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

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1 Introduction

A strand of literature argues that investors require premiums for bearing higher-moment risk exposures when investing in assets with non-normal return distributions. Rubinstein (1973), Kraus and Litzenberger (1976), and Vanden (2006), among others, introduce a role for higher-moment risks in the Capital Asset Pricing Model (CAPM), and Harvey and Siddique (2000) demonstrate that the expected returns of assets with systematic skewness include rewards for this risk.

More than passive stock portfolios, a class of actively managed portfolios – hedge funds, should be exposed to higher-moment risk. There are several reasons for why one would expect this to be true. First, Ang et al. (2006) document that volatility risk is priced in the cross-section of stock returns. Goyal and Santa-Clara (2003) find a significant positive relation between lagged average stock volatility risk and the stock market returns. However, some of these findings have been refuted by Bali et al. (2005) and Bali and Cakici (2007). In contrast to evidence from individual stocks, there is stronger evidence of pricing of higher moments in option markets (see e.g., Guo (1998), Chernov and Ghysels (2001), Buraschi and Jackworth (2001), Coval and Shumway (2001), Pan (2002), Bakshi and Kapadia (2003), among others). Combining this evidence with the fact that hedge funds have option-like exposures due to their use of dynamic trading strategies (see e.g., Fung and Hsieh (2001), Mitchell and Pulvino (2001), Agarwal and Naik (2004), Chan et al. (2005), and Diez and Garcia (2006)), hedge funds, should be naturally exposed to higher-moment risks, much more than in the case of individual stocks.

Second reason for why hedge funds should show greater exposure to higher-moment risks is due to the option-like nature of their compensation contracts. Hedge fund managers are rewarded by incentive fee contracts, which effectively can be seen as a call option on the assets under management, with the exercise price depending on hurdle rate and high-watermark provisions (see e.g., Goetzmann et al. (2003) and Agarwal et al. (2006)). Therefore, the net-of-fee returns of hedge funds exhibit hockey-stick-like payoffs where higher moments are likely to get compensated (Cochrane (2005) and Diez and Garcia (2006)).

We contribute to the extant literature by examining the pricing of higher-moment equity risks in the cross-section of hedge fund returns. In the process, we bring an important innovation to the hedge fund literature by constructing model-free and forward-looking measures of higher-moment equity risks. Specifically, we compute the prices of second, third, and fourth moments of equity 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).[1] Since it may be difficult to pin down higher moments beyond order four, we focus on the exposure to the risks of three higher central moments, namely volatility, skewness, and kurtosis, in this paper.

There are several benefits of the use of option prices to extract the prices of higher-moment risks. First, since option prices convey important information about the future, our measures of higher moments are inherently forward-looking. Recently, Christoffersen et al. (2006) have demonstrated the relevance of using forward-looking measures of market betas instead of their historical and backward-looking measures, in explaining the cross-section of stock returns. One limitation 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. Our approach of using prices of higher moments extracted from cross-section of options overcomes this limitation.[2] Second, as Broadie et al. (2006), Jones (2006), and Driessen and Maenhout (2006) argue, index option prices reflect risk premiums such as

[1] 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), Jackwerth and Rubinstein (1996), and Jiang and Tian (2005), among others.

[2] Recently, Kapadia (2007) advocates the use of cross-sectional skewness to explain both the future common time-variation and the premium associated with high idiosyncratic volatility firms in order to avoid the tradeoff between time-variation and accuracy involved in the time-series measures of skewness.

the volatility and jump risk premiums that are hard to infer directly from the equity index time–series.

In this paper, we focus on the influence of higher moments of equity risk on hedge fund returns. It is plausible that higher moments of other markets such as fixed income, commodities, and currencies also are potentially important sources of hedge fund returns. However, due to the lack of availability of matching high-quality option data in these markets, it is harder to construct proxies for higher-moment risks in these markets. To the extent that the movements in the markets as captured by the higher moments are correlated across different asset markets, we believe that our analysis does shed light on the general influence of higher-moment risks.

Our empirical investigation yields several new findings. First of all, our results indicate a negative risk premium for equity market return volatility and kurtosis, and a positive risk premium for equity market skewness. Using two different 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 changes in higher-moment equity return risk. We show that it is important to perform conditional sorts based on the exposures to the three higher moments as these exposures are correlated with each other. Using three-way sorts of portfolios of hedge funds based on their exposures to higher-moment risks, we find significant risk premiums for volatility, skewness, and kurtosis of about –6 percent, 3 percent, and –3 percent per year. Hence, a significant short-volatility exposure can potentially explain a large proportion of the variation in hedge fund returns. As a contrast, we do not find significant dispersion in alphas when we sort mutual funds based on their exposures to higher-moment equity risks. This further supports the motivation for our study to examine hedge funds, which exhibit nonlinearities in their returns and thereby making them more sensitive to the influence of higher-moment risks. These results have important implications for asset allocation, risk management, and performance evaluation in the hedge fund industry. For example, a fund of hedge funds that wishes to hedge one of the higher moment risks can benefit from such an analysis by simultaneously investing in hedge funds that offset higher moment risks. Further, our findings shed light on exposure to higher moments being important sources of hedge fund returns and therefore an integral component of the return generating process of hedge funds.

Overall, our paper contributes to our understanding of asset returns in three ways. First, it shows the importance of higher moments in analyzing the performance of hedge funds that should have most significant exposure to the higher-moment risks by virtue of their dynamic trading strategies. Second, we provide evidence on another category of actively managed portfolios – mutual funds, being not exposed to the higher moment risks in a significant way. Finally, we contribute to the growing body of theoretical and empirical research that suggests that higher-moment risks are priced.

The remainder of the paper is organized as follows. Section 2 describes the data and construction of variables. Section 3 provides evidence on sensitivity of hedge funds' returns to higher moment risks, and estimates the prices of higher moments of equity market returns. Section 4 conducts various specification analyses. Section 5 investigates the dispersion in alphas of mutual funds sorted on their exposures to higher-moment equity risks. Section 6 concludes.

2 Fund Samples and Risk Factors

2.1 Proxies for higher-moment risks

Since our higher moment equity risk proxies 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 spanning the relevant payoffs as shown in Theorem 1 of Bakshi et al. (2003), and in Christoffersen et al. (2006), using the price of out-of-money calls and puts. Specifically, for equity index price S_t, the τ–period equity return, $R(t,\tau) \equiv \ln(S_{t+\tau}) - \ln(S_t)$ and interest rate r, we derive:

$$\begin{aligned}
\mathbb{M}_{2,t} &\equiv e^{-r\tau}\,\mathbb{E}^{\mathbb{Q}}\left[(R(t,\tau)-\mathbb{M}_{1,t})^2\right], && \textbf{Price of Second Central Return Moment} \quad (1)\\
\mathbb{M}_{3,t} &\equiv e^{-r\tau}\,\mathbb{E}^{\mathbb{Q}}\left[(R(t,\tau)-\mathbb{M}_{1,t})^3\right], && \textbf{Price of Third Central Return Moment} \quad (2)\\
\mathbb{M}_{4,t} &\equiv e^{-r\tau}\,\mathbb{E}^{\mathbb{Q}}\left[(R(t,\tau)-\mathbb{M}_{1,t})^4\right], && \textbf{Price of Fourth Central Return Moment} \quad (3)
\end{aligned}$$

where $\mathbb{E}^{\mathbb{Q}}[.]$ is the expectation under the risk-neutral measure. Therefore, $\mathbb{M}_{k,t}$ reflects the market price of the payoff corresponding to $(\ln(S_{t+\tau}) - \ln(S_t))^k$ for $k = 1,\ldots,4$. The current calculation of the VIX index by the CBOE is based on $\mathbb{M}_{2,t}$ in (1), where the option positioning is presented in (17) in the Appendix. For completeness, the option positioning that gives $\mathbb{M}_{3,t}$ and $\mathbb{M}_{4,t}$ are also presented in the Appendix.

We note that $\mathbb{M}_{2,t}$, $\frac{\mathbb{M}_{3,t}}{\mathbb{M}_{2,t}^{3/2}}$, and $\frac{\mathbb{M}_{4,t}}{\mathbb{M}_{2,t}^{2}}$ are to be interpreted as the price of volatility, skewness, and kurtosis respectively. To be consistent with the extant literature where first difference in CBOE index implied volatility has been used to proxy for aggregate volatility risk (see Ang et al. (2006)), we define,

$$\begin{aligned}
\Delta\mathrm{VOL}_t &\equiv \mathbb{M}_{2,t} - \mathbb{M}_{2,t-1}, && (4)\\
\Delta\mathrm{SKEW}_t &\equiv \frac{\mathbb{M}_{3,t}}{\mathbb{M}_{2,t}^{3/2}} - \frac{\mathbb{M}_{3,t-1}}{\mathbb{M}_{2,t-1}^{3/2}}, && (5)\\
\Delta\mathrm{KURT}_t &\equiv \frac{\mathbb{M}_{4,t}}{\mathbb{M}_{2,t}^{2}} - \frac{\mathbb{M}_{4,t-1}}{\mathbb{M}_{2,t-1}^{2}}. && (6)
\end{aligned}$$

Figure 1 shows the price of volatility, skewness, and kurtosis plotted at a monthly frequency over January 1994 to December 2004. In addition, for comparison, the VIX index (from CBOE) is plotted over time. The figure demonstrates that our forward-looking measure of second central moment closely mimics the VIX index.

2.2 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. Our resulting sample covers 5,336 funds out of which 3,309 are active as of the end of 2004. This sample is free from survivorship bias as it includes 2,027 dead funds that disappeared for reasons including liquidation, merger/restructuring, and voluntary stopping of reporting.[3]

Data on returns of mutual funds are from the 2004 CRSP Mutual Fund Survivorship-bias Free Database over the period January 1994 to December 2004. We follow a procedure similar to Pastor and Stambaugh (2002) and use the additional information CRSP provides on fund classifications, expenses, and load data to construct a sample of US equity funds. We exclude funds with no classification, expense, or load data in the annual summary at the end of each previous year. Additionally, we examine fund classifications and exclude flexible funds, bond funds, mortgage-backed funds, multi-manager funds, money market funds, balanced funds, international funds, and funds that invest in precious metals.

From the remaining funds, we select funds that are classified as small/cap growth, growth, growth & income, income, or sector fund. The selection of these types of funds is consistent with the literature (see in particular Carhart (1997) and Bollen and Busse (2005)). Finally, we drop funds with less than 12 consecutive returns over the entire sample period. Our data extraction procedure closely parallels Huij and Verbeek (2007). In total, our sample covers 12,717 funds over the period January 1994 to December 2004. Since CRSP includes all funds that existed during this period, our data are free of the survivorship-bias as documented by Brown and Goetzmann (1992) and Brown and Goetzmann

[3] "Defunct" may be a more appropriate term for "dead" funds as funds in the database could be missing due to reasons other than poor performance such as mergers, and funds failing to report after good performance. We refer the reader to Fung and Hsieh (2000), Liang (2000), and Getmansky et al. (2004).

(1995). All mutual fund returns are reported net of operating expenses.

2.3 Factor data

To evaluate risk-adjusted performance of hedge funds and mutual funds, we employ two different multifactor models, namely the Carhart (1997) four-factor model (henceforth, Carhart-4) and the Fung and Hsieh (2004) seven-factor model (henceforth, FH-7). Although the first model is more appropriate for mutual funds and the second one is more suited for hedge funds, we analyze hedge funds using both these models for the sake of completeness and to allow for better comparison of our results across the two types of managed portfolios.

As is standard, the Carhart-4 model takes the form:

$$r_{i,t} = \alpha^{i}_{C4} + \beta^{1,i}_{C4}\,\mathrm{RMRF}_t + \beta^{2,i}_{C4}\,\mathrm{SMB}_t + \beta^{3,i}_{C4}\,\mathrm{HML}_t + \beta^{4,i}_{C4}\,\mathrm{UMD}_t + \varepsilon^{i,t}_{C4} \tag{7}$$

where $r_{i,t}$ is the excess return of fund i in month t (i.e., in excess of the risk-free rate), RMRF_t is the value-weighted excess return of all NYSE, AMEX, and NASDAQ stocks in month t, SMB_t and HML_t are the returns on factor mimicking portfolios for market equity (Small Minus Big) and book-to-market-equity (High Minus Low) in month t as in Fama and French (1993), 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. One-month Treasury bill rate from Ibbotson and Associates is the proxy for the risk-free rate.

The FH-7 model is specified as:

$$r_{i,t} = \alpha^{i}_{FH7} + \beta^{1,i}_{FH7}\,\mathrm{SNPMRF}_t + \beta^{2,i}_{FH7}\,\mathrm{SCMLC}_t + \beta^{3,i}_{FH7}\,\mathrm{BD10RET}_t + \beta^{4,i}_{FH7}\,\mathrm{BAAMTSY}_t + \beta^{5,i}_{FH7}\,\mathrm{PTFSBD}_t + \beta^{6,i}_{FH7}\,\mathrm{PTFSFX}_t + \beta^{7,i}_{FH7}\,\mathrm{PTFSCOM}_t + \varepsilon^{i,t}_{FH7} \tag{8}$$

where SNPMRF_t is the S&P 500 return minus risk free rate in month t, SCMLC_t is the Wilshire small cap minus large cap return in month t, $\mathrm{BD10RET}_t$ is the change in the constant maturity yield of the 10 year treasury in month t, $\mathrm{BAAMTSY}_t$ is the change in the spread of Moody's Baa minus the 10 year treasury in month t, PTFSBD_t is the bond primitive trend following strategy (PTFS) in month t (see Fung and Hsieh (2004)), PTFSFX_t is the currency PTFS in month t, $\mathrm{PTFSCOM}_t$ is the commodity PTFS in month t, and $\varepsilon^{i,t}_{FH7}$ is fund i's residual return in month t. The returns on the factors in the FH-7 model are obtained from David Hsieh's data library available on his website.

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

For the main tests 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 considerable correlation between the funds' exposures, we demonstrate that a three-way sort is more appropriate for disentangling the effect of each of the three higher moments. Hence, thereafter we use the three-way sorted rank portfolios through the remainder of the section and rest of the paper. We first evaluate the rank portfolios' out-of-sample performance and then estimate the spread between the portfolios' risk-adjusted returns after controlling for well-known risk factors using the Carhart-4 and FH-7 model used in the mutual fund and hedge fund literature, respectively. Furthermore, we construct ex-post factors that mimic aggregate higher moment risks and show that these factors capture risks distinct from those spanned by the two multifactor models. We then go on to estimate Fama and MacBeth (1973) cross-sectional regressions to estimate the premiums for exposure to the higher moment risk factors. This helps us establish the relative importance of each of these factors after controlling for the correlation between the funds' exposures to them.

3.1 Independent sorts on ΔVOL, ΔSKEW, and ΔKURT

We first construct a set of base assets that have significant dispersion in the sensitivity to the higher-moment risks. For this purpose, we form decile portfolios of hedge funds in the following way. Every month, we sort all available hedge funds into ten mutually exclusive portfolios based on their exposures to (i) volatility ΔVOL, (ii) skewness ΔSKEW, and (iii) kurtosis ΔKURT. We obtain the funds' exposures by estimating rolling CAPM-type regressions that are augmented by price changes of volatility, skewness, and kurtosis, over the past 12 months:

$$r_{i,t} = \alpha^{i}_{4F} + \beta^{1,i}_{4F}\,\mathrm{RMRF}_t + \beta^{2,i}_{4F}\,\Delta\mathrm{VOL}_t + \beta^{3,i}_{4F}\,\Delta\mathrm{SKEW}_t + \beta^{4,i}_{4F}\,\Delta\mathrm{KURT}_t + \varepsilon^{i,t}_{4F}. \quad (9)$$

As argued by Ang et al. (2006), a short estimation window (12 months in our case) is a natural compromise between estimating coefficients with a reasonable degree of precision and pinning down conditional coefficients in an environment with time-varying factor loadings. It is important to use shorter estimation windows in case of 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 the macroeconomic conditions and arbitrage opportunities (see Bollen and Whaley (2007)). For robustness, later we address the possibility of estimation error in the factor sensitivities due to shorter estimation window by employing a Bayesian framework.

Given the limited number of observations in our estimation window to estimate factor loadings, it is important to keep the number of factors to a minimum in constructing the portfolios. Hence, to maintain parsimony, we use only the market factor with the three higher-moment risks in the formation period but we are careful to control for various other risk factors in the post-formation period. These include the four factors from Carhart (1997) and the seven factors from Fung and Hsieh (2004) that have been shown to explain the returns of mutual funds and hedge funds, respectively.

Based on the funds' exposures to the higher moments, funds are sorted into deciles, whereby the top decile D1 contains the ten percent of funds with the highest exposure to the relevant higher moment, and the bottom decile D10 consists of those with the lowest exposure to that moment. Then, we compute the out-of-sample returns of each of these deciles to ensure that there is no spurious correlation between the estimated exposures and returns. Furthermore, we account for the illiquidity associated with hedge fund investments where the investors face significant impediments to capital withdrawals in the form of lockup, notice, and redemption periods. Hence we allow for three months' wait for reformation of the decile portfolios to make our analysis more realistic and consistent with the frictions associated with hedge fund investing.[4]

We compute equally-weighted returns of sorted rank portfolios and readjust the portfolio weights if a fund disappears from our sample after ranking. Since we use 12-month windows for our rolling regressions to form the decile portfolios, the portfolios' out-of-sample returns are from January 1995 to December 2004. On average, 1,780 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. Finally, we estimate the risk-adjusted returns (or alphas) using the portfolios' out-of-sample returns. Table 1 reports the decile portfolios'

[4] Agarwal et al. (2006) report an average waiting period of three months before investors can withdraw their capital from hedge funds.

pre-ranking exposures to ΔVOL, ΔSKEW, and ΔKURT from Equation (9) as well as the post-ranking annualized alpha estimates, their *t*-statistics, and adjusted *R*-squared values from the regressions in Equation (7) and (8).

The results in Table 1 show that the decile portfolios exhibit almost monotonically increasing pattern in post-ranking alphas and monotonically decreasing pattern in pre-ranking betas on ΔVOL, ΔSKEW, and ΔKURT. The *R*-squared values indicate that the Carhart-4 model and FH-7 model do a reasonably good job in explaining the time-series variation in the decile portfolios' returns. Moreover, the results point towards higher-moment equity risk being priced in the cross-section of hedge fund returns. Therefore, our paper contributes to the growing literature on the possible pricing of higher moment risks and preferences over higher moments (see, for instance, Bansal et al. (1993), Bansal and Viswanathan (1993), and Dittmar (2002)). For reasons already discussed, hedge funds should be exposed to higher moment risks much more than traditional investment vehicles such as stocks and bonds. However, the results also indicate considerable correlation between the funds' exposures to ΔVOL, ΔSKEW, and ΔKURT. Consequently, we cannot disentangle the effect of each of the three higher moments when we use independent sorts. In the next subsection, we demonstrate that a three-way sort resolves this problem and allows us to distinguish the influence of each of the three higher moment risks.

3.2 Conditional three-way sorts on ΔVOL, ΔSKEW, and ΔKURT

We extend the two-way sorting procedure of Fama and French (1992) to perform three-way sorts of hedge fund portfolios based on their exposures to ΔVOL, ΔSKEW, and ΔKURT. To ensure that we have enough funds in the sorted portfolios, we use terciles instead of deciles portfolios used earlier in independent sorts. This provides us with a total of 27 (3x3x3) portfolios sorted first on the funds' exposures to ΔVOL, then to ΔSKEW, and finally to ΔKURT. The main attractive feature of this approach is that it enables us to decrease the dispersion in portfolios exposures to two out of the three higher-moment risks without sacrificing the dispersion in the third higher-moment risk. Hence the differences in the portfolios' risk-adjusted returns can be distinctly attributed to one of the three higher moments at a time. Besides the difference in the sorting, we follow exactly the same procedure as in the previous section to estimate the pre-ranking betas, and post-ranking annualized alphas, their t-statistics and R-squared values from the regressions in equation (7) and (8). We report these results in Table 2.

We present our results for the 27 portfolios (P1 to P27) resulting from the terciles – high (H), medium (M), low (L) – of conditional sorts on the funds' exposures to the three higher-moment risks. Since P1 (P27) represents the portfolios with the highest (lowest) exposure to all three moments, they have 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 interesting to observe that there is a significant spreads in the alphas of the sets of three portfolios (P1 to P3, P4 to P6, and so on) that have similar intensity of exposure to two out of the three higher moments but differ in their intensity of exposure to the third moment. For example, portfolio with high exposure to ΔVOL and ΔSKEW and varying exposures to ΔKURT – P1 to P3 – show Carhart-4 alphas ranging between -4.63 percent to -1.25 percent per year and FH-7 alphas ranging between -6.33 percent and -1.33 percent per year, which can be attributed distinctly to exposure to kurtosis risk. One can similarly estimate range of alphas due to differences in exposures to volatility and skewness risks.

3.3 Higher-moment risk premiums for volatility, skewness, and kurtosis

Given the patterns in both alphas and betas, the next logical step is to estimate the spread in the post-ranking returns of portfolios that are conditionally sorted on each of the three higher moments. This is not a trivial task given the three-way sorts that we need to perform. However, following the insights from the seminal work of Fama and French (1992) one can estimate the spreads by taking the difference of returns of portfolios with extreme exposure to one of the three higher moment risk factors after controlling for the other two. For instance, the spread in case of portfolios with the highest and lowest exposure to volatility risk would be the difference in the average of first 9 portfolios (P1 to P9) and the average of the last 9 portfolios (P19 to P27). We define this spread as FVOL as computed as

$$\begin{aligned} \mathrm{FVOL} = 1/9(P1+P2+P3+P4+P5+P6+P7+P8+P9) - 1/9 \\ (P19+P20+P21+P22+P23+P24+P25+P26+P27) \end{aligned} \tag{10}$$

Similarly, we compute the spreads in the returns for the highest and lowest exposures to kurtosis as by computing FKURT:

$$\begin{aligned} \mathrm{FKURT} = 1/9(P1+P4+P7+P10+P13+P16+P19+P22+P25) - \\ 1/9(P3+P6+P9+P12+P15+P18+P21+P24+P27) \end{aligned} \tag{11}$$

The factor mimicking portfolio for skewness FSKEW is computed in a slightly different way: the proxies for volatility FVOL and kurtosis FKURT capture the premium that is payed by hedge funds to have a *positive* return reaction on increases in the aggregate prices of equity volatility and kurtosis. However, if we would compute the proxy for skewness FSKEW in the same way as the proxies for volatility FVOL and kurtosis FKURT, FSKEW would capture the premium hedge funds pay for having a *negative* return reaction on increases in the aggregate price of equity skewness. This difference is caused by skewness having a negative price (see e.g., Figure 1). To be consistent with the interpretation of the proxies for volatility and kurtosis, we compute FSKEW the following:

$$\begin{aligned} \text{FSKEW} = 1/9(&P7+P8+P9+P16+P17+P18+P25+P26+P27)- \\ &1/9(P1+P2+P3+P10+P11+P12+P19+P20+P21) \end{aligned} \tag{12}$$

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

The annualized time-series averages of the three higher moment risk factors and their t-statistics reported in Table 3 suggests that not only are these statistically significant, they are also economically large – -6.27 percent, 2.96 percent, and -2.48 percent for FVOL, FSKEW, and FKURT, respectively. Further, the low correlations between the three factors confirm that they capture distinct dimensions of higher-moment risks. This underscores the importance of using three-way conditional sorts for the formation of ranking portfolios.

Finally, we examine if these higher-moment risk factors are not simply proxying for the different risks captured by the Carhart-4 and FH-7 models. For this purpose, we regress each of the higher-moment risk factors on the Carhart-4 and FH-7 factors separately and report our results in Table 3. The fact that the alphas are not that different from the raw returns together with the relatively low R-squared values of the regressions suggests that the two multifactor models do not capture the higher moment risks. Hence, the discovery of these hitherto unexplored higher moment risk factors have important implications for performance evaluation and risk characterization of hedge funds.

3.4 Cross-sectional Fama and MacBeth (1973) regressions and higher moment risk premiums

To investigate whether the size and book-to-market-equity factors capture distinct dimensions of risk, Fama and French (1992) test whether both variables have a significant loading in a cross-sectional regression on stock returns. We follow this line of reasoning and perform cross-sectional Fama and MacBeth (1973) regressions to estimate the premiums for each of the higher-moment risks simultaneously using our conditionally sorted 27 quantile portfolios as test assets. As described earlier, these portfolios exhibit factor loadings on the higher moment risks that are significantly dispersed for the cross-sectional regressions to possess sufficient power. Each month, we estimate the factor loadings for these 27 portfolios of hedge funds using the following regression using a rolling windows of 12 months:

$$\begin{aligned} r_{i,t} = \alpha^{i}_{7F} + \beta^{1,i}_{7F}\,\mathrm{RMRF}_t + \beta^{2,i}_{7F}\,\mathrm{SMB}_t + \beta^{3,i}_{7F}\,\mathrm{HML}_t + \beta^{4,i}_{7F}\,\mathrm{UMD}_t + \\ \beta^{5,i}_{7F}\,\mathrm{FVOL}_t + \beta^{6,i}_{7F}\,\mathrm{FSKEW}_t + \beta^{7,i}_{7F}\,\mathrm{FKURT}_t + \varepsilon^{i,t}_{C4} \end{aligned} \tag{13}$$

By including the Carhart-4 factors, we control for the other risk factors while estimating the higher moment betas. Similarly, one can control for the set of risk factors more pertinent to hedge funds by replacing the Carhart-4 factors by the FH-7 factors in above equation. The cross-sectional estimates of betas each month together with the portfolios' returns over the subsequent month provide us with the estimates of higher moment risk premiums. We then take the time-series averages of these premiums and calculate standard errors in the spirit of Fama and MacBeth (1973). In Table 4, we report the annualized time-series averages and the associated t-statistics from both Carhart-4 and FH-7 models augmented with the three higher moment risk factors.

We find significant risk premiums for each of the three higher moment risk factors – the volatility risk premium varies from -5.68 percent per year after controlling for other factors in the Carhart-4 model to –5.73 percent per year after controlling for the other factors in the FH-7 model. The corresponding figures for skewness risk premium are 2.62 and 2.59 percent per year, while those for kurtosis risk premium are -2.35 and -2.45 percent per year. These results suggest that these estimates of the higher moment risk premiums fall within a narrow range and do not change much due to the inclusion of the other risk factors. Further, these results corroborate our previous findings that the higher moment risk factors do not subsume each other as can be seen from the significant t-statistics in parentheses next to the estimates in Table 4.

To put the findings from this part of our investigation in perspective, these results provide evidence of hedge funds earning significant proportion of their returns on account of their exposures to higher moment equity risks.

3.5 Results using the Carhart-4 and FH-7 model 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 our higher-moment risk factors FVOL, FSKEW, and FKURT are able to capture these premiums. For this purpose, we augment the two multifactor models with the three higher-moment risk factors and estimate the regression in Equation (13) for our three-way sorted hedge fund portfolios. Additionally, we control for the FH-7 risk factors by replacing the Carhart-4 factors by the FH-7 factors in Equation (13).

We conjecture that if FVOL, FSKEW, and FKURT are able to capture the higher-moment premiums, we should observe that the quantile portfolios exhibit monotonically increasing or decreasing loadings on the higher-moment risk factors over the same period that is used to estimate alphas. Furthermore, the augmented factor models should have increased explanatory power to describe the cross-section of the hedge fund portfolios' returns (i.e., the spread in alphas should decrease), and the times-series of the portfolios' returns (i.e., the R-squared values of the regressions should increase).

We report the annualized alphas, FVOL, FSKEW, and FKURT factor loadings, and the adjusted-R^2's for the 27 conditionally sorted portfolios in Table 5. First, we consider the portfolios' factor loadings on the higher-moment risk factors. We find strong patterns of post-ranking factor loadings on the higher-moment risk factors. The ex-post factor loadings on FVOL ranging from 0.41 to 0.98 using the Carhart-4 factors for P1 to P9, from -0.08 to 0.22 for P10 to P18, and ranging from -0.66 to -0.27 for P19 to P27. For the ex-post factor loadings on FSKEW and FKURT, we observe similar increasing and decreasing patterns. Crucial in the present context, the observation that these results hold for all three higher moments and for both model specifications, supports a factor risk-based explanation.

Next, we consider the hedge fund portfolios' alphas. It appears that the patterns in alphas across the hedge fund portfolios are not nearly as striking as the patterns in alphas resulting from the base Cartart-4 and FH-7 model in Table 2. We find annualized alphas ranging from 1.25% to 7.48% (2.14% to 7.87%) per year for the augmented Carhart-4 (FH-7) model respectively. In fact, the spread between the top and bottom quantile portfolios is less than one percent per year. Hence, we conclude that FVOL, FSKEW, and FKURT are able to capture the cross-sectional spread in hedge fund alphas due to higher-moment risks exposures.

Finally, we observe significant explanatory power for both the models with *R*-squares ranging from 53 percent to 79 percent for the augmented Carhart-4 model, and from 53 percent to 81 percent for the augmented FH-7 model. For comparison, the *R*-squares for the base Carhart-4 model in Table 2 ranges from 23 percent to 61 percent, and from 26 percent to 57 percent for the base FH-7 model.

Overall, these results underscore the importance of including the three higher moment risk factors in addition to other risk factors in Carhart-4 and FH-7 models.

4 Robustness

In this section, we perform a battery of robustness tests and show that our results in the previous section are not driven by estimation error and cannot be explained by both liquidity, the OTM put factor of Agarwal and Naik (2004), and the extended Fung and Hsieh (2004) model which includes two additional factors – look-back straddles on stocks and interest rates.

4.1 Robustness to liquidity

Since periods of high volatility coincide with periods of high market illiquidity (Pastor and Stambaugh (2003)), it is important to separate the exposure of hedge funds to liquidity risk with that to volatility risk. Hence, in this subsection, we test the robustness of our hedge fund results to the inclusion of the liquidity risk factor,LIQ, as in Pastor and Stambaugh (2003). For this purpose, we augment the Carhart-4 model with LIQ from Wharton Research Data Services (WRDS):

$$r_{i,t} = \alpha^{i}_{5Fb} + \beta^{1,i}_{5Fb}\,\mathrm{RMRF}_t + \beta^{2,i}_{5Fb}\,\mathrm{SMB}_t + \beta^{3,i}_{5Fb}\,\mathrm{HML}_t + \beta^{4,i}_{5Fb}\,\mathrm{UMD}_t + \beta^{5,i}_{5Fb}\,\mathrm{LIQ}_t + \varepsilon^{i,t}_{5Fb}. \qquad (14)$$

Likewise, we augment the FH-7 model with LIQ. Using the models augmented with the liquidity factor, we then re-estimate the alphas for the hedge fund decile portfolios sorted using each of the higher moment betas.

Table 6 reports the annualized alphas for our three-way sorted portfolios. We continue to observe significant spreads in alphas as for the Carhart-4 and FH-7 models earlier in our Table 2. Further, the systematic pattern in alphas persists even after controlling for liquidity.

We also report the post-formation factor loadings on the liquidity factor in Table 6. We do not find either an increasing or decreasing pattern in these loadings for the hedge fund quantile portfolios. This further confirms that liquidity effects cannot account for the spreads in alphas resulting from sensitivity of hedge funds to higher moment risks.

4.2 Robustness to FH-9 model

Next, we investigate to what extent the spreads in alphas for our three-way sorted portfolios are captured by the extended Fung and Hsieh (2004) nine-factor model (henceforth. FH-9) which augments the base model with look-back straddles on stocks and interest rates:

$$\begin{aligned} r_{i,t} = \alpha^{i}_{FH9} + \beta^{1,i}_{FH9}\,\mathrm{SNPMRF}_t + \beta^{2,i}_{FH9}\,\mathrm{SCMLC}_t + \beta^{3,i}_{FH9}\,\mathrm{BD10RET}_t + \beta^{4,i}_{FH9}\,\mathrm{BAAMTSY}_t + \\ \beta^{5,i}_{FH9}\,\mathrm{PTFSBD}_t + \beta^{6,i}_{FH9}\,\mathrm{PTFSFX}_t + \beta^{7,i}_{FH9}\,\mathrm{PTFSCOM}_t + \\ \beta^{8,i}_{FH9}\,\mathrm{PTFSSTK}_t + \beta^{9,i}_{FH9}\,\mathrm{RF}_t + \varepsilon^{i,t}_{FH9} \end{aligned} \tag{15}$$

where $\mathrm{PTFSSTK}_t$ is the stock primitive trend following strategy in month t, and RF_t is the risk-free rate in in month t.

Table 7 reports the alphas estimates resulting from the FH-9 model and the post-formation factor loadings on look-back straddles on stocks and interest rates. We observe that the pattern in alphas remains unchanged. Furthermore, there is no increasing or decreasing pattern in the factor loadings. These results indicate that our results are not driven by hedge fund exposures to look-back straddles on stocks and interest rates.

4.3 Robustness to OTM put factor

We also test for robustness to the OTM put option factor by Agarwal and Naik (2004) and augment the Carhart-4 model with OTMPUT:

$$r_{i,t} = \alpha^{i}_{5Fc} + \beta^{1,i}_{5Fc}\mathrm{RMRF}_t + \beta^{2,i}_{5Fc}\mathrm{SMB}_t + \beta^{3,i}_{5Fc}\mathrm{HML}_t + \beta^{4,i}_{5Fc}\mathrm{UMD}_t + \beta^{5,i}_{5Fc}\mathrm{OTMPUT}_t + \varepsilon^{i,t}_{5Fb} \tag{16}$$

Likewise, we augment the FH-7 model with OTMPUT. Using both augmented models, we then re-estimate the alphas for the three-way sorted hedge fund portfolios.

Table 8 reports the annualized alphas for our three-way sorted portfolios. We continue to observe significant spreads in alphas as for the Carhart-4 and FH-7 models earlier in our Table 2.

We also report the post-formation factor loadings on the OTM put option factor in Table 6. We do not find either an increasing or decreasing pattern in these loadings for the hedge fund quantile portfolios.

4.4 Robustness to estimation error

Because of the short portfolio formation periods, the rankings for sorts on the hedge funds' exposures to the moments might be affected by estimation error. The concern is that hedge funds that are actually not exposed to higher moment equity risks (and thus do not enjoy risk premiums for higher moment risk exposures) might end up in the extreme quantile portfolios. One therefore faces the possibility that the risk premiums on higher moments might actually be larger than we observe through our analysis.

To investigate this issue, we employ a Bayesian framework to estimate pre-rank betas in the formation period more efficiently. Bayesian approaches to estimate fund alphas and factor sensitivities based on a limited number of return observations have been employed successfully 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. We employ an empirical Bayes approach from Huij and Verbeek (2007) to estimate the regression in equation (9) in the formation period.

To evaluate the three-way sorted portfolios' out-of-sample risk-adjusted performance, we employ the Carhart-4 and FH-7 models. The results in Table 9 demonstrate 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. For example, when we use the Carhart-4 model, we find a spread in alphas between the top and bottom quantile of –20.13 percent per year. Thus, our results are not sensitive to an alternative methodology of using Bayesian beta estimates.

5 Results for mutual funds

In this section, we compare and contrast the results for hedge funds with another group of actively managed portfolios — mutual funds. Unlike hedge funds, mutual funds are relative-return managers, i.e., their performance is evaluated against a benchmark. This implies that their performance can be well-described by the returns on standard asset classes (see Fung and Hsieh (1997)).

Further, in contrast to hedge funds, mutual funds seldom use short-selling, derivatives, and leverage (see Koski and Pontiff (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 risks. We examine if this indeed is the case by repeating our analysis for mutual funds.

We start by placing mutual funds into three-way sorted portolios based on their exposure to each of the three higher moments. We then compute the equally-weighted decile returns over the subsequent (out-of-sample) month, and evaluate the decile portfolios' out-of-sample returns using the Carhart-4 model.

The results in Table 10 are striking. While we do observe some pattern in risk-adjusted returns across the decile portfolios, the patterns are not nearly as pronounced as for our sample of hedge funds. In Table 11 we present the estimates of the premiums earned by mutual funds for their exposure to higher-moment equity risk. The higher-moment risk factors are computed in the same way as for hedge funds in Section 3. The results indicate mutual funds earning a marginal statistically significant premium of -5 percent per year for exposure to equity volatility. However, we do not find mutual funds earning a premium for their exposure to equity skewness and kurtosis. These results support our claim of hedge funds being somewhat unique in their being exposed to higher moment risks on account of their use of dynamic trading strategies.

6 Concluding Remarks and Summary

Hedge fund returns exhibit significant non-linearities on account of their use of dynamic trading strategies involving state-contingent bets and positions in derivatives. This should lead to hedge funds being significantly exposed to higher moments of equity risk. In this paper, we examine the higher moment equity return risk in the cross-section of hedge fund returns. Based on forward-looking measures of the three higher moments — volatility, skewness, and risk, constructed from S&P 100 index options (see Bakshi et al. (2003) and Christoffersen et al. (2006)), we document several new findings.

First, we find a significant dispersion in alphas of funds sorted on the exposure to three higher moments with alphas decreasing monotonically for the two even higher moments and monotonically increasing for the odd higher moment. Using three-way sorts of portfolios of hedge funds based on their exposures to higher-moment risks, we find significant risk premiums for volatility, skewness, and kurtosis of about –6 percent, 3 percent, and –3 percent per year. Interestingly, we do not find significant dispersion in alphas when we sort mutual funds based on their sensitivity to innovations in higher moment equity return risks. This supports the motivation for our study to examine hedge funds, which exhibit nonlinearities in their returns and thereby being more sensitive to the influence of higher moment risks.

Finally, we demonstrate that ignoring the higher moment risk factors in multifactor models to estimate hedge fund alphas can potentially lead to overestimating the alphas, thereby incorrectly inferring that hedge funds are delivering alphas when in fact they are significantly exposed to higher moment risks. We show that when existing factor models for evaluating hedge fund performance are augmented with higher moment risk factors, we can better explain the variation in hedge fund returns over time.

Our study has several important implications. It sheds light on the sources of hedge fund returns and helps us understand the risk factors that determine hedge fund performance. Our results have implications for risk management in portfolios of hedge funds that can be designed to neutralize one or more of these higher moment risks. Finally, our results should assist in identifying if the hedge fund manager is skilled, or if the hedge fund returns simply reflect the premiums for bearing higher moment risks.

Appendix

For brevity of equation presentation write $R(t,\tau)$ as R. Discounted expectation under the risk-neutral density, $q[R]$, then gives the price of the underlying payoff. Tapping the model-free approach formalized in Bakshi et al. (2003), Britten-Jones and Neuberger (2000), Carr and Madan (2001), we observe the following:

$$e^{r\tau}\mathbb{M}_{2,t} = \int_{\Re} R^2\, q[R]\, dR - \left(\int_{\Re} R\, q[R]\, dR\right)^2, \tag{17}$$

where

$$\int_{\Re} R^2 q[R] dR = e^{r\tau}\int_{S_t}^{\infty} \frac{2\left(1-\ln\left(\frac{K}{S_t}\right)\right)}{K^2} C[K]\, dK + e^{r\tau}\int_0^{S_t} \frac{2\left(1+\ln\left(\frac{S_t}{K}\right)\right)}{K^2} P[K]\, dK, \tag{18}$$

and

$$e^{r\tau}\mathbb{M}_{1,t} \equiv \int_{\Re} R\, q[R]\, dR = e^{r\tau} - 1 - e^{r\tau}\left(\int_0^{S_t} \frac{1}{K^2} P[K]\, dK + \int_{S_t}^{\infty} \frac{1}{K^2} C[K]\, dK\right). \tag{19}$$

In (18) and (19), $C[K]$ and $P[K]$ respectively represent the price of the call option and the put option with strike price K and τ-periods to expiration, and r is the interest rate. Equation (18) is a consequence of spanning and pricing the payoff $(\ln(S(t+\tau)/S(t)))^2$. Likewise,

$$\int_{\Re} R^3 q[R] dR = \int_{S_t}^{\infty} \frac{6\ln\left(\frac{K}{S_t}\right) - 3(\ln\left(\frac{K}{S_t}\right))^2}{K^2} C[K]\, dK - \int_0^{S_t} \frac{6\ln\left(\frac{S_t}{K}\right) + 3(\ln\left(\frac{S_t}{K}\right))^2}{K^2} P[K]\, dK, \tag{20}$$

$$\int_{\Re} R^4 q[R] dR = \int_{S_t}^{\infty} \frac{12(\ln\left(\frac{K}{S_t}\right))^2 - 4(\ln\left(\frac{K}{S_t}\right))^3}{K^2} C[K] dK + \int_0^{S_t} \frac{12(\ln\left(\frac{S_t}{K}\right))^2 + 4(\ln\left(\frac{S_t}{K}\right))^3}{K^2} P[K] dK, \tag{21}$$

from which we can explicitly construct $\mathbb{M}_{3,t}$ and $\mathbb{M}_{4,t}$.

The computation of the price of moments requires options with constant maturity. Focus on the price of volatility and fix τ as 28 days. Consider the Riemann integral approximation of $\int_{\Re} R^2 q[R]\, dR$ in (18). First, discretize the integral for the long position in calls as:

$$\sum_{j=1}^{\mathcal{J}} \left(n\left[j-1\right]+n\left[j\right]\right)\frac{\Delta K}{2}, \tag{22}$$

where $n[j] \equiv z[K_{\max} - j\Delta K] \times C[K_{\max} - j\Delta K]$, $K_{\max}$ is the maximum level of the strike price, $\mathcal{J}$ is the number of call/put options, and $z[K] \equiv \frac{2}{K^2}\left(1-\ln\left(\frac{K}{S_t}\right)\right)$. Second, the integral for the long position in puts can be discretized as:

$$\sum_{j=1}^{\mathcal{J}} \left(m\left[j-1\right]+m\left[j\right]\right)\frac{\Delta K}{2}, \tag{23}$$

where $m[j] \equiv z[K_{\min} + j\Delta K] \times P[K_{\min} + j\Delta K]$ and $K_{\min}$ represents the minimum level of the strike price. □

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Tables and Figures

Table 1: Single-sorted portfolios of hedge funds sorted by exposure to higher moment equity risk.

					Carhart-4 Model			FH-7 Model		
		ΔVOL	ΔSKEW	ΔKURT	Alpha	Alpha-*t*	Adj.Rsq.	Alpha	Alpha-*t*	Adj.Rsq
		A. Sorts on exposure to ΔVOL								
D1	H	1.60	7.57	1.45	-2.42%	-0.88	59%	-3.17%	-1.08	50%
D2		0.65	2.98	0.55	-0.18%	-0.12	65%	0.04%	0.03	61%
D3		0.36	1.64	0.30	0.99%	0.79	63%	1.58%	1.22	58%
D4		0.19	0.91	0.15	2.19%	2.21	62%	2.63%	2.63	59%
D5		0.07	0.49	0.06	3.37%	3.88	62%	3.77%	4.40	62%
D6		-0.03	0.18	-0.01	3.71%	4.30	61%	4.30%	5.08	61%
D7		-0.14	-0.22	-0.10	3.45%	3.19	58%	4.23%	3.97	58%
D8		-0.28	-0.72	-0.21	4.21%	3.83	62%	4.70%	4.37	62%
D9		-0.54	-1.63	-0.41	5.84%	3.94	54%	6.44%	4.57	56%
D10	L	-1.52	-4.87	-1.10	9.11%	3.96	50%	9.78%	4.44	52%
		B. Sorts on exposure to ΔSKEW								
D1	H	0.87	13.62	2.05	-3.87%	-1.35	57%	-4.68%	-1.59	53%
D2		0.36	5.43	0.80	1.41%	0.83	61%	1.90%	1.10	57%
D3		0.20	3.03	0.43	1.94%	1.59	67%	2.60%	2.13	65%
D4		0.11	1.67	0.23	2.13%	2.12	66%	2.95%	2.80	61%
D5		0.04	0.73	0.08	3.24%	3.57	65%	3.78%	4.10	62%
D6		-0.01	-0.04	-0.03	3.84%	4.37	62%	4.44%	5.03	60%
D7		-0.07	-0.85	-0.16	3.48%	3.35	60%	4.08%	3.93	58%
D8		-0.14	-1.96	-0.34	3.11%	2.50	58%	4.08%	3.31	57%
D9		-0.27	-4.00	-0.66	5.22%	3.81	55%	5.65%	4.35	58%
D10	L	-0.72	-11.36	-1.74	9.54%	4.08	33%	9.19%	4.30	41%

Table 1 continued

		ΔVOL	ΔSKEW	ΔKURT	Carhart-4 Model Alpha	Alpha-*t*	Adj.Rsq.	FH-7 Model Alpha	Alpha-*t*	Adj.Rsq.
		C. Sorts on exposure to ΔKURT								
D1	H	1.00	12.50	2.28	-3.27%	-1.16	57%	-4.37%	-1.53	54%
D2		0.39	5.04	0.88	0.41%	0.24	62%	0.58%	0.35	60%
D3		0.21	2.78	0.48	2.00%	1.70	65%	2.50%	2.12	63%
D4		0.12	1.53	0.25	2.19%	2.27	68%	3.03%	2.94	61%
D5		0.06	0.71	0.09	2.89%	3.17	60%	3.45%	3.69	56%
D6		-0.01	0.00	-0.04	2.98%	3.33	63%	3.49%	3.90	61%
D7		-0.08	-0.74	-0.18	3.72%	3.45	60%	4.47%	4.20	60%
D8		-0.18	-1.76	-0.38	4.47%	3.74	59%	5.25%	4.40	58%
D9		-0.30	-3.57	-0.74	5.06%	3.52	55%	5.79%	4.12	55%
D10	L	-0.85	-10.20	-1.98	9.58%	4.23	35%	9.84%	4.59	39%

Each month hedge funds are sorted 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:

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

where RMRF_t is the excess return on the market portfolio in month t, $\Delta\mathrm{VOL}_t$ is the first difference of the price of volatility in month t, $\Delta\mathrm{SKEW}_t$ is first difference of the price of skewness in month t, $\Delta\mathrm{KURT}_t$ is the first difference of the price of kurtosis in month t, and $\varepsilon^{i,t}_{4F}$ is the residual return in month t. The table lists average pre-ranking higher moment betas and post-ranking alphas, t-statistics and adjusted R-squared values of the deciles from the Carhart (1997) and Fung and Hsieh (2004) model which are estimated over the stacked time series of portfolio returns over the subsequent month after ranking. Alphas are annualized. The sample is from 1994 to 2004 and covers 5,336 hedge funds.

Table 2: Triple-sorted portfolios of hedge funds sorted by exposure to higher moment equity risk.

					Carhart-4 Model			FH-7 Model		
		ΔVOL	ΔSKEW	ΔKURT	Alpha	Alpha-*t*	Adj.Rsq	Alpha	Alpha-*t*	Adj.Rsq
P1	H / H / H	0.66	17.52	3.13	-4.63%	-1.15	51%	-6.33%	-1.51	44%
P2	H / H / M	0.51	9.04	1.51	-2.94%	-1.29	58%	-3.72%	-1.56	52%
P3	H / H / L	0.67	6.79	0.76	-1.25%	-0.47	51%	-1.33%	-0.48	43%
P4	H / M / H	0.79	3.61	0.94	1.26%	0.69	51%	1.14%	0.64	50%
P5	H / M / M	0.52	2.80	0.49	2.00%	1.48	58%	2.44%	1.79	55%
P6	H / M / L	0.50	2.05	0.12	0.58%	0.40	61%	1.48%	0.98	55%
P7	H / L / H	1.81	-0.58	0.41	-1.26%	-0.65	44%	-0.82%	-0.44	45%
P8	H / L / M	1.00	-1.36	-0.08	1.01%	0.63	52%	2.04%	1.24	45%
P9	H / L / L	0.80	-6.11	-0.95	2.77%	1.00	30%	3.11%	1.15	29%
P10	M / H / H	0.02	5.77	0.95	0.06%	0.03	47%	0.48%	0.28	50%
P11	M / H / M	-0.01	2.50	0.34	2.48%	2.15	51%	3.33%	2.87	48%
P12	M / H / L	0.00	1.89	0.06	2.76%	2.38	55%	3.60%	3.01	50%
P13	M / M / H	0.05	0.57	0.18	3.65%	4.04	55%	3.94%	4.40	54%
P14	M / M / M	0.02	0.27	0.02	3.50%	4.81	45%	3.69%	5.22	46%
P15	M / M / L	-0.01	0.00	-0.14	3.28%	3.45	53%	4.17%	4.36	50%
P16	M / L / H	0.05	-1.18	-0.03	4.57%	4.10	48%	4.69%	4.36	49%
P17	M / L / M	0.06	-1.73	-0.28	4.26%	4.16	54%	4.82%	4.75	52%
P18	M / L / L	0.03	-5.09	-0.90	5.00%	3.23	42%	5.73%	3.79	42%

Table 2 continued

					Carhart-4 Model			FH-7 Model		
		ΔVOL	ΔSKEW	ΔKURT	Alpha	Alpha-*t*	Adj.Rsq	Alpha	Alpha-*t*	Adj.Rsq
P19	L / H / H	-0.70	6.92	1.04	1.07%	0.43	48%	2.40%	0.99	47%
P20	L / H / M	-0.85	2.25	0.17	4.19%	2.85	52%	4.63%	3.24	53%
P21	L / H / L	-1.63	1.49	-0.31	7.37%	3.57	39%	8.47%	4.20	39%
P22	L / M / H	-0.44	-0.78	-0.03	3.56%	2.38	53%	4.35%	2.97	53%
P23	L / M / M	-0.43	-1.43	-0.34	5.56%	4.84	55%	5.97%	5.32	55%
P24	L / M / L	-0.65	-2.06	-0.75	5.12%	2.96	51%	6.14%	3.62	51%
P25	L / L / H	-0.70	-4.88	-0.58	5.28%	3.18	57%	5.23%	3.20	57%
P26	L / L / M	-0.46	-6.78	-1.22	8.44%	4.55	45%	9.11%	5.18	48%
P27	L / L / L	-0.62	-14.80	-2.79	13.96%	4.50	23%	13.79%	4.64	26%

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 RMRF_t is the excess return on the market portfolio in month t, $\Delta\mathrm{VOL}_t$ is the first difference of the price of volatility in month t, $\Delta\mathrm{SKEW}_t$ is first difference of the price of skewness in month t, $\Delta\mathrm{KURT}_t$ is the first difference of the price of kurtosis in month t, and $\varepsilon_{4F}^{i,t}$ is the residual return in month t. The table lists average pre-ranking higher moment betas and post-ranking alphas, t-statistics and adjusted R-squared values of the quantile portfolio from the Carhart (1997) and Fung and Hsieh (2004) model which are estimated over the stacked time series of portfolio returns over the subsequent month after ranking. Alphas are annualized. The sample is from 1994 to 2004 and covers 5,336 hedge funds.

Table 3: Higher moment equity risk factors based on hedge fund returns.

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

This table reports the annualized time-series averages and t-statistics of the three higher moment equity risk factors based on hedge fund returns. The higher moment equity risk factors are constructed the following:

$$\text{FVOL} = 1/9(P1+P2+P3+P4+P5+P6+P7+P8+P9) - 1/9(P19+P20+P21+P22+P23+P24+P25+P26+P27)$$

$$\text{FSKEW} = 1/9(P7+P8+P9+P16+P17+P18+P25+P26+P27) - 1/9(P1+P2+P3+P10+P11+P12+P19+P20+P21)$$

$$\text{FKURT} = 1/9(P1+P4+P7+P10+P13+P16+P19+P22+P25) - 1/9(P3+P6+P9+P12+P15+P18+P21+P24+P27)$$

where $P1$ to $P27$ are the equally-weighted triple sorted quantile portfolios of hedge funds based on their higher moment betas in Table 2. In addition, the table lists the correlations between the three higher moment equity risk factors and the alphas, t-statistics and R-squared values of the higher moment equity risk factors from the Carhart (1997) and Fung and Hsieh (2004) model which are estimated over the stacked time series of portfolio returns over the subsequent month after ranking. Alphas are annualized. The sample is from 1994 to 2004 and covers 5,336 hedge funds.

Table 4: Fama and MacBeth (1973) cross-sectional regression estimates of higher moment equity risk premiums for hedge funds.

	Carhart-4 Model		FH-7 Model	
FVOL	-5.68%	(-3.47)	-5.73%	(-3.38)
FSKEW	2.62%	(1.88)	2.59%	(1.80)
FKURT	-2.35%	(-2.32)	-2.45%	(-2.41)

This table reports the time-series averages and t-statistics of the premium estimates for the three higher moment equity risk factors. The premiums are estimated using a rolling Fama and MacBeth (1973) cross-sectional regression approach. Each month we estimate factor loadings for the equally-weighted triple sorted quantile portfolios of hedge funds based on their higher moment betas in Table 2 using a regression with the Carhart (1997) and Fung and Hsieh (2004) factors together with the $FVOL$, $FSKEW$, and $FKURT$ factors for rolling windows of 12 months, where FVOL, FSKEW, and FKURT are the factor mimicking aggregate risk for volatility, skewness, and kurtosis, respectively. Then, we solve for the expected returns over the subsequent month for hypothetical hedge funds with unit exposure to FVOL, FSKEW, and FKURT as a function of the estimated betas from the time-series regressions. The premium estimates are annualized. The sample is from 1994 to 2004 and covers 5,336 hedge funds.

Table 5: Triple-sorted portfolios of hedge funds sorted by exposure to higher moment equity risk.

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

Table 5 continued

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

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 RMRF_t is the excess return on the market portfolio in month t, $\Delta\mathrm{VOL}_t$ is the first difference of the price of volatility in month t, $\Delta\mathrm{SKEW}_t$ is first difference of the price of skewness in month t, $\Delta\mathrm{KURT}_t$ is the first difference of the price of kurtosis in month t, and $\varepsilon^{i,t}_{4F}$ is the residual return in month t. The table lists 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 Carhart (1997) and Fung and Hsieh (2004) factors together with the $FVOL$, $FSKEW$, and $FKURT$ factors for rolling windows of 12 months, where FVOL, FSKEW, and FKURT are the factor mimicking aggregate risk for volatility, skewness, and kurtosis, respectively. Alphas are annualized. In addition, the table lists the post-ranking factor loadings on FVOL, FSKEW, and FKURT. The sample is from 1994 to 2004 and covers 5,336 hedge funds.

Table 6: Robustness: Triple-sorted portfolios of hedge funds sorted by exposure to higher moment equity risk and liquidity.

		Carhart-4 Model				FH-7 Model			
		Alpha	Alpha-t	LIQ	Adj.Rsq	Alpha	Alpha-t	LIQ	Adj.Rsq
P1	H / H / H	-3.70%	-0.97	0.21	56 %	-6.84%	-1.84	0.27	56%
P2	H / H / M	-2.73%	-1.19	0.05	59 %	-3.93%	-1.74	0.11	58%
P3	H / H / L	-1.51%	-0.57	-0.06	51 %	-1.41%	-0.51	0.05	44%
P4	H / M / H	1.53%	0.86	0.06	53 %	0.98%	0.58	0.08	56%
P5	H / M / M	2.05%	1.51	0.01	58 %	2.36%	1.77	0.04	57%
P6	H / M / L	0.39%	0.27	-0.04	62 %	1.44%	0.95	0.02	55%
P7	H / L / H	-1.16%	-0.59	0.02	44 %	-0.90%	-0.48	0.04	46%
P8	H / L / M	0.99%	0.62	0.00	51%	1.96%	1.20	0.04	47%
P9	H / L / L	2.86%	1.02	0.02	29%	3.02%	1.12	0.05	30%
P10	M / H / H	-0.06%	-0.03	-0.03	47%	0.48%	0.28	0.00	49%
P11	M / H / M	2.29%	2.02	-0.04	53%	3.34%	2.86	0.00	47%
P12	M / H / L	2.58%	2.27	-0.04	57%	3.59%	2.99	0.01	49%
P13	M / M / H	3.61%	3.98	-0.01	55%	3.93%	4.37	0.01	54%
P14	M / M / M	3.52%	4.81	0.00	45%	3.66%	5.22	0.02	47%
P15	M / M / L	3.16%	3.35	-0.03	54%	4.17%	4.34	0.00	50%
P16	M / L / H	4.66%	4.18	0.02	48%	4.65%	4.35	0.02	50%
P17	M / L / M	4.22%	4.09	-0.01	53%	4.81%	4.72	0.01	52%
P18	M / L / L	5.04%	3.24	0.01	42%	5.71%	3.76	0.01	42%
P19	L / H / H	1.09%	0.44	0.00	48%	2.36%	0.97	0.02	47%
P20	L / H / M	4.10%	2.78	-0.02	52%	4.63%	3.22	0.00	52%
P21	L / H / L	7.05%	3.48	-0.07	42%	8.52%	4.23	-0.03	39%
P22	L / M / H	3.58%	2.38	0.00	53%	4.32%	2.95	0.02	53%
P23	L / M / M	5.52%	4.78	-0.01	55%	5.96%	5.28	0.01	55%
P24	L / M / L	4.67%	2.88	-0.10	57%	6.24%	3.78	-0.06	53%
P25	L / L / H	5.36%	3.21	0.02	57%	5.27%	3.22	-0.02	57%
P26	L / L / M	8.50%	4.55	0.01	44%	9.10%	5.16	0.00	48%
P27	L / L / L	14.18%	4.56	0.05	23%	13.77%	4.61	0.01	25%

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 RMRF_t is the excess return on the market portfolio in month t, $\Delta\mathrm{VOL}_t$ is the first difference of the price of volatility in month t, $\Delta\mathrm{SKEW}_t$ is first difference of the price of skewness in month t, $\Delta\mathrm{KURT}_t$ is the first difference of the price of kurtosis in month t, and $\varepsilon^{i,t}_{4F}$ is the residual return in month t. The table lists post-ranking alphas, t-statistics and adjusted R-squared values of the quantile portfolio from regressions with the Carhart (1997) and Fung and Hsieh (2004) factors together with the LIQ factor, where LIQ is the factor mimicking aggregate risk for liquidity. Alphas are annualized. In addition, the table lists the post-ranking factor loadings on LIQ. The sample is from 1994 to 2004 and covers 5,336 hedge funds.

Table 7: Robustness: Triple-sorted portfolios of hedge funds sorted by exposure to higher moment equity risk and the FH-9 model.

		Alpha	Alpha-t	PTFSSTK	RF	Adj.Rsq
P1	H / H / H	-6.08%	-1.30	-0.01	0.00	43%
P2	H / H / M	-3.04%	-1.15	0.01	0.01	52%
P3	H / H / L	0.42%	0.14	0.00	0.02	43%
P4	H / M / H	2.07%	1.05	-0.01	0.01	50%
P5	H / M / M	2.65%	1.74	0.00	0.00	54%
P6	H / M / L	3.03%	1.85	0.00	0.02	56%
P7	H / L / H	-0.68%	-0.33	0.00	0.00	44%
P8	H / L / M	3.18%	1.75	-0.01	0.02	46%
P9	H / L / L	5.50%	1.86	-0.01	0.04	31%
P10	M / H / H	-0.50%	-0.26	0.00	-0.01	50%
P11	M / H / M	3.44%	2.68	-0.01	0.00	48%
P12	M / H / L	4.14%	3.14	-0.01	0.01	50%
P13	M / M / H	4.52%	4.58	0.00	0.01	54%
P14	M / M / M	4.15%	5.32	0.00	0.01	46%
P15	M / M / L	4.52%	4.30	-0.01	0.01	51%
P16	M / L / H	5.66%	4.82	0.00	0.01	50%
P17	M / L / M	6.10%	5.59	0.00	0.02	55%
P18	M / L / L	7.22%	4.46	-0.01	0.02	46%
P19	L / H / H	1.95%	0.73	-0.01	-0.01	47%
P20	L / H / M	4.62%	2.90	0.00	0.00	52%
P21	L / H / L	9.73%	4.39	-0.01	0.02	40%
P22	L / M / H	4.49%	2.80	-0.01	0.00	54%
P23	L / M / M	6.59%	5.54	-0.02	0.01	59%
P24	L / M / L	7.57%	4.08	-0.01	0.02	51%
P25	L / L / H	5.71%	3.16	-0.01	0.01	57%
P26	L / L / M	11.23%	6.14	-0.02	0.03	54%
P27	L / L / L	16.44%	5.12	-0.02	0.04	29%

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 RMRF_t is the excess return on the market portfolio in month t, $\Delta\mathrm{VOL}_t$ is the first difference of the price of volatility in month t, $\Delta\mathrm{SKEW}_t$ is first difference of the price of skewness in month t, $\Delta\mathrm{KURT}_t$ is the first difference of the price of kurtosis in month t, and $\varepsilon^{i,t}_{4F}$ is the residual return in month t. The table lists post-ranking alphas, t-statistics and adjusted R-squared values of the quantile portfolio from regressions with the FH-9 factors. Alphas are annualized. In addition, the table lists the post-ranking factor loadings on PTFSSTK and RF. The sample is from 1994 to 2004 and covers 5,336 hedge funds.

Table 8: Robustness: Triple-sorted portfolios of hedge funds sorted by exposure to higher moment equity risk and OTM put factor.

		Carhart-4 Model				FH-7 Model			
		Alpha	Alpha-t	OTMPUT	Adj.Rsq	Alpha	Alpha-t	OTMPUT	Adj.Rsq
P1	H / H / H	-4.69%	-1.13	-0.04	51%	-6.87%	-1.61	-0.59	43%
P2	H / H / M	-3.25%	-1.37	-0.23	58%	-4.22%	-1.74	-0.54	42%
P3	H / H / L	-2.15%	-0.79	-0.65	51%	-2.16%	-0.77	-0.89	44%
P4	H / M / H	1.12%	0.60	-0.10	51%	0.93%	0.51	-0.23	50%
P5	H / M / M	1.69%	1.21	-0.23	58%	2.14%	1.54	-0.33	55%
P6	H / M / L	0.13%	0.09	-0.33	61%	1.03%	0.68	-0.48	55%
P7	H / L / H	-1.64%	-0.82	-0.28	44%	-1.16%	-0.61	-0.36	45%
P8	H / L / M	0.23%	0.14	-0.56	53%	1.45%	0.88	-0.64	47%
P9	H / L / L	2.10%	0.73	-0.49	30%	2.50%	0.91	-0.66	30%
P10	M / H / H	-0.52%	-0.28	-0.42	47%	0.12%	0.07	-0.39	50%
P11	M / H / M	1.99%	1.68	-0.36	52%	3.06%	2.59	-0.30	48%
P12	M / H / L	2.18%	1.85	-0.42	56%	3.22%	2.68	-0.41	51%
P13	M / M / H	3.29%	3.56	-0.26	56%	3.68%	4.08	-0.28	55%
P14	M / M / M	3.06%	4.17	-0.32	48%	3.45%	4.87	-0.25	47%
P15	M / M / L	2.67%	2.79	-0.44	55%	3.78%	3.97	-0.41	52%
P16	M / L / H	4.20%	3.67	-0.27	48%	4.48%	4.11	-0.23	50%
P17	M / L / M	3.73%	3.58	-0.38	55%	4.52%	4.42	-0.32	53%
P18	M / L / L	4.67%	2.92	-0.24	42%	5.50%	3.57	-0.25	42%
P19	L / H / H	1.30%	0.51	0.16	48%	2.58%	1.04	0.19	47%
P20	L / H / M	3.76%	2.49	-0.31	52%	4.38%	3.02	-0.27	53%
P21	L / H / L	6.93%	3.26	-0.31	39%	8.26%	4.02	-0.22	39%
P22	L / M / H	2.73%	1.80	-0.60	55%	3.98%	2.69	-0.40	53%
P23	L / M / M	5.21%	4.41	-0.25	56%	5.83%	5.09	-0.16	55%
P24	L / M / L	4.58%	2.58	-0.39	51%	5.85%	3.39	-0.31	51%
P25	L / L / H	5.27%	3.07	-0.01	57%	5.40%	3.24	0.19	56%
P26	L / L / M	8.79%	4.59	0.25	44%	9.32%	5.21	0.23	48%
P27	L / L / L	14.95%	4.69	0.71	23%	14.47%	4.81	0.74	26%

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 RMRF_t is the excess return on the market portfolio in month t, $\Delta\mathrm{VOL}_t$ is the first difference of the price of volatility in month t, $\Delta\mathrm{SKEW}_t$ is first difference of the price of skewness in month t, $\Delta\mathrm{KURT}_t$ is the first difference of the price of kurtosis in month t, and $\varepsilon^{i,t}_{4F}$ is the residual return in month t. The table lists post-ranking alphas, t-statistics and adjusted R-squared values of the quantile portfolio from regressions with the Carhart (1997) and Fung and Hsieh (2004) factors together with the OTMPUT factor, where OTMPUT is the factor mimicking aggregate risk for an out-of-money put option. Alphas are annualized. In addition, the table lists the post-ranking factor loadings on OTMPUT. The sample is from 1994 to 2004 and covers 5,336 hedge funds.

Table 9: Robustness: Triple-sorted portfolios of hedge funds sorted by exposure to higher moment equity risk and Bayesian estimates of higher-moment risk exposures.

		Carhart-4 Model			FH-7 Model		
		Alpha	Alpha-*t*	Adj.Rsq	Alpha	Alpha-*t*	Adj.Rsq
P1	H / H / H	-5.75%	-1.42	51%	-7.77%	-1.78	40%
P2	H / H / M	-3.71%	-1.50	56%	-4.39%	-1.72	50%
P3	H / H / L	-1.75%	-0.61	45%	-1.18%	-0.39	36%
P4	H / M / H	1.45%	0.73	27%	0.98%	0.54	38%
P5	H / M / M	-0.33%	-0.18	52%	0.28%	0.16	50%
P6	H / M / L	-0.30%	-0.14	56%	-0.25%	-0.11	46%
P7	H / L / H	2.06%	1.50	32%	2.41%	1.78	31%
P8	H / L / M	0.61%	0.39	44%	1.22%	0.76	37%
P9	H / L / L	0.34%	0.11	24%	0.85%	0.28	22%
P10	M / H / H	1.48%	0.66	43%	2.06%	0.97	47%
P11	M / H / M	3.44%	2.13	33%	4.19%	2.65	33%
P12	M / H / L	3.49%	2.91	42%	4.25%	3.45	36%
P13	M / M / H	3.78%	2.98	55%	4.56%	3.67	55%
P14	M / M / M	3.33%	3.01	40%	3.44%	3.21	40%
P15	M / M / L	4.80%	3.22	41%	5.20%	3.53	40%
P16	M / L / H	4.63%	4.35	48%	4.68%	4.57	49%
P17	M / L / M	3.65%	2.64	49%	4.26%	3.12	47%
P18	M / L / L	2.90%	1.54	42%	4.51%	2.46	42%
P19	L / H / H	2.06%	0.81	46%	3.43%	1.36	44%
P20	L / H / M	3.59%	2.30	46%	4.65%	3.00	44%
P21	L / H / L	5.93%	4.22	34%	6.62%	4.78	33%
P22	L / M / H	4.71%	2.33	48%	5.80%	2.86	45%
P23	L / M / M	6.13%	4.04	44%	6.39%	4.37	46%
P24	L / M / L	6.30%	3.22	38%	7.68%	4.14	42%
P25	L / L / H	5.76%	3.57	61%	5.81%	3.59	59%
P26	L / L / M	8.34%	4.06	49%	8.26%	4.22	52%
P27	L / L / L	14.38%	4.65	26%	14.14%	4.82	30%

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 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 RMRF_t is the excess return on the market portfolio in month t, $\Delta\mathrm{VOL}_t$ is the first difference of the price of volatility in month t, $\Delta\mathrm{SKEW}_t$ is first difference of the price of skewness in month t, $\Delta\mathrm{KURT}_t$ is the first difference of the price of kurtosis in month t, and $\varepsilon^{i,t}_{4F}$ is the residual return in month t. The table lists post-ranking alphas, t-statistics and adjusted R-squared values of the quantile portfolio from regressions with the Carhart (1997) and Fung and Hsieh (2004) factors.Alphas are annualized. The sample is from 1994 to 2004 and covers 5,336 hedge funds.

Table 10: Triple-sorted portfolios of mutual funds sorted by exposure to higher moment equity risk.

					Carhart-4 Model		
		ΔVOL	ΔSKEW	ΔKURT	Alpha	Alpha-t	Adj.Rsq
P1	H / H / H	1.00	10.73	1.79	-1.49%	-0.52	89%
P2	H / H / M	0.76	7.00	1.06	-3.14%	-1.36	91%
P3	H / H / L	0.64	5.77	0.66	-3.88%	-1.97	93%
P4	H / M / H	0.63	3.60	0.82	-6.06%	-3.11	92%
P5	H / M / M	0.50	3.03	0.50	-5.24%	-3.56	95%
P6	H / M / L	0.45	2.40	0.21	-3.33%	-2.24	95%
P7	H / L / H	0.50	0.22	0.43	-5.59%	-2.02	84%
P8	H / L / M	0.42	-0.52	0.07	-4.76%	-2.55	91%
P9	H / L / L	0.42	-2.69	-0.41	-5.53%	-2.62	88%
P10	M / H / H	0.07	4.44	0.73	-2.36%	-1.16	89%
P11	M / H / M	0.05	2.40	0.31	-2.51%	-2.02	95%
P12	M / H / L	0.01	1.79	0.03	-0.66%	-0.45	94%
P13	M / M / H	0.03	0.33	0.20	-3.09%	-3.34	97%
P14	M / M / M	-0.01	0.02	-0.01	-1.51%	-2.38	98%
P15	M / M / L	-0.04	-0.32	-0.21	-2.11%	-1.77	95%
P16	M / L / H	-0.02	-1.79	-0.04	-3.22%	-2.36	93%
P17	M / L / M	-0.06	-2.39	-0.31	-1.79%	-1.37	93%
P18	M / L / L	-0.06	-4.22	-0.72	-1.41%	-0.70	85%
P19	L / H / H	-0.38	2.53	0.37	0.37%	0.17	86%
P20	L / H / M	-0.38	0.40	-0.06	-0.73%	-0.51	93%
P21	L / H / L	-0.46	-0.10	-0.38	1.11%	0.57	87%
P22	L / M / H	-0.39	-1.80	-0.18	-0.40%	-0.28	92%
P23	L / M / M	-0.42	-2.26	-0.41	1.20%	0.79	90%
P24	L / M / L	-0.54	-2.70	-0.69	1.82%	0.80	82%
P25	L / L / H	-0.49	-4.38	-0.53	0.24%	0.11	84%
P26	L / L / M	-0.59	-5.29	-0.88	1.25%	0.49	77%
P27	L / L / L	-0.79	-8.11	-1.51	0.41%	0.12	67%

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 RMRF_t is the excess return on the market portfolio in month t, $\Delta\mathrm{VOL}_t$ is the first difference of the price of volatility in month t, $\Delta\mathrm{SKEW}_t$ is first difference of the price of skewness in month t, $\Delta\mathrm{KURT}_t$ is the first difference of the price of kurtosis in month t, and $\varepsilon^{i,t}_{4F}$ is the residual return in month t. The table lists average pre-ranking higher moment betas and post-ranking alphas, t-statistics and adjusted R-squared values of the quantile portfolio from the Carhart (1997) model which are estimated over the stacked time series of portfolio returns over the subsequent month after ranking. Alphas are annualized. The sample is from 1994 to 2004 and covers 12,717 mutual funds.

Table 11: Higher moment equity risk factors based on mutual fund returns.

	mean	t-stat	correlations			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%

This table reports the annualized time-series averages and t-statistics of the three higher moment equity risk factors based on mutual fund returns. The higher moment equity risk factors are constructed the following:

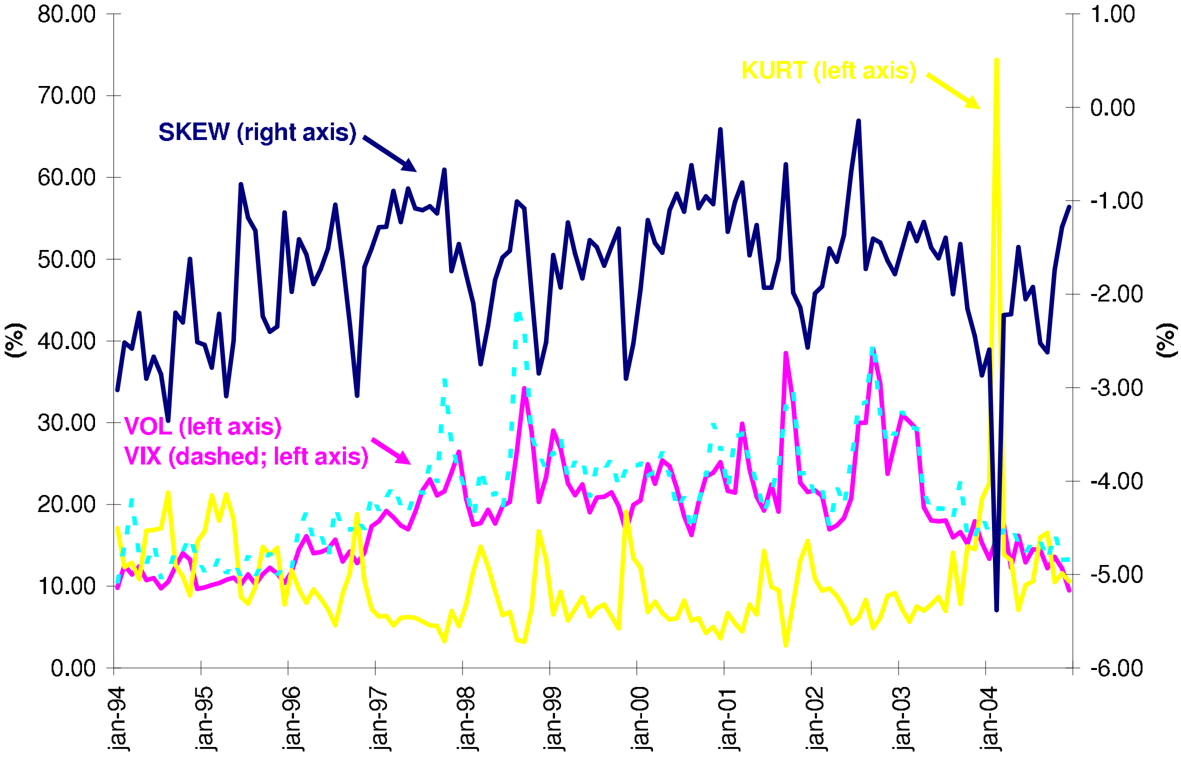
$$\mathrm{FVOL} = 1/9(P1+P2+P3+P4+P5+P6+P7+P8+P9) - 1/9(P19+P20+P21+P22+P23+P24+P25+P26+P27)$$

$$\mathrm{FSKEW} = 1/9(P7+P8+P9+P16+P17+P18+P25+P26+P27) - 1/9(P1+P2+P3+P10+P11+P12+P19+P20+P21)$$

$$\mathrm{FKURT} = 1/9(P1+P4+P7+P10+P13+P16+P19+P22+P25) - 1/9(P3+P6+P9+P12+P15+P18+P21+P24+P27)$$

where $P1$ to $P27$ are the equally-weighted triple sorted quantile portfolios of hedge funds based on their higher moment betas in Table 2. In addition, the table lists the correlations between the three higher moment equity risk factors and the alphas, t-statistics and R-squared values of the higher moment equity risk factors from the Carhart (1997) model which are estimated over the stacked time series of portfolio returns over the subsequent month after ranking. Alphas are annualized. The sample is from 1994 to 2004 and covers 12,717 mutual funds.

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



The figure show the time-series of VOL, SKEW, and KURT plotted at a monthly frequency. The sample is from January 1984 to December 2004. In addition, for comparison, the VIX index (from CBOE) is plotted over January 1994 to December 2004.