8 | | 0.23 | -0.61 | -1.76 | -0.38 | 5.25% | 4.40 | 58% | 4.47% | 3.74 | 59% |
| D9 | | 0.27 | -1.05 | -3.57 | -0.74 | 5.79% | 4.12 | 55% | 5.06% | 3.52 | 55% |
| D10 | L | 0.28 | -2.93 | -10.20 | -1.98 | 9.84% | 4.59 | 39% | 9.58% | 4.23 | 35% |

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) and Carhart (1997) 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:

$$r_{i,t} = \alpha^{i}_{4F} + \underbrace{\beta^{1,i}_{4F}\,\text{RMRF}_t}_{\text{market}} + \underbrace{\beta^{2,i}_{4F}\,\Delta\text{VOL}_t + \beta^{3,i}_{4F}\,\Delta\text{SKEW}_t + \beta^{4,i}_{4F}\,\Delta\text{KURT}_t}_{\text{combined impact of tail risks}} + \varepsilon^{i,t}_{4F},$$

where $r_{i,t}$ represents excess return on the hedge fund, $\text{RMRF}_t$ is excess return on the market portfolio in month $t$, and $\Delta\text{VOL}_t$, $\Delta\text{SKEW}_t$ and $\Delta\text{KURT}_t$ are our proxies for equity volatility risk, skewness risk, and kurtosis risk, as defined in (9)–(11). $\varepsilon^{i,t}_{4F}$ 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 4,833 hedge funds.

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: | | | | FH-7 Model (post-ranking) | | | Carhart-4 Model (post-ranking) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | RMRF | ΔVOL | ΔSKEW | ΔKURT | Alpha | Alpha-$t$ | Adj.Rsq | Alpha | Alpha-$t$ | Adj.Rsq |
| P1 | H / H / H | 0.80 | 6.27 | 17.52 | 3.13 | -6.33% | -1.51 | 44% | -4.63% | -1.15 | 51% |
| P2 | H / H / M | 0.56 | 3.45 | 9.04 | 1.51 | -3.72% | -1.56 | 52% | -2.94% | -1.29 | 58% |
| P3 | H / H / L | 0.41 | 2.77 | 6.79 | 0.76 | -1.33% | -0.48 | 43% | -1.25% | -0.47 | 51% |
| P4 | H / M / H | 0.40 | 2.73 | 3.61 | 0.94 | 1.14% | 0.64 | 50% | 1.26% | 0.69 | 51% |
| P5 | H / M / M | 0.31 | 1.81 | 2.80 | 0.49 | 2.44% | 1.79 | 55% | 2.00% | 1.48 | 58% |
| P6 | H / M / L | 0.26 | 1.72 | 2.05 | 0.12 | 1.48% | 0.98 | 55% | 0.58% | 0.40 | 61% |
| P7 | H / L / H | 0.30 | 2.28 | -0.58 | 0.41 | -0.82% | -0.44 | 45% | -1.26% | -0.65 | 44% |
| P8 | H / L / M | 0.22 | 1.75 | -1.36 | -0.08 | 2.04% | 1.24 | 45% | 1.01% | 0.63 | 52% |
| P9 | H / L / L | 0.11 | 2.33 | -6.11 | -0.95 | 3.11% | 1.15 | 29% | 2.77% | 1.00 | 30% |
| P10 | M / H / H | 0.35 | 0.19 | 5.77 | 0.95 | 0.48% | 0.28 | 50% | 0.06% | 0.03 | 47% |
| P11 | M / H / M | 0.23 | 0.20 | 2.50 | 0.34 | 3.33% | 2.87 | 48% | 2.48% | 2.15 | 51% |
| P12 | M / H / L | 0.23 | 0.11 | 1.89 | 0.06 | 3.60% | 3.01 | 50% | 2.76% | 2.38 | 55% |
| P13 | M / M / H | 0.19 | 0.17 | 0.57 | 0.18 | 3.94% | 4.40 | 54% | 3.65% | 4.04 | 55% |
| P14 | M / M / M | 0.12 | 0.08 | 0.27 | 0.02 | 3.69% | 5.22 | 46% | 3.50% | 4.81 | 45% |
| P15 | M / M / L | 0.12 | -0.03 | 0.00 | -0.14 | 4.17% | 4.36 | 50% | 3.28% | 3.45 | 53% |
| P16 | M / L / H | 0.24 | 0.06 | -1.18 | -0.03 | 4.69% | 4.36 | 49% | 4.57% | 4.10 | 48% |
| P17 | M / L / M | 0.14 | -0.05 | -1.73 | -0.28 | 4.82% | 4.75 | 52% | 4.26% | 4.16 | 54% |
| P18 | M / L / L | 0.12 | -0.01 | -5.09 | -0.90 | 5.73% | 3.79 | 42% | 5.00% | 3.23 | 42% |

*Table 2 continued*

| | | Pre-ranking exposures for: | | | | FH-7 Model (post-ranking) | | | Carhart-4 Model (post-ranking) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | RMRF | ΔVOL | ΔSKEW | ΔKURT | Alpha | Alpha-$t$ | Adj.Rsq | Alpha | Alpha-$t$ | Adj.Rsq |
| P19 | L / H / H | 0.39 | -2.40 | 6.92 | 1.04 | 2.40% | 0.99 | 47% | 1.07% | 0.43 | 48% |
| P20 | L / H / M | 0.29 | -1.59 | 2.25 | 0.17 | 4.63% | 3.24 | 53% | 4.19% | 2.85 | 52% |
| P21 | L / H / L | 0.30 | -2.16 | 1.49 | -0.31 | 8.47% | 4.20 | 39% | 7.37% | 3.57 | 39% |
| P22 | L / M / H | 0.24 | -1.54 | -0.78 | -0.03 | 4.35% | 2.97 | 53% | 3.56% | 2.38 | 53% |
| P23 | L / M / M | 0.19 | -1.51 | -1.43 | -0.34 | 5.97% | 5.32 | 55% | 5.56% | 4.84 | 55% |
| P24 | L / M / L | 0.22 | -2.25 | -2.06 | -0.75 | 6.14% | 3.62 | 51% | 5.12% | 2.96 | 51% |
| P25 | L / L / H | 0.28 | -2.44 | -4.88 | -0.58 | 5.23% | 3.20 | 57% | 5.28% | 3.18 | 57% |
| P26 | L / L / M | 0.21 | -2.95 | -6.78 | -1.22 | 9.11% | 5.18 | 48% | 8.44% | 4.55 | 45% |
| P27 | L / L / L | 0.15 | -5.65 | -14.80 | -2.79 | 13.79% | 4.64 | 26% | 13.96% | 4.50 | 23% |

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) and Carhart (1997) 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:

$$r_{i,t} = \alpha^{i}_{4F} + \beta^{1,i}_{4F}\,\mathrm{RMRF}_t + \beta^{2,i}_{4F}\,\Delta\mathrm{VOL}_t + \beta^{3,i}_{4F}\,\Delta\mathrm{SKEW}_t + \beta^{4,i}_{4F}\,\Delta\mathrm{KURT}_t + \varepsilon^{i,t}_{4F},$$

where $r_{i,t}$ represents excess return on the hedge fund, $\mathrm{RMRF}_t$ is excess return on the market portfolio in month $t$, and $\Delta\mathrm{VOL}_t$, $\Delta\mathrm{SKEW}_t$ and $\Delta\mathrm{KURT}_t$ are our proxies for equity volatility risk, skewness risk, and kurtosis risk. $\varepsilon^{i,t}_{4F}$ represents the residual return in month $t$. Reported post-ranking alphas are annualized. The sample is from 1994 to 2004 and covers 4,833 hedge funds.

Table 3: Summary statistics of higher–moment risk factors premiums, and alphas from Multifactor models

| | mean | $t$-stat | correlation matrix | | | FH-7 Model | | | Carhart-4 Model | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | FVOL | FSKEW | FKURT | Alpha | Alpha-$t$ | Adj.Rsq | Alpha | Alpha-$t$ | Adj.Rsq |
| FVOL | -6.27% | -3.62 | 1.00 | | | -6.90% | -3.98 | 9% | -6.34% | -4.11 | 31% |
| FSKEW | 2.96% | 2.01 | -0.41 | 1.00 | | 4.02% | 2.72 | 8% | 3.88% | 2.75 | 21% |
| FKURT | -2.48% | -2.24 | 0.26 | -0.33 | 1.00 | -3.34% | -2.95 | 5% | -2.89% | -2.43 | 0% |

Reported are annualized time-series averages and $t$-statistics of the three higher–moment risk factor premiums. We also present 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 quantified 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 quantile portfolios of hedge funds based on their higher-moment betas in Table 2. For $\text{HMF}_t = \{\text{FVOL}_t, \text{FSKEW}_t, \text{FKURT}_t\}$, each return factor is regressed on the Fung and Hsieh (2004) model specification:

$$\text{HMF}_t = \alpha + \beta_1 \text{SNPMRF}_t + \beta_2 \text{SCMLC}_t + \beta_3 \text{BD10RET}_t + \beta_4 \text{BAAMTSY}_t + \beta_5 \text{PTFSBD}_t + \beta_6 \text{PTFSFX}_t + \beta_7 \text{PTFSCOM}_t + \varepsilon_t,$$

and the Carhart (1997) model specification:

$$\text{HMF}_t = \alpha + \beta_1 \text{RMRF}_t + \beta_2 \text{SMB}_t + \beta_3 \text{HML}_t + \beta_4 \text{UMD}_t + \varepsilon_t,$$

The annualized alphas, $t$-statistics, and R-squared values are shown, where the t-statistics are based on the heteroskedastically consistent estimator.

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 and augmented Carhart 4-factor models

| | | Augmented FH-7 Model | | | | | | Augmented Carhart-4 Model | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Alpha | Alpha-*t* | FVOL | FSKEW | FKURT | Adj.Rsq | Alpha | Alpha-*t* | FVOL | FSKEW | FKURT | Adj.Rsq |
| P1 | H / H / H | 7.87% | 2.56 | 1.17 | -0.76 | 0.91 | 75% | 7.48% | 2.35 | 0.98 | -0.61 | 1.21 | 74% |
| P2 | H / H / M | 4.17% | 2.57 | 0.74 | -0.67 | 0.03 | 81% | 4.37% | 2.46 | 0.71 | -0.65 | 0.10 | 79% |
| P3 | H / H / L | 3.72% | 1.93 | 0.62 | -1.13 | -1.14 | 77% | 4.00% | 1.93 | 0.62 | -1.10 | -1.01 | 75% |
| P4 | H / M / H | 5.64% | 3.50 | 0.47 | 0.04 | 0.43 | 66% | 5.07% | 3.01 | 0.41 | 0.08 | 0.52 | 65% |
| P5 | H / M / M | 6.17% | 5.32 | 0.44 | -0.16 | 0.02 | 73% | 5.64% | 4.71 | 0.46 | -0.19 | -0.01 | 72% |
| P6 | H / M / L | 3.49% | 2.73 | 0.41 | -0.30 | -0.61 | 73% | 2.55% | 2.06 | 0.41 | -0.31 | -0.63 | 76% |
| P7 | H / L / H | 2.14% | 1.17 | 0.41 | 0.35 | 0.47 | 56% | 1.25% | 0.67 | 0.38 | 0.37 | 0.54 | 56% |
| P8 | H / L / M | 4.00% | 2.61 | 0.55 | 0.33 | -0.14 | 60% | 2.45% | 1.64 | 0.50 | 0.38 | -0.07 | 64% |
| P9 | H / L / L | 3.93% | 1.70 | 0.90 | 0.75 | -0.72 | 57% | 3.52% | 1.44 | 0.87 | 0.82 | -0.55 | 54% |
| P10 | M / H / H | 3.67% | 2.38 | -0.03 | -0.59 | 0.31 | 67% | 3.82% | 2.38 | 0.07 | -0.66 | 0.27 | 65% |
| P11 | M / H / M | 4.66% | 3.99 | 0.04 | -0.32 | -0.07 | 56% | 3.94% | 3.38 | 0.06 | -0.33 | -0.07 | 58% |
| P12 | M / H / L | 3.64% | 3.25 | -0.03 | -0.41 | -0.42 | 63% | 2.61% | 2.36 | -0.08 | -0.38 | -0.38 | 66% |
| P13 | M / M / H | 4.69% | 4.83 | 0.06 | 0.01 | 0.10 | 54% | 4.27% | 4.36 | 0.05 | 0.02 | 0.12 | 56% |
| P14 | M / M / M | 3.82% | 4.96 | 0.05 | -0.03 | -0.09 | 46% | 3.63% | 4.54 | 0.04 | -0.02 | -0.06 | 45% |
| P15 | M / M / L | 3.98% | 4.06 | 0.04 | -0.15 | -0.32 | 56% | 3.27% | 3.40 | 0.06 | -0.16 | -0.34 | 60% |
| P16 | M / L / H | 5.65% | 5.01 | 0.10 | 0.14 | 0.24 | 53% | 5.45% | 4.69 | 0.10 | 0.14 | 0.26 | 53% |
| P17 | M / L / M | 4.56% | 4.19 | 0.08 | 0.03 | -0.21 | 54% | 4.07% | 3.70 | 0.08 | 0.04 | -0.19 | 55% |
| P18 | M / L / L | 4.61% | 3.10 | 0.21 | 0.35 | -0.35 | 53% | 4.09% | 2.67 | 0.22 | 0.35 | -0.33 | 53% |

*Table 4 continued*

| | | Augmented FH-7 Model | | | | | | Augmented Carhart-4 Model | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Alpha | Alpha-$t$ | FVOL | FSKEW | FKURT | Adj.Rsq | Alpha | Alpha-$t$ | FVOL | FSKEW | FKURT | Adj.Rsq |
| P19 | L / H / H | 2.90% | 1.27 | -0.54 | -0.70 | 0.43 | 61% | 1.47% | 0.64 | -0.58 | -0.66 | 0.51 | 62% |
| P20 | L / H / M | 4.52% | 3.45 | -0.35 | -0.51 | 0.09 | 67% | 3.94% | 2.94 | -0.40 | -0.47 | 0.16 | 67% |
| P21 | L / H / L | 5.88% | 3.44 | -0.41 | -0.73 | -0.81 | 63% | 5.30% | 2.94 | -0.43 | -0.69 | -0.70 | 61% |
| P22 | L / M / H | 3.32% | 2.29 | -0.38 | -0.23 | 0.20 | 61% | 2.35% | 1.61 | -0.44 | -0.18 | 0.29 | 62% |
| P23 | L / M / M | 4.63% | 4.05 | -0.27 | -0.14 | -0.03 | 61% | 3.87% | 3.40 | -0.35 | -0.09 | 0.06 | 63% |
| P24 | L / M / L | 3.73% | 2.39 | -0.29 | -0.44 | -0.65 | 65% | 3.31% | 2.07 | -0.28 | -0.45 | -0.62 | 65% |
| P25 | L / L / H | 3.75% | 2.35 | -0.31 | 0.25 | 0.51 | 65% | 4.29% | 2.58 | -0.27 | 0.23 | 0.56 | 64% |
| P26 | L / L / M | 5.74% | 3.36 | -0.20 | 0.40 | -0.11 | 59% | 4.99% | 2.73 | -0.27 | 0.46 | 0.01 | 55% |
| P27 | L / L / L | 6.65% | 2.42 | -0.52 | 0.56 | -0.38 | 47% | 6.81% | 2.32 | -0.66 | 0.65 | -0.16 | 42% |

Reported are post-ranking alphas, $t$-statistics and adjusted $R$-squared values of the quantile portfolios from regressions with the Fung and Hsieh (2004) and Carhart (1997) factors together with the FVOL, FSKEW, and FKURT factors, where FVOL, FSKEW, and FKURT are the risk factor premiums for volatility, skewness, and kurtosis risks, respectively. Alphas are annualized. The post-ranking factor loadings on FVOL, FSKEW, and FKURT are also presented. 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:

$$r_{i,t} = \alpha_{4F}^{i} + \beta_{4F}^{1,i}\,\mathrm{RMRF}_t + \beta_{4F}^{2,i}\,\Delta\mathrm{VOL}_t + \beta_{4F}^{3,i}\,\Delta\mathrm{SKEW}_t + \beta_{4F}^{4,i}\,\Delta\mathrm{KURT}_t + \varepsilon_{4F}^{i,t},$$

where $\mathrm{RMRF}_t$ is excess return on the market portfolio in month $t$, and $\Delta\mathrm{VOL}_t$, $\Delta\mathrm{SKEW}_t$ and $\Delta\mathrm{KURT}_t$ are our proxies for equity volatility risk, skewness risk, and kurtosis risk. The sample is from 1994 to 2004 and covers 4,833 hedge funds.

Table 5: Portfolios of mutual funds triple-sorted by exposure to higher-moment risks

| | | Pre-ranking Exposures for: | | | | Carhart-4 Model (post-ranking) | | |
|---|---|---|---|---|---|---|---|---|
| | | RMRF | ΔVOL | ΔSKEW | ΔKURT | 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% |

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: $r_{i,t} = \alpha^{i}_{4F} + \beta^{1,i}_{4F}\,\mathrm{RMRF}_t + \beta^{2,i}_{4F}\,\Delta\mathrm{VOL}_t + \beta^{3,i}_{4F}\,\Delta\mathrm{SKEW}_t + \beta^{4,i}_{4F}\,\Delta\mathrm{KURT}_t + \varepsilon^{i,t}_{4F}$, where $\mathrm{RMRF}_t$ is excess return on the market portfolio in month $t$, and $\Delta\mathrm{VOL}_t$, $\Delta\mathrm{SKEW}_t$ and $\Delta\mathrm{KURT}_t$ are our proxies for equity volatility risk, skewness risk, and kurtosis risk.

Table 6: Estimates of higher–moment risk factors premiums using mutual fund returns

| | mean | $t$-stat | correlation matrix | | | Carhart-4 Model | | |
|---|---|---|---|---|---|---|---|---|
| | | | FVOL | FSKEW | FKURT | Alpha | Alpha-$t$ | Adj.Rsq |
| FVOL | -4.31% | -1.24 | 1.00 | | | -4.92% | -1.98 | 56% |
| FSKEW | 1.82% | 0.70 | -0.57 | 1.00 | | 0.79% | 0.35 | 34% |
| FKURT | -1.10% | -0.71 | 0.42 | -0.21 | 1.00 | -0.90% | -0.56 | 7% |

Reported are annualized time-series averages and $t$-statistics of the three higher–moment risk factor premiums and their correlations. The higher–moment return factors are quantified 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 quantile portfolios of mutual funds based on their higher-moment betas. For $\text{HMF}_t = \{\text{FVOL}_t, \text{FSKEW}_t, \text{FKURT}_t\}$, each return factor is regressed on the Carhart (1997) model specification:

$$\text{HMF}_t = \alpha + \beta_1\,\text{RMRF}_t + \beta_2\,\text{SMB}_t + \beta_3\,\text{HML}_t + \beta_4\,\text{UMD}_t + \varepsilon_t,$$

The annualized alphas, $t$-statistics, and R-squared values are shown, where the t-statistics are based on the heteroskedastically consistent estimator. The sample is from 1994 to 2004 and covers 9,769 mutual funds.

Table 7: 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<br>Panel A: Bayesian estimation | | | FH-7 Model<br>Panel B: Backfilling Bias | | |
|---|---|---|---|---|---|---|---|
| | | Alpha | Alpha-$t$ | Adj.Rsq | Alpha | Alpha-$t$ | Adj.Rsq |
| P1 | H / H / H | -7.77% | -1.78 | 40% | -8.38% | -1.89 | 40% |
| P2 | H / H / M | -4.39% | -1.72 | 50% | -3.20% | -1.33 | 52% |
| P3 | H / H / L | -1.18% | -0.39 | 36% | -1.54% | -0.56 | 42% |
| P4 | H / M / H | 0.98% | 0.54 | 38% | -1.26% | -0.65 | 48% |
| P5 | H / M / M | 0.28% | 0.16 | 50% | 0.24% | 0.15 | 51% |
| P6 | H / M / L | -0.25% | -0.11 | 46% | 1.32% | 0.77 | 45% |
| P7 | H / L / H | 2.41% | 1.78 | 31% | -1.21% | -0.53 | 40% |
| P8 | H / L / M | 1.22% | 0.76 | 37% | 1.83% | 0.93 | 34% |
| P9 | H / L / L | 0.85% | 0.28 | 22% | 1.01% | 0.33 | 28% |
| P10 | M / H / H | 2.06% | 0.97 | 47% | 0.33% | 0.14 | 34% |
| P11 | M / H / M | 4.19% | 2.65 | 33% | 3.45% | 2.39 | 41% |
| P12 | M / H / L | 4.25% | 3.45 | 36% | 3.01% | 2.41 | 47% |
| P13 | M / M / H | 4.56% | 3.67 | 55% | 3.58% | 3.29 | 48% |
| P14 | M / M / M | 3.44% | 3.21 | 40% | 4.16% | 5.40 | 50% |
| P15 | M / M / L | 5.20% | 3.53 | 40% | 4.23% | 3.92 | 52% |
| P16 | M / L / H | 4.68% | 4.57 | 49% | 4.26% | 3.19 | 42% |
| P17 | M / L / M | 4.26% | 3.12 | 47% | 4.40% | 3.95 | 50% |
| P18 | M / L / L | 4.51% | 2.46 | 42% | 5.97% | 3.30 | 33% |
| P19 | L / H / H | 3.43% | 1.36 | 44% | 0.42% | 0.14 | 39% |
| P20 | L / H / M | 4.65% | 3.00 | 44% | 5.68% | 3.05 | 42% |
| P21 | L / H / L | 6.62% | 4.78 | 33% | 7.89% | 3.25 | 34% |
| P22 | L / M / H | 5.80% | 2.86 | 45% | 4.46% | 2.42 | 43% |
| P23 | L / M / M | 6.39% | 4.37 | 46% | 4.46% | 3.51 | 51% |
| P24 | L / M / L | 7.68% | 4.14 | 42% | 5.49% | 3.04 | 45% |
| P25 | L / L / H | 5.81% | 3.59 | 59% | 5.49% | 2.82 | 49% |
| P26 | L / L / M | 8.26% | 4.22 | 52% | 6.59% | 3.02 | 40% |
| P27 | L / L / L | 14.14% | 4.82 | 30% | 11.92% | 3.48 | 20% |

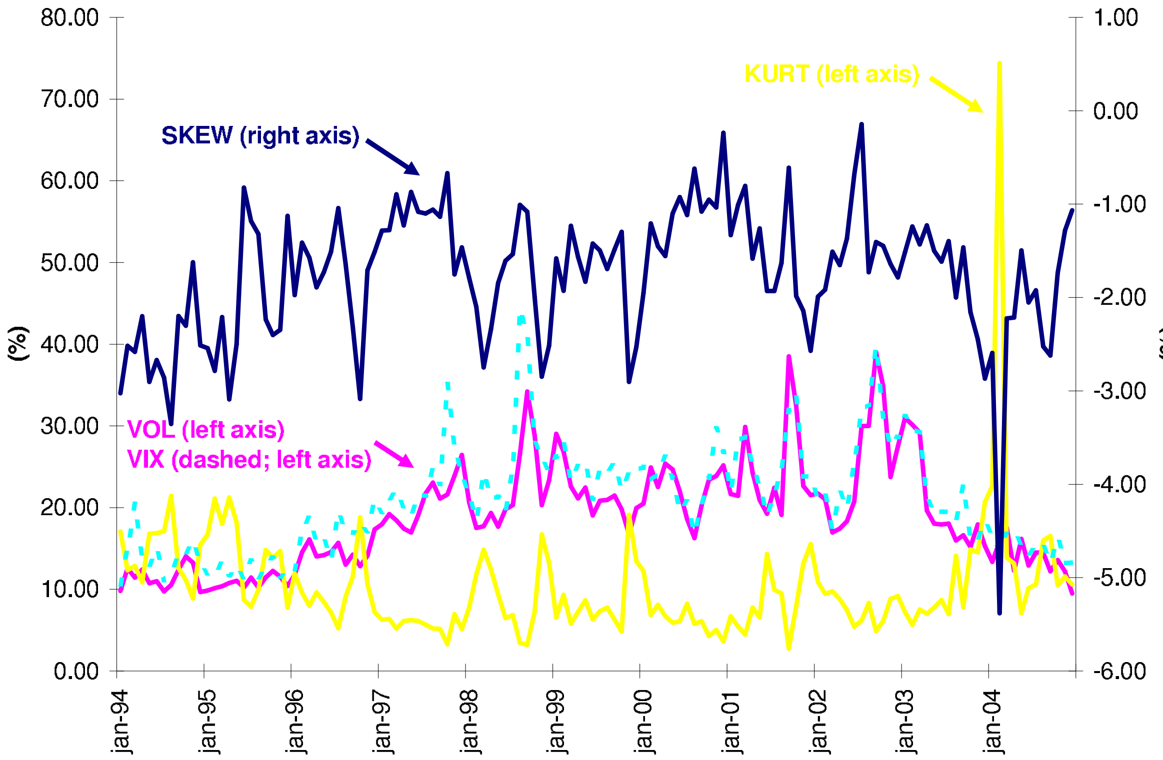
Two types of empirical tests are conducted. Panel A reports results based on Bayesian estimation. Panel B reports results accounting for the backfiling bias that reduces the sample universe to 3,243 hedge funds. Reported throughout are post-ranking alphas, $t$-statistics and adjusted $R$-squared values 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: $r_{i,t} = \alpha^{i}_{4F} + \beta^{1,i}_{4F}\,\mathrm{RMRF}_t + \beta^{2,i}_{4F}\,\Delta\mathrm{VOL}_t + \beta^{3,i}_{4F}\,\Delta\mathrm{SKEW}_t + \beta^{4,i}_{4F}\,\Delta\mathrm{KURT}_t + \varepsilon^{i,t}_{4F}$, where $\mathrm{RMRF}_t$ is excess return on the market portfolio in month $t$, and $\Delta\mathrm{VOL}_t$, $\Delta\mathrm{SKEW}_t$ and $\Delta\mathrm{KURT}_t$ are our proxies for equity volatility risk, skewness risk, and kurtosis risk. All reported alphas are annualized.

Table 8: 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 | -6.08% | -1.30 | 43% | -6.87% | -1.61 | 43% | -6.84% | -1.84 | 56% |
| P2 | H / H / M | -3.04% | -1.15 | 52% | -4.22% | -1.74 | 42% | -3.93% | -1.74 | 58% |
| P3 | H / H / L | 0.42% | 0.14 | 43% | -2.16% | -0.77 | 44% | -1.41% | -0.51 | 44% |
| P4 | H / M / H | 2.07% | 1.05 | 50% | 0.93% | 0.51 | 50% | 0.98% | 0.58 | 56% |
| P5 | H / M / M | 2.65% | 1.74 | 54% | 2.14% | 1.54 | 55% | 2.36% | 1.77 | 57% |
| P6 | H / M / L | 3.03% | 1.85 | 56% | 1.03% | 0.68 | 55% | 1.44% | 0.95 | 55% |
| P7 | H / L / H | -0.68% | -0.33 | 44% | -1.16% | -0.61 | 45% | -0.90% | -0.48 | 46% |
| P8 | H / L / M | 3.18% | 1.75 | 46% | 1.45% | 0.88 | 47% | 1.96% | 1.20 | 47% |
| P9 | H / L / L | 5.50% | 1.86 | 31% | 2.50% | 0.91 | 30% | 3.02% | 1.12 | 30% |
| P10 | M / H / H | -0.50% | -0.26 | 50% | 0.12% | 0.07 | 50% | 0.48% | 0.28 | 49% |
| P11 | M / H / M | 3.44% | 2.68 | 48% | 3.06% | 2.59 | 48% | 3.34% | 2.86 | 47% |
| P12 | M / H / L | 4.14% | 3.14 | 50% | 3.22% | 2.68 | 51% | 3.59% | 2.99 | 49% |
| P13 | M / M / H | 4.52% | 4.58 | 54% | 3.68% | 4.08 | 55% | 3.93% | 4.37 | 54% |
| P14 | M / M / M | 4.15% | 5.32 | 46% | 3.45% | 4.87 | 47% | 3.66% | 5.22 | 47% |
| P15 | M / M / L | 4.52% | 4.30 | 51% | 3.78% | 3.97 | 52% | 4.17% | 4.34 | 50% |
| P16 | M / L / H | 5.66% | 4.82 | 50% | 4.48% | 4.11 | 50% | 4.65% | 4.35 | 50% |
| P17 | M / L / M | 6.10% | 5.59 | 55% | 4.52% | 4.42 | 53% | 4.81% | 4.72 | 52% |
| P18 | M / L / L | 7.22% | 4.46 | 46% | 5.50% | 3.57 | 42% | 5.71% | 3.76 | 42% |
| P19 | L / H / H | 1.95% | 0.73 | 47% | 2.58% | 1.04 | 47% | 2.36% | 0.97 | 47% |
| P20 | L / H / M | 4.62% | 2.90 | 52% | 4.38% | 3.02 | 53% | 4.63% | 3.22 | 52% |
| P21 | L / H / L | 9.73% | 4.39 | 40% | 8.26% | 4.02 | 39% | 8.52% | 4.23 | 39% |
| P22 | L / M / H | 4.49% | 2.80 | 54% | 3.98% | 2.69 | 53% | 4.32% | 2.95 | 53% |
| P23 | L / M / M | 6.59% | 5.54 | 59% | 5.83% | 5.09 | 55% | 5.96% | 5.28 | 55% |
| P24 | L / M / L | 7.57% | 4.08 | 51% | 5.85% | 3.39 | 51% | 6.24% | 3.78 | 53% |
| P25 | L / L / H | 5.71% | 3.16 | 57% | 5.40% | 3.24 | 56% | 5.27% | 3.22 | 57% |
| P26 | L / L / M | 11.23% | 6.14 | 54% | 9.32% | 5.21 | 48% | 9.10% | 5.16 | 48% |
| P27 | L / L / L | 16.44% | 5.12 | 29% | 14.47% | 4.81 | 26% | 13.77% | 4.61 | 25% |

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 FF-7 model augmented with the OTMPUT factor of Agarwal and Naik (2004); Panel C employs the FF-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: $r_{i,t} = \alpha^{i}_{4F} + \beta^{1,i}_{4F}\,\mathrm{RMRF}_t + \beta^{2,i}_{4F}\,\Delta\mathrm{VOL}_t + \beta^{3,i}_{4F}\,\Delta\mathrm{SKEW}_t + \beta^{4,i}_{4F}\,\Delta\mathrm{KURT}_t + \varepsilon^{i,t}_{4F}$, where $\mathrm{RMRF}_t$ is excess return on the market portfolio in month $t$, and $\Delta\mathrm{VOL}_t$, $\Delta\mathrm{SKEW}_t$ and $\Delta\mathrm{KURT}_t$ are our proxies for equity volatility risk, skewness risk, and kurtosis risk. All reported alphas are annualized.

Figure 1: Plots of VOL, SKEW, and KURT.




The higher-order moment calculations are based on the static option positioning specified in (9)-(11). We use S&P 100 index options with 28 days expiration. Consider the Riemann integral approximation of (5) and discretize the integral for the long position in calls as: $\sum_{j=1}^{J}(N[j-1]+N[j])\frac{\Delta K}{2}$, where $N[j] := z[K_{\max} - j\Delta K] \times C[K_{\max} - j\Delta K]$, $K_{\max}$ is the maximum level of the strike price, $J$ is the number of call/put options, and $z[K] := \frac{2}{K^2}\left(1 - \ln\left(\frac{K}{S(t)}\right)\right)$. Similarly, the integral for the long position in puts can be discretized as: $\sum_{j=1}^{J}(M[j-1]+M[j])\frac{\Delta K}{2}$, where $M[j] := z[K_{\min} + j\Delta K] \times P[K_{\min} + j\Delta K]$ and $K_{\min}$ represents the minimum level of the strike price. The figure shows time-series variation in $\sqrt{12\,\mathbb{M}_{2,t}}$ (denoted VOL), $\frac{\mathbb{M}_{3,t}}{(\mathbb{M}_{2,t})^{3/2}}$ (denoted SKEW), and $\frac{\mathbb{M}_{4,t}}{(\mathbb{M}_{2,t})^{2}}$ (denoted KURT). To enable comparisons of $\sqrt{12\,\mathbb{M}_{2,t}}$ with the VIX index from CBOE, the VIX is plotted over the same period. The sample period is January 1994 to December 2004. The sample values of the higher-moments are

| | VOL | SKEW | KURT |
|---|---|---|---|
| Mean | 18.83% | -1.76 | 10.34 |

and

| | VOL | SKEW | KURT |
|---|---|---|---|
| Stdev. | 7.38% | 0.72 | 7.20 |

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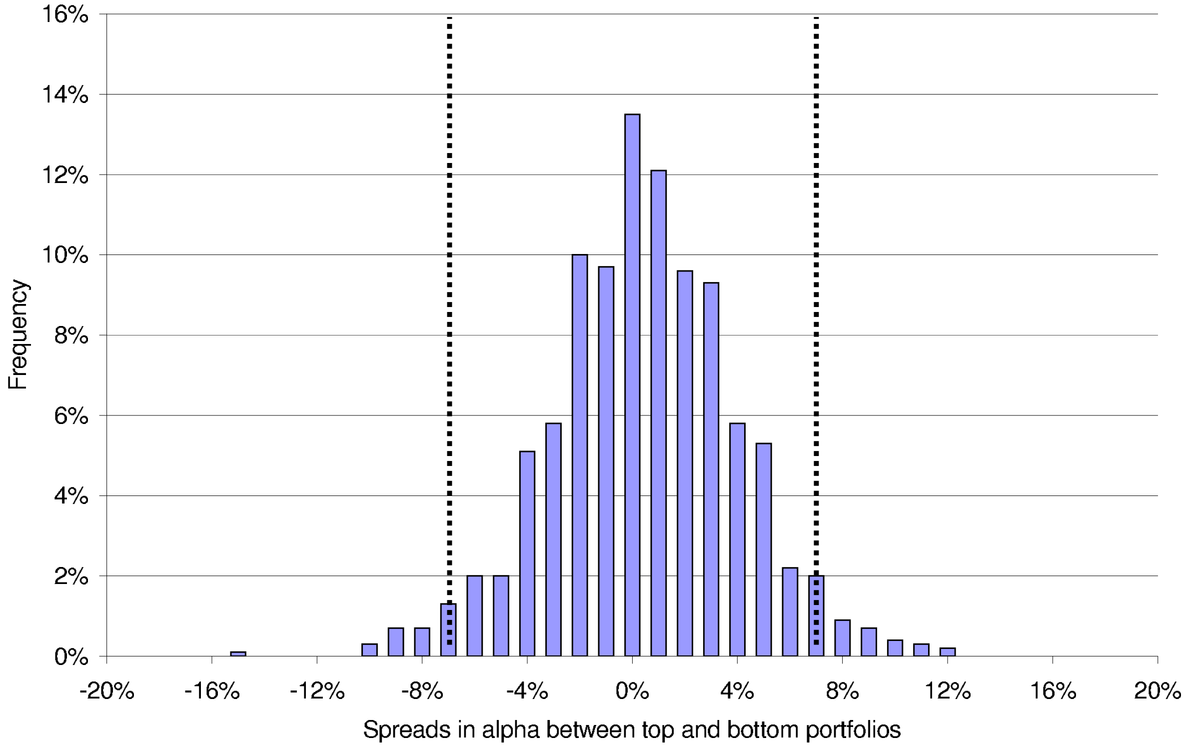
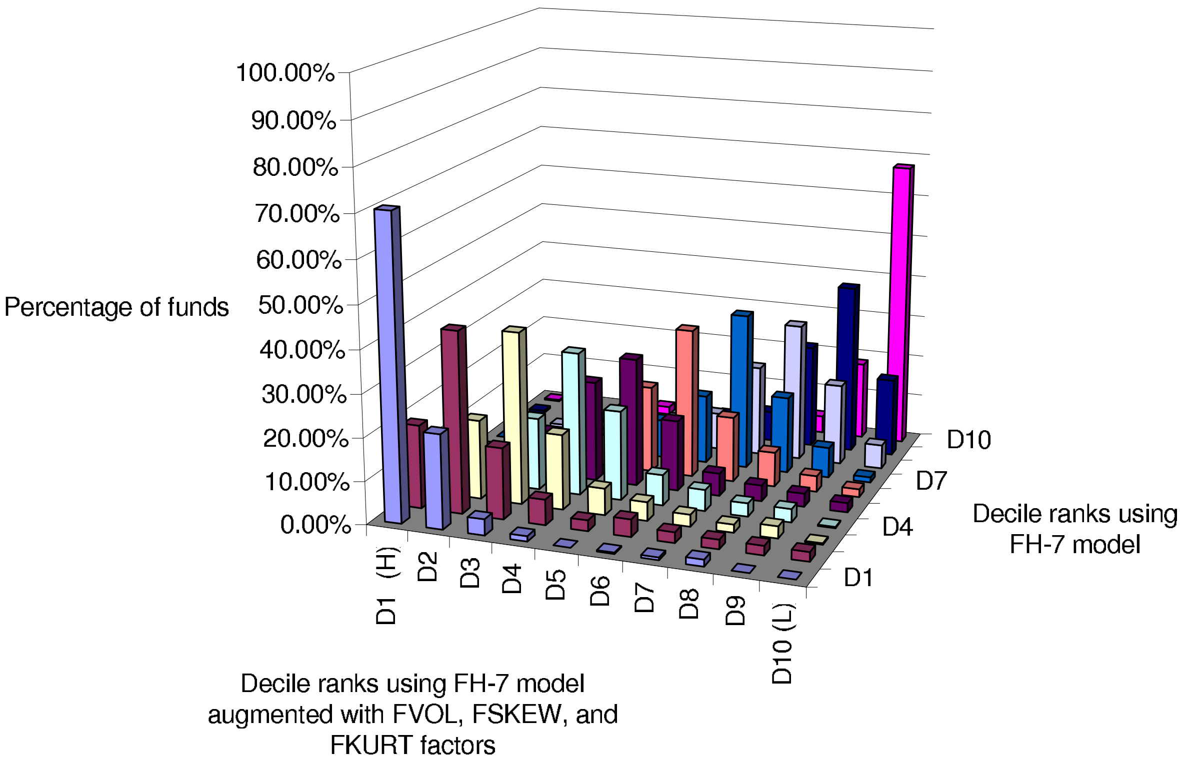
Figure 2: Bootstrapped results on the frequency distribution of spreads in alphas between the top and bottom portfolios of hedge funds triple-sorted by their exposure to ΔVOL, ΔSKEW and ΔKURT




We generate a simulated sample of hedge fund returns by using the bootstrap procedure discussed in subsection 2.4. 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 -7 percent to +7 percent per annum, as marked.

Figure 3: 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 with at least 36 consecutive return observations.