Tail Risks across Investment Funds

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ABSTRACT

Managed portfolios are subject to tail risks, which can be either index level (systematic) or fund-specific. Examples of fund-specific extreme events include those due to big bets or fraud. This paper studies the two components in relation to compensation structure in managed portfolios. A simple model generates fund-specific tail risk and its asymmetric dependence with the market, and makes predictions for where such risks should be concentrated. The model predicts that systematic tail risks increase with an increased weight on systematic returns in compensation and idiosyncratic tail risks increase with the degree of convexity in contracts. The model predictions coincide with empirical results. Hedge funds are subject to higher idiosyncratic tail risks and ETFs exhibit higher systematic tail risks. In the skewness and kurtosis decompositions, I find that coskewness is the primary source for fund skewness, but fund kurtosis could be mainly driven by cokurtosis, volatility comovement, or residual kurtosis, varying across fund types.

JEL Classification: G01, G11, G12

I Introduction

It is well-known that financial asset returns exhibit asymmetry, excess kurtosis, and fat-tailedness. Mandelbrot (1963) and Fama (1965) provide theoretical arguments and empirical evidence that price changes closely follow stable Paretian distributions. Along with the observation of time-varying volatility and volatility clustering, financial economists have been trying to find sources that can contribute to skewness and kurtosis in return data, both conditionally and unconditionally. The observation of non-normality and jumps in returns and volatility corroborates the existence of higher moments[1]. Most importantly, financial markets do crash, as in 1929, Black Tuesday in 1987, the Asian financial crisis in 1997, the Russian financial crisis in 1998, the Long-Term Capital Management crisis in 1998, the dot-com bubble burst in 2000, and the more recently the crash of 2008. Tail risks are important and relevant.

Tail risks are of central importance to investors. A large negative event can significantly reduce portfolio value and the literature has tried to model this. The safety first criterion, first introduced by Roy (1952), requires utility-maximizing investors to concern themselves with downside risk. Arzac and Bawa (1977) apply this concept to a portfolio choice problem. They show that the optimal solution is comparable to the mean-variance allocation, and when assets are normal or stable Paretian, a 2-parameter CAPM holds in a market of both safety-first investors and risk-averse expected utility maximizers. One important extension of the safety first criteria is Value-at-Risk (VaR). In recent literature on portfolio choice and delegated principal-agents problems, many models are enriched with a VaR constraint to limit downside risk[2]. In principle, the motivation behind downside risk is that investors are concerned with losses in extreme events and thus they will demand compensation for such extreme, but rare risks, and consider these risks in their investment decisions.

Tail risks can complicate investors' economic decisions. Harvey, Liechty, Liechty, and Müller (2010) emphasize the importance of higher moments in portfolio allocation. Cvitanic, Polimenis, and Zapatero (2008) show that ignoring higher moments in portfolio allocation can imply welfare losses and overinvestment in risky assets. Moreover, Samuelson (1970) points out that in discrete time, the mean-variance efficiency becomes inadequate when higher moments matter for portfolio allocation. In a mean-variance-skewness-kurtosis framework, tail risks are not diversified away and the omission of higher moments can lead to an inefficient portfolio for investors.

The lack of diversification in investor holdings suggests that investors will care about not

[1]For example, Eraker, Johannes, and Polson (2003), Bai, Russell, and Tiao (2003), and Andersen, Bollerslev, and Diebold (2007)).

[2]See e.g. Campbell, Chacko, Rodrig6uez, and Viceira (2004), van Binsbergen, Brandt, and Koijen (2008)

only systematic tail risks, but also idiosyncratic tail risks in their portfolio returns. The traditional CAPM assumes homogeneous investor expectations for real returns. However, Levy (1978), Merton (1987), and Malkiel and Xu (2001) extend the CAPM and conclude that investors hold undiversified portfolios for exogenous reasons, such as trading constraints or market frictions. The empirical evidence is supported by Odean (1999) and Polkovnichenko (2005). Due to distinctive fund characteristics, the level of systematic and idiosyncratic tail risks can differ across fund types and strategies.

Given that most investors delegate their wealth to fund managers, and optimal portfolio allocation and risk management are first-order priorities for fund managers, it is important to understand the structure of tail risks in managed portfolios.

This paper ties fund managers' compensation schemes with tail risks and tries to understand the decomposition of tail risks across fund types. The literature on agency costs, incentive contracts and the fund flow-performance relationship offer grounds for fund managers' risk-taking behavior. Motivated by relative performance measures and convex payoff structures, fund managers may take fund-specific tail risks (big bets) endogenously. Brennan (1993) proposes an agency based model with relative performance and suggests that option-like compensation can induce the skewness of fund returns. On the other hand, fund managers may take tail risks in expectation of market booms and crashes.

I use a simple model to illustrate how fund managers adjust the systematic and idiosyncratic risk of funds in response to the weight between systematic and idiosyncratic returns (the return decomposition effect) and to the convexity of incentive contracts (the convexity effect). The model predicts the following: First, the more systematic returns the contracts depend on, the more systematic risk the fund managers would take. This action would increase total fund skewness and decrease total fund kurtosis. Second, when the convexity of the incentive contract increases, the increased convexity encourage fund managers to take big bets and funds exhibit lower skewness and higher kurtosis.

The investment funds under this study include closed-end funds (CEFs), exchange-traded funds (ETFs), open-ended funds (OEFs), and hedge funds (HFs). In the finance literature, few have looked at the link between tail risks and returns across different types of funds. However, different fund types are subject to different rules and regulations. Importantly, different fund types are subject to different compensation schemes and agency costs.

Empirical results confirm with model predictions. HFs are subject to higher idiosyncratic tail risks, but ETFs exhibit higher systematic tail risks. In addition, HF returns are the most negatively skewed and ETFs have negative skewness close to zero. The decomposition of skewness shows that coskewness is the most important source of skewness across fund types. This consistency does not hold for kurtosis decomposition. The source of kurtosis for ETFs and OEFs mainly come from cokurtosis, but CEFs and HFs have the largest weights on volatility comovement and residual kurtosis, respectively. However, idiosyncratic cokurtosis is consistently the least important contributing factor to kurtosis across fund styles and types. The result of the kurtosis decomposition shows higher significance levels than the skewness decomposition.

The rest of the paper proceeds as follows. Section II explains how fund strategies affect tail risks. Section III offers descriptions of and comparisons across different types of investment funds. Section IV describes the model to produce tail returns and risks in response to the weight between systematic/idiosyncratic risk and the convexity in compensation across fund types. Section V outlines the data. Section VI explains the empirical methods. Section VII presents the empirical results. Section VIII checks on the robustness analysis. Section IX concludes.

II How Fund Strategies Impact Tail Risks

Two strategies that traditional fund managers use to outperform benchmarks or peers are stock picking and beta timing. These two strategies have their own implications for fund tail risks. If market factors are skewed and fund managers use aggressive bets on beta timing, fund returns can be skewed. Time-varying betas can induce time-varying systematic skewness risk. If a fund manager relies on stock selection to generate alpha, idiosyncratic skewness risk of the fund reflects the skewness of the stocks held over time. The turnover of individual stocks in managed portfolios can also cause time-varying fund skewness risk. Similarly, time-varying changes in fund kurtosis risk can result from these two strategies.

Interestingly, stock picking and beta timing strategies can implicitly bring about other forms of the higher moment risk premium. Idiosyncratic risk is theoretically uncorrelated with the overall market risk. However, if idiosyncratic risk is priced, the higher moments of idiosyncratic shocks can be correlated with systematic shocks. Similarly, the covariance risk between the higher moments of systematic shocks and idiosyncratic shocks can be priced.

Fund risk can be decomposed into systematic and idiosyncratic components. Funds' systematic tail risk comoves with the market. Two lines of research support this argument - coskewness and cokurtosis. The rejection of the single-factor CAPM motivates numerous studies with a nonlinear pricing kernel. Kraus and Litzenberger (1976) provide theoretical and empirical evidence that unconditional systematic skewness matters for market valuation. Harvey and Siddique (2000) extend the study to conditional skewness. Dittmar (2002) concludes that conditional systematic kurtosis is relevant to the cross-section of returns. If fund managers want to increase the funds' systematic coskewness, in expectation of an upswing in the market, they can add positively coskewed financial assets in accordance with fund strategies. Adding an asset with positive coskewness to a fund makes the fund more right skewed or increases the total skewness of the fund. Similarly, funds managers can increase portfolio cokurtosis by adding assets with high cokurtosis to achieve the desired level of total fund kurtosis.

Another mechanism that fund managers can use to increase overall portfolio skewness and kurtosis operates through idiosyncratic skewness and kurtosis. Some financial assets with specific characteristics, such as small-cap stocks, illiquid foreign securities, convertible bonds, may have more skewed distributions. Adding these assets can make investment funds more skewed. Likewise, foreign currencies have fatter tails than stocks or bonds. Currency fund managers can adjust the level of kurtosis by dropping currencies with higher kurtosis.

The covariance of the higher moments of idiosyncratic shocks and market returns can also be extracted from skewness and kurtosis decompositions. Chabi-Yo (2009) shows that idiosyncratic coskewness and cokurtosis are equivalent to a weighted average of individual security call and put betas. He further concludes that these covariance terms can explain the higher moment premium. The impact of idiosyncratic coskewness and cokurtosis on fund skewness and kurtosis depends on the risk-return relation and the magnitude of conditional heteroscedasticity and heteroskewticity.

The dependence of conditional volatility and skewness on market returns can vary significantly across different kinds of investment funds. If a fund's volatility covaries negatively with market returns, high market returns will induce lower fund-specific volatility, and in turn, lower fund skewness. Therefore, negatively skewed fund returns can be generated through conditional heteroscedasticity. Likewise, the covariance between market returns and a fund's idiosyncratic skewness can result in excess kurtosis of a fund. For example, if fund managers prefer funds being less fat-tailed, in expectation to an increase in market returns, they can add assets with high idiosyncratic skewness covarying negatively with market returns. Fund managers can use conditional heteroskewticity from different assets to manage the total level of kurtosis of funds.

The comovements of shocks to market volatility and fund-specific volatility is the last component derived from the kurtosis decomposition. The negative relationship between these two shocks can reduce the kurtosis level of funds. Since investors prefer assets with lower kurtosis, fund managers can add assets, whose volatility moves oppositely to market volatility to achieve this goal.

III Comparisons across Investment Funds

Financial institutions have been offering a wide variety of financial products to meet investors' needs in the past years. Investors can choose a specific mutual fund based on their risk aversion and objectives. OEFs can be actively or passively managed, but CEFs are actively managed. HFs use leverage and are exposed to higher risks, and therefore they are tailored to more sophisticated investors. Recently, exchange traded funds (ETFs) are gaining popularity among investors, because of their stock-like characteristics and flexibility in long and short trades. ETFs are passively managed index-based portfolios.

An OEF issues and redeems shares at the net asset value (NAV) whenever investors request to put in or take out the money. No limitations are put on the number of new shares and the market price is the same as the NAV. The NAV of the OEF is calculated directly from the prices of stocks or bonds held in the fund. An OEF is required to report its NAV by 4 pm Eastern Standard Time. Thus, trades on open-ended mutual funds can only be executed end of the day when NAVs are determined.

Unlike an OEF, a CEF has a finite number of shares traded on the exchange. A fixed number of shares are sold at the initial public offering (IPO) and investors are not allowed to redeem shares after the IPO. Due to a set amount of shares traded on the exchanges, a CEF can be traded at a premium or a discount. Numerous studies have attributed unrealized capital gains, liquidity of held assets, agency costs, and investment sentiments as possible reasons for the CEF discount. Since redemptions of shares are restricted, a CEF is able to invest in less liquid securities than an OEF, but bears no flow-performance relation. Also, because management ability is priced in a CEF, investors can bet on the manager's skills to generate alpha in excess of a benchmark. Another feature of a CEF is its use of leverage. About 80% of CEFs are income oriented and around 70% of CEFs are leveraged. A CEF can borrow additional investment capital by issuing auction rate securities, preferred shares, long-term debt, or reverse-repurchase agreements, etc. Therefore, a CEF can have higher risks and earn higher returns from illiquidity premiums, active management, and leverage.

ETFs, like CEFs, are traded on stock exchanges. However, market prices of ETFs diverge from their NAVs in a very narrow range. Since major market participants can redeem shares of an ETF for a basket of underlying assets, if the prices of ETFs deviate too much from their NAVs, an arbitrage opportunity takes place. Similar to both OEFs and CEFs, ETFs also serve various asset allocation objectives and offer diversification to investors' portfolios. Most ETFs passively track their target market indices. But some ETFs, in contrast to mutual funds, are designed to provide 2 or 3 times leverage on the benchmarks. This characteristic mimics option-like payoffs without expiration dates. Furthermore, some ETFs such as bond ETFs have low trading volume compared to others. The characteristics of tail returns and risks for ETFs with low trading volume may resemble CEFs.

Mutual funds and ETFs are under SEC regulations, but HFs face minimal regulations by SEC. Only HFs with more than $100,000,000 in assets are required to register as investment advisors and so to report holding information through 13-F. Therefore, HF managers are not binded to avoid certain investment strategies. Fung and Hsieh (1997) identifies that HFs adopt dynamic strategies. Also, performance fees of HFs are asymmetric and around 15-20%. Lock-ups and redemption notification periods allow HFs to invest in illiquidity assets (Aragon (2007)). This characteristic of illiquidity in assets is similar to CEFs, but the high-water mark provisions give HF managers more incentives to smooth returns over time and can cause more stale price problems in HF returns. In addition, HF managers use leverage, such as writing calls, to boost capital base for investments and fund returns. In short, illiquidity, leverage, high-water marks, few investment constraints, asymmetric performance fees, lack of transparency, and redemption requirements can induce HF managers to take excessive risks.

Based on their differences in fund characteristics, four types of funds differ in the magnitude of active management, transparency to investor, and agency costs. This can induce different tail distributions across fund types although they serve the same objective to deliver risk-adjusted returns for investors.

Another important aspect on tail risks across fund types is their differences in compensation structure. A HF manager faces a high-water mark and an option-like compensation contract and is compensated by positive returns in excess of high-water marks but not penalized by negative returns. Therefore, a HF manager may take idiosyncratic bets to turn around the fund performance. An OEF manager's compensation is often based on the total assets under management, and thus she has an incentive to increase fund flows. Sirri and Tufano (1998) and Chevlier and Ellison (1997) conclude significant nonlinearities in the relation between fund flows and returns. In addition, the relative performance evaluation to a benchmark may motivate a mutual fund manager to take bets on performance to climb up the ranking. An ETF manager is often evaluated based on how close she tracked the benchmark, and thus payoff depends more on the systematic parts of returns. Pension fund managers are often compensated by the idiosyncratic components of excess returns. Overall, the compensation structure may impact a fund manager' risk-taking behavior and in turn induce tail returns and risks of the fund.

I take the view of a fund manager and build a model based upon the concept of compensation structure. It predicts that how the compensation structure can induce systematic and idiosyncratic skewness and kurtosis in fund returns and her optimal allocation between the market portfolio and a negative skewed bet on idiosyncratic returns. Furthermore, the model predictions are used to explain tail risks across fund types.

IV The Model

A Return Dynamics and Tail Dependence

Suppose that a fund manager faces a portfolio choice problem today at time t between a market portfolio and a big bet based on their past returns. Making investment decisions based on past returns mirrors one realistic and simple investment strategy and coincides with the focus of this study on unconditional analysis. In addition, this setup also proposes the decomposition of fund returns into systematic and idiosyncratic components.

Assume the joint distribution of returns of these two assets are independent and identically distributed (i.i.d) through time and their complete moments and joint distribution are observable before the allocation is updated. Thus for j= $1...t$, the fund's return dynamics is modeled as follows:

$$R_{i,j} \quad = \quad w^*_{uncond,t+1} R_{p,j} + (1 - w^*_{uncond,t+1}) R_{BB,j} \tag{1}$$

where $R_{i,j}$ is the returns at time j for fund i. $R_{p,j}$ and $R_{BB,j}$ are the returns of the market portfolio and the big bet at time j, respectively. $w^*_{uncond,t+1}$ is the optimal unconditional weight for the period $t+1$ for the market portfolio and $w^*_{uncond,t+1} \in [0, 1]$[3]. For simplicity, I drop subscript t in the following analysis to concentrate on the unconditional analysis.

The market portfolio represents the systematic risk of the fund and suffers from macroeconomic shocks. The market portfolio is assumed to be well-diversified (e.g. constructed by N risky assets) and follows the normal distribution. The market portfolio can be any observable tradeable assets, such as portfolios of funds or portfolios of stocks, as long as the well-diversification assumption holds. The weight on the market portfolio captures fund managers' market timing strategy at time t.

The big bet reflects the fund-specific risk or microeconomic shocks. Fund managers often engage in security selection to undertake idiosyncratic risk to generate alpha. Simonson (1972) provides evidence for speculative behavior of mutual fund managers. HF managers commonly engage in negatively skewed bets. A negatively skewed bet is characterized as a trade that has a 99% chance of making gains but a 1% chance of losing big money. Examples are short (derivatives) positions, credit related instruments, syndicated loans, and pass-through securities,

[3] I also test on $w^*_{uncond,t+1} \in [-1, 1]$ for investors without short sale constraints and results hold.

etc. Big bets can endogenously generate tail risks and induce asymmetric payoffs in investment funds. Moreover, trades that endogenously generate left tail risks can help fund managers manipulate performance measurement (Goetzmann, Ingersoll, Spiegel, and Welch (2007)).

The big bet not only reflects the asset executed under its strategy, but also can be used to gamble on past fund performance. If a fund underperforms its peers but the fund manager likes to win the tournament at year-end for higher compensation, s/he can take a big bet to gamble on fund performance. This idiosyncratic asset can be futures, options, or foreign currencies, etc., as long as fund-specific strategies on this asset may suffer from blow up risk.

The literature on pay-performance well document this misbehavior of changing risk characteristics in response to relative performance to benchmarks from the agent (manager) (e.g. Murphy (1999)). Brown, Harlow, and Starks (1996) find that mid-year losers tend to increase fund risk in the latter part of the year than mid-year winners. Chevalier and Ellison (1997) conclude that mutual fund managers alter fund risk at the end of year based on their incentives. Kempf and Ruenzi (2008) find that mutual funds adjust their risk according to the relative ranking in a tournament within the fund families.

To capture the bet having a low probability of blowing up, but a large chance of winning, I use the skewed t-distribution to model the big bet. In other words, the skewed t-distribution characterizes any individual idiosyncratic assets with excessive left tail risks. Moreover, the skewed-t distribution has slowly decaying power law tails and thus best represents individual financial asset returns observed in the data.

The generalized skewed t-distribution is first suggested by Hansen (1994) and it is applied afterwards to allow asymmetry and fat-tailedness in financial asset returns (Jondeau and Rockinger (2003), and Patton (2004)). In addition, Theodossiou (1998) and Daal and Yu (2007) show that the skewed t-distribution provides a better fit than the GARCH-jump models to financial asset returns in both the U.S. and emerging markets. Recent studies also adopt the skewed t-distribution to model asset returns and show their impact on asset allocation, risk management, credit risk, and option pricing (e.g. Aas and Haff (2006), Dokov, Stoyanov, Rachev (2007)). In this study, the marginal distribution of the big bet follows the skewed t-distribution with $\lambda = -0.6$ (skewness) and $\nu = 7$ (degree of freedom) to generate negative skewness and excess kurtosis. However, both parameters are in the reasonable range from the aforementioned empirical papers.

The difference in characteristics between the market portfolio and the big bet lies in the tail risks. The assumed difference on the marginal distribution of these two assets helps isolate the effects of the tail risks between two assets. Thus, the tail risks of the fund mainly come from the asymmetrically distributed and fat-tailed idiosyncratic bets. Furthermore, since only unexpected shocks matter for unexpected returns, both the market portfolio and the big bet are standardized to be mean zero and variance one.

There are alternatives to endogenously generate tail risks for a fund through the idiosyncratic big bet. For instance, one can add jumps in asset prices and volatility to generate skewness and kurtosis. The other approach is to model the mixture of normal distributions in returns and volatility. However, both approaches require more assumed values of parameters.

The dependence structure of two assets helps introduce possible relations between higher moments of their asset returns. Fund managers' strategies on beta timing and security selection do not only affect the magnitude of the systematic and idiosyncratic components of returns. Even both components are uncorrelated, if idiosyncratic volatility is priced, the higher moments of the idiosyncratic shocks are not necessarily uncorrelated with the market returns.

The dependence structure between the market portfolio and the big bet can impact the tail risks of the fund from the following two sources. First, the change of the moments and the return distribution of the portfolio depends on the covariance, coskewness, and cokurtosis risk between the market portfolio and the big bet. For example, Boguth (2010) models the state-dependent idiosyncratic variance and its correlation with the mean and variance of the systematic factor through common shocks to induce fund skewness and kurtosis. Second, recent studies have documented the asymmetric tail dependence among financial assets (Longin and Solnik (2001) and Ang and Chen (2002)). The asymmetric tail dependence among assets held in the fund can yield tail returns and risks of a fund. Since the tail dependence structure of two assets captures effects from these sources, I use the tail dependence structure of two assets to reflect its impact on tail risks of the fund.

I model the tail dependence of two assets by T-Copula[4]. The bivariate copula is the joint distribution of two marginal distributions. Financial asset returns tend to comove together more strongly in bad economic states than good ones. The copula helps model the asymmetric joint risk among financial assets. Its application includes credit default risk, catastrophic risk for insurers, systemic risk among financial institutions, etc.

Correlation is only appropriate to measure elliptically distributed risks, such as the multivariate normal distribution. When the fund returns are non-linear, correlation alone cannot correctly infer the dependence among assets held in the fund. The dependence structure, correlation or tail dependent parameter κ, and marginal distributions are equally important to identify the dependence relationship of two random variables. I focus on T-Copula because of its prominence in the tail dependence literature. The results are based on $\kappa = 0$ [5]. Note that the assumption of zero

[4] I also test on Normal and Rotated Gumbel copula and results hold. Normal copula has zero tail dependence and Rotated Gumbel copula has lower tail dependence only.

[5] Results hold for $\kappa = 0.5$ and 0.9, reflecting different levels of covariance, coskewness, cokurtosis risk between the market portfolio and the big bet.

tail dependence also minimizes any effects between the higher moments of the idiosyncratic shocks and the market returns so that systematic and idiosyncratic tail risks can be separately defined.

The setup of this model follows Patton (2004). He studies the optimal conditional weight between the big-cap and small-cap portfolio under various tail dependence structures. To solve the optimal weight for two given assets, it is necessary to estimate the conditional mean and variance. Unlike his study, my focus is on the unconditional weight and I do not restrict the market portfolio and the big bet to be any specific financial assets. Because I want to emphasize the differences in tail risks between two assets, I adopt two arbitrary standardized financial assets[6]. If I am interested in two specific financial assets, such as S&P 500 and a stock option on Citibank, I can multiply the standardized time-series by their respective volatilities and add back their respective means to derive the optimal unconditional weight of these two specific assets. I show one example with mutual fund data in the robustness analysis section.

This simple allocation problem can be interpreted as fund managers' ability to adjust funds' systematic and idiosyncratic risk. For example, market-neutral HFs have low systematic risk but high idiosyncratic risk. ETF or index funds have high systematic risk, but relatively low idiosyncratic risk. In daily fund management, fund managers can adopt market-timing or stock-picking strategies to decide the allocation between systematic and idiosyncratic returns.

B The Optimization Problem

The main optimization problem is how the design of compensation schemes, i.e. the return decomposition effect and the convexity effect, affects the asset allocation of systematic risk and idiosyncratic risk. Systematic risk and idiosyncratic risk are represented by the market portfolio and the big bet, respectively.

Under the assumption of i.i.d returns, the unconditional weight can be solved by maximizing the sum of utility functions up-to-date.

$$w^*_{uncond,t+1} \equiv argmax \frac{1}{t} \sum_{j=1}^{j=t} U(W_j) \tag{2}$$

where W_j is the manager's total compensation at time j. For simplicity, I drop the subscrip j in the following notation.

First, the linear contract based on fund manager's systematic and fund-specific returns with

[6] I follow Kan and Zhou (1999) to standardize the systematic factor to simulate asset returns.

the nonnegative allocation weight α and $1-\alpha$, respectively[7]:

$$W_{linear} = \alpha(1 + w_{uncond}R_p) + (1-\alpha)(1 + (1 - w_{uncond})R_{BB})$$

where α is specified in the incentive contract. The return decomposition parameter α reflects the weight of the systematic component on the compensation. For the larger α, the manager's compensation depends more on the systematic component of returns.

Next, let's consider that fund managers' total compensation is based on the convex payoff W_{opt}=1+$max(\phi_{hwm}(R_i$+$K), 0)$ and W_{linear}, weighted by nonnegative g and $1-g$, respectively:

$$\begin{aligned} W &= gW_{opt} + (1-g)W_{linear} \qquad (3)\\ &= g(1 + max(\phi_{hwm}(R_i + K), 0)) \qquad (4)\\ &\quad +(1-g)\alpha(1 + w_{uncond}R_p) + (1-g)(1-\alpha)(1 + (1 - w_{uncond})R_{BB}) \end{aligned}$$

where ϕ_{hwm} is the incentive fee for high-water marks and is commonly quoted as 20% in the HF industry. The convexity parameter g is exogenously given and varies across fund types. The lareger the g, the more convex the compensation. K measures the cumulative losses up to time t and is modeled as $K_t = min(0, K_{t-1} + R_t)$.

I directly model the option-like payoff of HFs, instead of an arbitrary fixed K. Although the fixed threshold can imply implicit convexity from the fund-flow performance of other types of funds, it is too arbitrary to assign a specific value to K and to justify its appropriateness. Furthermore, incentive fees in the mutual fund industry are calculated based on cumulative performance over previous periods as well. Elton, Gruber, and Blake (2003) show that fulcrum fees can always be converted to non-negative incentive fees. To my knowledge, there are no empirical studies to estimate the range of K across funds. Thus, I model the threshold as cumulative losses. Nonetheless, results still hold for a fixed K.

This setup for the total compensation can be applied to different types of investment funds. For example, pension fund managers are often paid out based on the fund returns in excess of the benchmark or the market, i.e. $\alpha = 0$. HF managers are often measured against a high-water mark and thus $g = 1$. For ETFs and index funds, tracking errors are critical in performance measure and no convex compensation scheme applies to the total payoff. Therefore, I can set α and g to be 1 and 0, respectively, in the model. Actively managed mutuals may be based on a combination of total fund returns and fund-specific returns ($0 < \alpha, g < 1$). In summary, this setup implicitly captures the relative performance measure used in ETFs, CEFs, OEFs, and

[7]Ramakrishnan and Thakor (1984) show that in the existence of moral hazard, contracts will depend on both systematic and idiosyncratic risks.

absolute performance measure used in HFs. The order of the magnitude of α (index tracking) across types of funds is ETFs, CEFs, OEFs, and HFs; the effect of g (convexity) is in the order of HFs, OEFs, CEFs, and ETFs.

The non-linear fund returns and option-like compensation schemes attribute to the nonlinearity of total wealth W. The utility below follows Mitton and Vorkink (2007) and Boguth (2010) and weighs in the effects of higher moments.

$$\mathbb{E}U(W) = \mathbb{E}W - \frac{1}{2\tau_2}\mathbb{E}(W - \mathbb{E}W)^2 + \frac{1}{3\tau_3}\mathbb{E}(W - \mathbb{E}W)^3 - \frac{1}{12\tau_4}\mathbb{E}(W - \mathbb{E}W)^4 \quad (5)$$

where τ_2, τ_3, and τ_4 are risk tolerance for the second, third, and fourth moments of wealth W. Main results use $\tau_2 = 1.5$, $\tau_3 = 0.15$, and $\tau_4 = 0.015$.

This type of utility captures the manager's concern for skewness and kurtosis relatively to dispersion. The positive sign of the third term denotes the manager's preference for skewness. The negative sign of the fourth term corresponds to the manager's dislike to kurtosis. The parameters of risk tolerance for the second, third, and fourth moments under this utility is translated into relative risk aversion between 5 and 10 when power utility is assumed[8].

Since the distribution of asset returns in this model is not solely determined by mean and variance and managerial compensation is convex, the utility taking account of the probability distribution of wealth up to the fourth moments is used and considered more appropriate than other standard utility forms. Although the mean-variance criterion is the best known and wildly used, the mean-variance portfolio theory is only applicable if preference is quadratic or asset returns follow normal distributions. The assumption on normal distributions contradicts the main theme of this study and the quadratic utility carries an unrealistic assumption of increasing absolute risk aversion. Numerous researchers also argue that the if the higher moments are relevant to investment decisions and the mean-variance assumptions are violated, the higher moments cannot be ignored (Arditti (1967,1971), Samuelson (1970), and Rubinstein (1973)). In addition, earlier literature demonstrates that mean-variance analysis fails when volatility to mean ratio is high or tail risks are considered (Hanoch and Levy (1970), Tsiang (1972), Scott and Horvath (1980), and Kane (1982)). Standard utility forms are also not appropriate in this study. Power utility fails to deal with negative wealth or face the possibility of bankruptcy and the assumption of constant absolute risk aversion for exponential utility is violated.

[8]According to Kane (1982), the skewness ratio and kurtosis ratio for the power utility are equal to 1+γ and (1+γ)(2+γ), respectively. γ is the relative risk aversion and skewness (kurtosis) ratio reflects preference for the third (fourth) moment relative to aversion to variance. Thus, the range of skewness ratio is between 6 and 11 and kurtosis ratio is between 42 and 132 for $\gamma = 5$ and 10. Parameters for risk tolerance used in the model suggest skewness ratio and kurtosis ratio to be 10 and 100, respectively

Since the optimization problem above has no closed-form solution, I following Patton (2004) to numerically solve the asset allocation problem. The details are in the Appendix A.

C Monte Carlo Results

Figure 1 presents the optimal weight for the market portfolio and the big bet. Figure 2 shows the snapshot of the optimal weight with respect to α and g, i.e. the return decomposition and convexity effect. Figure 3 displays the optimal skewness and kurtosis for a fund.

Figure 1: The Optimal Weight on the Market Portfolio

The return decomposition parameter α and the convexity parameter g are the weight of systematic returns and the magnitude of convexity on the fund manager's compensation, respectively. z-axis is the optimal unconditional weight.

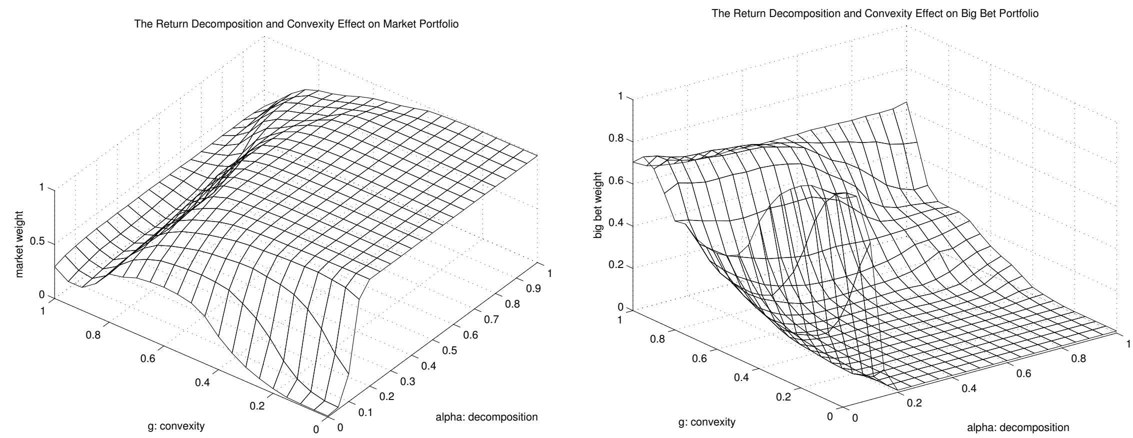


Figure 2: The Return Decomposition and Convexity Effect on the Optimal Weight for the Market Portfolio and the Big Bet

The graphs on the top panel show the return decomposition effect on the market portfolio (left) and the big bet (right). The graphs on the bottom panel show the convexity effect on both assets. The snapshot is taken as the average weight across g and α.

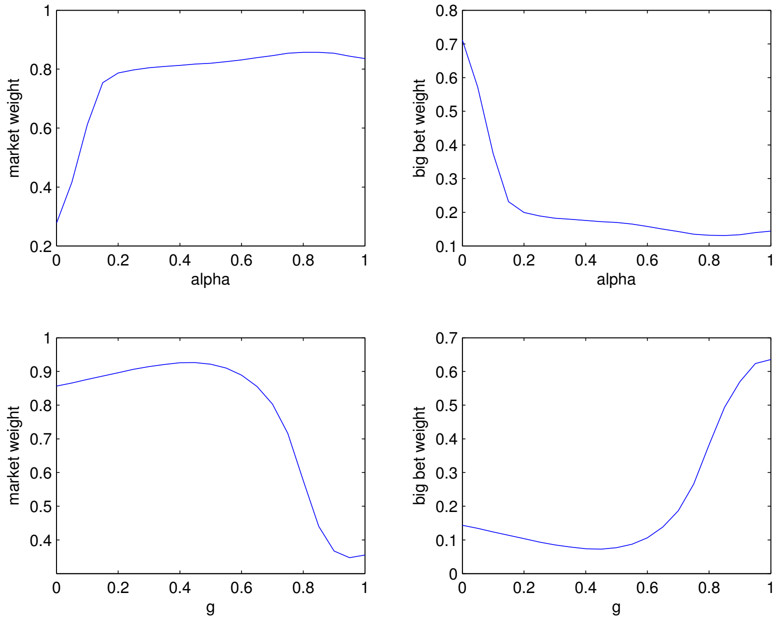
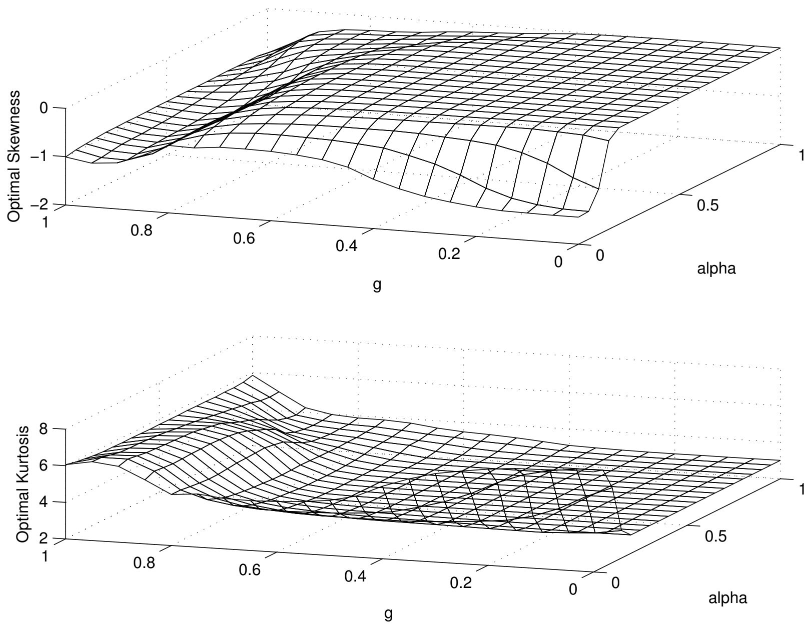


Figure 3: The Optimal Fund Skewness and Kurtosis



The model predicts that as convexity in the contract increases (i.e. g increases), fund managers will increase weights on the idiosyncratic big bet and thus reduce fund skewness and increase fund kurtosis.

On the other hand, if the fund managers' compensation ties more to the systematic returns (i.e. α increases), more weights will be allocated to the market portfolio to increase fund skewness and reduce fund kurtosis.

The interpretation is as follows. Consider two types of fund managers in the economy: conservative and aggressive. A fund manager whose compensation depends more on the systematic components of returns (i.e. a larger α) can be viewed as the conservative one. The fund manager for ETFs is one example. The model predicts that conservative managers prefer positive skewness of funds. The greater skewness and lower kurtosis will increase expected utility. On the contrary, when a fund manager is entitled with a more convex compensation scheme (i.e. a larger g), their investment styles are more aggressive. HFs are the example. The model predicts that the aggressive fund managers prefer idiosyncratic tail risks by lowering skewness and increasing kurtosis to improve the expected returns for the next period.

According to the model's predictions, HFs' skewness and kurtosis should come mostly from the idiosyncratic component, as the increased g induces more weights on the idiosyncratic big bet. The increased weight on the idiosyncratic part in turn lowers the skewness and raises the kurtosis of the fund. ETFs are represented by higher α and lower g. Figure 4 implies that ETFs exhibit positive skewness and lower kurtosis. OEFs and CEFs are associated with α and g between 0 and 1. OEFs can have lower α and higher g than CEFs, i.e. fund managers for OEFs are rewarded for higher idiosyncratic returns from stock-picking and convexity. Therefore, the weight of the idiosyncratic component on total fund skewness and kurtosis should follow the following order: HFs, OEFs, CEFs, and ETFs.

One intriguing implication from the model is that if the incentive contracts depend mostly on idiosyncratic returns with little convexity (i.e. α and g are both very low) , the model suggests that fund managers will invest mostly in the idiosyncratic big bet to increase expected returns. This risk-taking behavior can induce relatively negative skewness and large fat-tailedness. However, it is hard to find this type of funds since most funds' compensation relies on convexity and systematic returns to some degrees.

This model does not incorporate agency costs or transparency, which I also outline as potential causes for differences in tail risks across investment funds. Incorporating them requires a setting of delegation from an investor to a fund manager in the model. However, these factors can be interpreted as more aggressive investment styles due to stronger misalignment of interests between investors and fund managers. This misalignment will result in more aggressive investments on the idiosyncratic assets with tail risks and induce lower fund skewness and higher fund kurtosis when the compensation payoff is more option-like, i.e. as g increases.

V The Data

The literature has documented the following biases in the investment fund datasets and they might differ across fund types and bias results on tail risks.

Incubation bias is referred to as fund families start several new funds, but only open funds that succeed in the evaluation period to the public. Evans (2007) shows that incubated mutual funds outperform non-incubated funds. Incubation creates upward bias on fund returns. When a fund enters to the database, its past return history is automatically added to the database. This addition of past returns causes backfilling bias and it can bias fund performance upwards and risk downwards.

Stale prices mean that reported asset prices do not reflect correct true prices, possibly due to illiquidity, non-synchronous trading, or bid-ask bounce. These characteristics can cause serial-correlation in returns. HFs suffer from this bias the most , due to their fund characteristics in lockups and redemption notification periods.

The survival probability of funds depends on past performance (Brown and Goetzmann (1995)). Managers who take significant risk and win will survive. Therefore, the database is left with high risk and high return surviving funds. If a study includes only funds that survive until the end of the sample period, survivorship bias occurs. The survivorship bias imparts a downward bias to risk, and an upward bias to alpha (e.g. Carhart (1997), Blake and Timmermann (1998)).

The survivorship bias is more complex for HFs. HFs may decide to stop reporting because of liquidation or self-selection (Ter Horst and Verbeek (2007), Jagannathan, Malakhov, and Novikov (2010)). Liquidation refers to underperforming funds exiting the database. Self-selection is associated with a fund's decision to be included in the database. For instance, outperforming HFs have less incentives to report performance to attract new investors and fund managers may switch to another data vendor for marketing purposes.

The look-ahead bias arises when funds are required to survive some minimum length of time after a reference date. One type of look-ahead bias applicable to this study is the look-ahead benchmark bias (Daniel, Sornett, and Wohrmann (2009)). Since the time series of stylesare not kept in the database, funds that change styles over time may suffer from the look-ahead benchmark bias. This omission can bias risk-adjusted returns and risks.

The aforementioned biases can apply to ETFs and CEFs as well. For instance, ETFs and CEFs are subject to look-ahead benchmark biases since no data vendors keep the history of their classification codes. In addition, CEFs may suffer from survivorship bias, due to its commonly observed discounts on traded prices. Although the exit rate for ETFs is low, survivorship bias might still affect their analysis on tail risks.

The ETFs, OEFs, CEFs, and HFs in this study are investment funds managed in the U.S. The list of ETFs and CEFs domiciled in the U.S. are screened out from Morningstar database, including both live and dead funds. Monthly returns of ETFs and CEFs from the CRSP monthly stock return table are merged with the list of funds from Morningstar database. ETFs and CEF returns start from 1993 and 1929, respectively. Monthly OEF returns are from CRSP U.S. survivorship-free mutual fund database. The CRSP mutual fund data start in 1962. HF sample is constructed by combining both live and dead funds from HFR database. The period for HFs starts from 1996. The end year for all four fund types is 2008. Investment funds with less than twelve months of returns are excluded and all investment funds maintain the same investment strategy for at least twelve months. This restriction is because that fund managers are usually evaluated at the end of year and the minimum of 12 observations offer sufficient degrees of freedom for GMM estimation [9].

ETFs and CEFs are from Morningstar survivorship free database. Although ETFs and CEFs might suffer look-ahead benchmark bias, but it is unlikely these funds will change investment styles through time, given funds' characteristics[10].

OEFs are from CRSP survivorship free database and portfolios of funds are constructed look-ahead bias free. Monthly returns are used only after the beginning of the assigned style. No ex-post style returns are used. I delete returns before the fund inception date to avoid incubation bias. This step follows from Evans' (2007) initial approach since I have no access to the complete list of mutual fund tickers and their creation dates from NASD. I also delete fund returns for the first year to remove backfill bias.

HFs combine both live and dead fund returns from HFR to eliminate survivorship bias. I further drop returns before the inception date to remove incubation bias. Aggarwal and Jorion (2010) use the data field "date added to database" in TASS dataset and find the median backfill period is 480 days. I adopt the same approach to clean out back-filled HF returns.

Nevertheless, my attempts to control these ex-post conditional biases may be imperfect. By construction, HFs might still suffer limited look-ahead benchmark bias and I assume no change of styles in ETFs and CEFs. Lack of NASD data might leave backfill bias in the mutual fund sample. In addition, it is known that the coverage of HFs has little overlap across different data vendors. Relying on only HFR data may not represent the whole HF industry.

Style classification codes for ETFs and CEFs are from Morningstar. The Morningstar classification codes for ETFs and CEFs are commonly used on many financial websites and thus this information is easily accessible to investors. For OEFs, I use the style classification codes in the CRSP mutual fund database. The database uses five different classification codes to cover disjoint time periods. POLICY codes are used before 1990. CRSP uses WIESENBERGER (WB_OBJ) codes between 1990 to the end of 1992. Strategic Insight Objective (SI_OBJ) codes cover from 1993 to September, 1998. Lipper Objective (Lipper_OBJ) codes are used up to 2008. Most recent funds are classified by Thomson Reuters Objective (TR_OBJ) codes. For HFs, HFR provides main and sub strategy classification codes for each fund. I use main strategy classification codes.

Benchmark data are from the following sources. Market excess returns, SMB and HML factors are obtained from Ken French's website[11]. The momentum factor is downloaded from CRSP. The seven HF factors [12] are downloaded from David Hsieh's website[13]. The Barclay U.S. government/credit index

[9]There are one mutual fund (CRSP Fund ID 031241 in fixed income index and 01108 in fixed income government) and two HFs (HFR Fund ID 17393 and 21981 in relative value) misspecified by the GMM estimation and thus removed from this study. All four funds have no monthly returns outside 3 standard deviations from their means. Removing these three funds has minimal effects on the univariate statistics of the style that they belong to.

[10]ETFs are index funds and CEFs do not allow the redemption of shares after IPO.

[11]$http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\_library.html.$

[12]The equity and bond market factor, the size spread factor, two credit spread factors, and three lookback straddles on bond futures, currency futures, and commodity futures.

[13]$http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls.$

(LHGVCRP) and corporate bond index (LHCCORP) are downloaded from Datastream.

I form groups of funds by styles for analysis. Each group has the same styles of funds. ETFs and CEFs are grouped by Morningstar styles[14]. OEFs are grouped by CRSP style codes[15]. HFs are grouped by HFR main strategies[16].

Table I summarizes univariate statistics of "average" funds across fund styles and types. By "average", it means that statistics for individual funds in the same group are averaged to represent "average" or individual fund statistics.

Tail risks are different at the aggregate and individual fund level[17]. HFs are the most negatively skewed. ETFs are the least negatively skewed and fixed income ETFs show positive skewness. OEFs and CEFs are in between. This order is predicted from the model, as the increased convexity and the increased weight on idiosyncratic returns of the incentive contract predict lower skewness.

However, the order of kurtosis is not fully predicted by the model. As predicted, ETFs do have low kurtosis and HFs do have high kurtosis. However, the level of kurtosis between HFs (ETFs) and CEFs (OEFs) is close and not explained by the model.

At the individual fund level, there are variations in tail risks across fund styles within the same fund type. It can be noted from the variation of the significance level of the Jarque-Berra test among fund styles. A more striking result is that the significance level of rejecting normality drops significantly for the average fund, compared to the equal-weighted portfolios of funds. Also, the Ljung-Box test fails to reject serial correlation for the average fund. However, these results do not necessarily suggest that individual funds do not exhibit negative skewness, excess kurtosis, or serial correlation. The number of monthly returns for the average fund is much lower than that of the portfolios of funds.

[14]Equity ETFs: Global, Currency, Sector, Balanced, Bear Market, Commodities, Large/Mid/Small Cap, Growth/Value, and Others. Fixed Income ETFs: Global, Sector, Long Term, Intermediate Term, Short Term, Government, High Yield, and Others. Equity CEFs are Global, Balanced, Sector, Commodities, Large/Mid/Small Cap, Growth/Value, and Others. Fixed Income CEFs are Global, Sector, Long Term, Intermediate Term, Short Term, Government, High Yield, and Others

[15]Equity funds are classified as Index, Commodities, Sector, Global, Balanced, Leverage and Short, Long Short, Mid Cap, Small Cap, Aggressive Growth, Growth, Growth and Income, Equity Income, and Others. Fixed income funds are classified as Index, Global, Short Term, Government, Mortgage, Corporate, and High Yield. The classification methodology is in Appendix B.

[16]Equity Hedge, Event-Driven, Fund of Funds, HFRI Index, HFRX Index, Macro, and Relative Value. Descriptions of these investment strategies are available available from HFR at http://www.hedgefundresearch.com.

[17]The tabulated summary of univariate statistics of equal-weighted portfolios of funds is available upon request. Note that since portfolios are constructed by averaging fund returns in the same group equal-weightedly at each point of time, fund characteristics may appear different from those of individual funds.

VI Empirical Design

A Frequency of Tail Returns

If an investment fund is well diversified, the distribution of returns should be close to normal, i.e. its skewness is zero and kurtosis is 3. However, table I suggests that tail returns and risks do exist in investment funds. Possible reasons are option-like managerial compensation, the limited liability of fund managers, the use of leverage, options or any assets with non-normality, hedging and stop-loss trading, asymmetric risk preferences, etc. One direct approach to observe tail returns and risks in investment funds is to measure the frequency of tail returns in a given fund.

Tail returns of an individual fund are defined as its monthly returns above or below 3 and 5 standard deviations from their mean. Äit-Sahalia (2004) estimates the probability of observing one jump conditional on a large log-return. The sources of the large log-return can come from a continuous Brownian part or a discontinuous jump part. He concludes that as far into the tail as 3.5 standard deviations, a large observed log-return can still be produced by the Brownian noise only. A large log-return above 3.5 standard deviations in a finite time would help identify at least one jump. As such, I use 3 and 5 standard deviations as thresholds to determine tail returns. A fund with a high frequency of monthly returns exceeding 5 standard deviation suggests that jumps can be identified in the fund returns. This statistics offers an indirect evidence to compare frequencies of jumps across fund types since returns at the monthly frequencies do not have enough power to identify jumps via the maximum likelihood approach.

For each fund, the frequency of tail returns is calculated as the percentage of monthly returns exceeding 5 and 3 fund standard deviations from their means. This measure is similar to the statistical R^2 in regression analysis and can reflect tracking errors and idiosyncratic risks induced by trading strategies.

Furthermore, I decompose funds' monthly returns into systematic and idiosyncratic components and compute the percentage of monthly systematic and idiosyncratic returns exceeding 5 and 3 standard deviation of their respective means. A fund with a higher frequency of systematic tail returns reflect its fund manager tends to deviate from the market or β is far from 1. If a fund shows a higher frequency of idiosyncratic tail returns, its manager prefer taking idiosyncratic risks to increase fund performance.

Let $COUNT_{i,t_i}$ be one if fund i's monthly return on month t_i is greater than 3 or 5 standard deviation from its mean. I derive the test statistics of the frequency of tail returns for fund i by assuming that $COUNT_{i,t_i}$ follows the Bernoulli distribution and the sequence of $COUNT_{i,t_i}$ is independent and identically distributed, i.e. $COUNT_{i,t_i}$ is 1 with probability p and 0 otherwise on each month. Thus, at the individual fund level, the frequency of tail returns and its test statistics can be represented as follows:

$$X_i = \frac{1}{T_i}\sum_{t_i=1}^{T_i} COUNT_{i,t_i} \quad \sim \quad N(p, \frac{p(1-p)}{T_i})$$

where T_i is the total observations for fund i and $t_i = (1, 2, ..., T_i) \in T_i$. At the style or type level,

$$Y_s = \frac{1}{N_s}\sum_{i=1}^{N_s} X_i \quad \sim \quad N(p, \frac{1}{N_s^2}(\sum_i \frac{p(1-p)}{T_i} + \sum_i \sum_{j \neq i} \rho_{tail}\sqrt{\frac{p(1-p)}{T_i}}\sqrt{\frac{p(1-p)}{T_j}}))$$

where N_s is the number of funds in the style or type s and ρ_{tail} is the average correlation of tail returns among funds. I calculate ρ_{tail} as follows. If returns across the fund style in a single month are jointly within 3 standard deviations from their means, all returns in that month are dropped to compute correlations. Then average correlations across funds in the same style to derive ρ_{tail}. ρ_{tail} reflects correlation from economy-wide shocks affecting all funds at the extreme states.

To compare any two fund styles or types (Y_s and Y_r) at the aggregate level:

$$\begin{aligned} Y_s - Y_r &\sim N(0, var(Y_s) + var(Y_r) - 2cov(Y_s, Y_r)) \\ cov(Y_s, Y_r) &= \frac{1}{N_s N_r}\sum_i \sum_j \rho_{tail}\sqrt{\frac{p(1-p)}{T_i}}\sqrt{\frac{p(1-p)}{T_j}} \end{aligned}$$

B Systematic and idiosyncratic risk

B.1 The Benchmarks

Different fund styles and types have different levels of systematic risk and are exposed to different risk factors. Therefore, a broad-based index is not the appropriate benchmark to decompose risk into systematic and idiosyncratic components across fund styles and types. CEF returns are subject to discounts and therefore any risk factors capturing cross-sectional variations of discounts would be priced. ETFs track market indexes and are most sensitive to market factors directly associated with the benchmarks they track. Because OEFs follow long-only and buy and hold strategies in order to beat their benchmarks, standard asset classes may be appropriate market factors. HFs have no benchmarks and fund managers simply tend to maximize total fund returns due to high watermark provisions. In addition, different HF styles pursue different directional/nondirectional trades and dynamic trading strategies, and differ in option-like payoffs. These HF characteristics lead to distinctive risk profiles among HFs and compared to other fund types.

Inappropriate factors may lead to a misleading measure of systematic and idiosyncratic risk decomposition. Roll (1978), Lehmann and Modest (1987), and others demonstrate that performance measure is likely to be sensitive to the choice of a benchmark. If the chosen market factors don't appropriately explain the the variations of systematic components of returns, too much idiosyncratic risk is mistakenly identified. Then empirical results will spuriously show fund skewness and kurtosis mostly come from the idiosyncratic component of returns.

I use the equal-weighted portfolios of funds to proxy for the market portfolio and to decompose systematic and idiosyncratic components of returns. This market proxy is used to study fund performance (e.g. Grinblatt and Titman (1994), Brown, Goetzmann, and Ibottson (1999), Ackermann, McEnally, Ravenscraft (1999), and Fung and Hsieh (2000)).

The advantages of using the portfolios of funds within the same style as benchmarks include the following: First, the ideal factor-mimicking portfolios should have the smallest idiosyncratic risk and they are empirically testable. The portfolios of funds are observable and capture diversification effects [18]. The portfolios of funds have the lowest idiosyncratic tail risks.

Second, valuable services are credited to a fund manager when the investment opportunity set is expanded by the trading strategy of the fund. Therefore, the reference portfolios should share common assets with the fund. For example, if the Janus Balanced Fund trades growth stocks and U.S. Treasury, both types of securities should be included in the reference assets. The portfolios of funds represent a joint set of reference assets for funds within the same trading strategy.

Third, many fund managers in the same style make similar bets or share similar trading strategies. Therefore, funds in the same style may be exposed to the same "priced" factors and controlling for them helps identify outperforming funds. The portfolios of funds are constructed by funds within the same style and can capture the time-series and cross-sectional variation of a common systematic risk within this style. Hunter, Kandel, Kandel, and Wermers (2010) use fund returns in the same group to construct an endogenous benchmark and show that the endogenous benchmark introduces a "priced" factor in addition to the Fama-French 3 factors. The endogenous benchmark can capture a common component in the variation over time and across funds within the group.

In addition, return characteristics and distributions differ across fund styles and types and the portfolios of funds capture distinctive differences. For example, HFs exhibit nonlinearities in returns and magnitudes of nonlinearities differ across HF styles. An index constructed by the funds in the same style helps control style-specific features of returns to decompose systematic and idiosyncratic components.

Fourth, the portfolios of funds create a peer group of managers who pursue the same style. Fund managers are increasingly evaluated relative to a performance benchmark specific to their style, instead of a broad-based benchmark. An inappropriate benchmark can induce incorrect measurement of relative performance. For example, a small-cap fund manager may underperform relative to a broad market index, but overperform relative to a small stock benchmark.

B.2 The Decomposition

I run the following regression to decompose the systematic and idiosyncratic components of risks:

$$R_{i,t} - \mathbb{E}(R_i) \quad = \quad \alpha_i + \beta_i(R_{p,t} - \mathbb{E}(R_p)) + u_{i,t} \tag{6}$$

$R_{i,t}$ and $R_{p,t}$ are returns for fund i and portfolio of funds p at time t. The portfolios of funds are constructed based on the investment styles outlined in section V. Therefore, $\beta_i(R_{p,t} - \mathbb{E}(R_p))$ and $u_{i,t}$

[18] The k^{th} order moment of portfolios of funds is $O(\frac{1}{n^{k-1}})$. As $n \to \infty$, $\mathbb{E}[R_p - \mathbb{E}(R_p)]^k = \mathbb{E}[\frac{1}{n}\sum R_i - \frac{1}{n}\sum \mathbb{E}(R_i)]^k = \frac{1}{n^k}\mathbb{E}[\sum R_i - \sum \mathbb{E}(R_i)]^k \leq \frac{n}{n^k}$

stand for the systematic and idiosyncratic component of de-meaned returns for fund i. Both components are orthogonal to each other.

The simple linear regression in (6) is advantageous to study systematic and idiosyncratic tail risks [19]. Under this single factor model, the skewness of r_i can be decomposed as follows:

$$\begin{aligned} \mathbb{E}(r_i^3) &= \mathbb{E}[(\beta_i r_p + u_i)^3] \\ &= \beta_i^3 \mathbb{E}(r_p^3) + 3\beta_i^2 \mathbb{E}(r_p^2 u_i) + 3\beta_i \mathbb{E}(r_p u_i^2) + \mathbb{E}(u_i^3) \\ &= \underbrace{\beta_i^2 cov(r_i, r_p^2) + 2\beta_i^2 cov(u_i, r_p^2)}_{COSKEW} + \underbrace{3\beta_i cov(u_i^2, r_p)}_{ICOSKEW} + \underbrace{\mathbb{E}(u_i^3)}_{RESSKEW} \end{aligned} \tag{7}$$

where r_i and r_p are de-meaned returns, i.e. $r_i = R_i - \mathbb{E}(R_i)$ and $r_p = R_p - \mathbb{E}(R_p)$. According to (7), the skewness decomposition consists of three parts: coskewness (COSKEW), idiosyncratic coskewness (ICOSKEW), and residual skewness (RESSKEW). Since both COSKEW and ICOSKEW contain β and covary with the market, I refer to them as systematic tail risks. The residual skewness represents idiosyncratic tail risk. Rubinstein (1973), Kraus and Litzenberger (1976), Harvey and Soddique (2000), and Vanden (2006) all demonstrate the importance of coskewness effects on asset pricing. Note that coskewness in this study is defined as the sum of two covariance terms - the covariance of fund returns and the covariance of fund residuals with market volatility. The latter is small under the assumption of orthogonality between the systematic and idiosyncratic components in the one-factor regression.

Moreno and Rodríguez (2009) show that coskewness is managed and the coskewness policy is persistent over time. In their remark, "managing coskewness" refers to having a specific policy regarding the assets incorporated in to the funds portfolio to achieve higher or lower portfolio coskewness. If a manager consistently adds negative skewness to the fund by incorporating negative coskewness assets, the fund will exhibit negative coskewness and investors will demand a higher risk premium.

The idiosyncratic coskewness, i.e. the covariance between idiosyncratic volatility and market returns, is advocated by Chabi-Yo (2009). The idiosyncratic coskewness is motivated to explain two market anomalies. First, idiosyncratic coskewness is related to idiosyncratic volatility premium. If idiosyncratic coskewness is positive, stocks with high idiosyncratic volatility have low expected returns. Ang, Hodrick, Xing, and Zhang (2006, 2009) raise this idiosyncratic volatility puzzle. If idiosyncratic coskewness is negative, stocks with high idiosyncratic volatility have high expected returns. This relation matches conventional intuition. Second, idiosyncratic coskewness can help explain the empirical finding that distressed stocks have low returns (Chabi-Yo and Yang (2009)).

[19] If I add the quadratic terms to (6), i.e. $R_{i,t} - \mathbb{E}(R_i) = \alpha_i + \beta_i(R_{p,t} - \mathbb{E}(R_p)) + \gamma_i(R_{p,t} - \mathbb{E}(R_p))^2 + \epsilon_{it}$, the skewness decomposition becomes $\mathbb{E}(r_i^3) = \beta_i^3\mathbb{E}(r_p^3) + 3\beta_i\mathbb{E}(r_p\epsilon_i^2) + \mathbb{E}(\epsilon_i^3) + [3\beta_i^2\gamma_i\mathbb{E}(r_p^4) + 3\beta_i\gamma_i^2\mathbb{E}(r_p^5) + 3\gamma_i\mathbb{E}(r_p^2\epsilon_i^2) + 3\gamma_i^2\mathbb{E}(r_p^4\epsilon_i) + 6\beta_i\gamma_i\mathbb{E}(r_p^3\epsilon_i) + \gamma_i^3\mathbb{E}(r_p^6)]$ = COSKEW + ICOSKEW + RESSKEW + other Higher moments. COSKEW, ICOSKEW, and RESSKEW are also components of the skewness decomposition for this particular equation. Similarly, the kurtosis decomposition expands as $\mathbb{E}(r_i^4) = \beta_i^4\mathbb{E}(r_p^4) + 4\beta_i\mathbb{E}(r_p\epsilon_i^3) + \mathbb{E}(\epsilon_i^4) + 4\beta_i^3\gamma_i\mathbb{E}(r_p^5) + 6\beta_i^2\gamma_i^2\mathbb{E}(r_p^6) + 4\beta_i\gamma_i^2\mathbb{E}(r_p^5) + \gamma_i^4\mathbb{E}(r_p^8) + 4\epsilon_i[3\beta_i^2\gamma_i\mathbb{E}(r_p^4) + 3\beta_i\gamma_i^2\mathbb{E}(r_p^5) + \gamma_i^3\mathbb{E}(r_p^6)] + 6\epsilon_i^2[2\beta_i\gamma_i\mathbb{E}(r_p^3) + \gamma_i^2\mathbb{E}(r_p^4)] + 4[\beta_i\mathbb{E}(r_p\epsilon_i^3) + \gamma_i\mathbb{E}(r_p^2\epsilon_i^3)]$ = COKURT + ICOKURT + RESKURT + VOLCOMV + other Higher moments.

Chabi-Yo (2009) also proves that idiosyncratic coskewness is equivalent to a weighted average of individual stock call and put betas. Coval and Shumway (2001) show that out-of-money calls (puts) have larger positive (negative) betas and lower expected returns. It can be shown that in a single factor model, during market upswings ($r_p > 0$), idiosyncratic coskewness is positive and idiosyncratic risk premium is negative; during market downswings ($r_p < 0$), idiosyncratic coskewness is negative and idiosyncratic risk premium is positive. In other words, stocks whose option betas with high sensitives to market returns have low average returns because they hedge against market upswings and downswings. Out-of-money options written on these stocks have large betas or higher sensitivities with market returns. Investors prefer options written on stocks with lottery-like returns.

Note that $cov(u_i^2, r_p)$ is equivalent to $cov[\mathbb{E}(u_i^2|r_p), r_p]$ or $\mathbb{E}[\mathbb{E}(u_i^2|r_p)r_p]$. This decomposition implies that the sign and the magnitude of ICOSKEW depends on the risk-return relation and the level of conditional heteroscedasticity. If an asset has high (low) idiosyncratic risk/conditional heteroscedasticity and its risk is negatively correlated with market returns, adding this asset to a fund will increase negative skewness through a large (small) negative ICOSKEW.

Mitton and Vorkink (2007) and Barberis and Huang (2008) document that idiosyncratic skewness is priced and its relation with expected returns is negative. Boyer, Mitton, and Vorkink (2009) empirically test the negative relation between idiosyncratic skewness and expected returns.

Similarly, the decomposition of kurtosis is derived as follows:

$$\begin{aligned}
\mathbb{E}(r_i^4) &= \mathbb{E}[(\beta_i r_p + u_i)^4] \\
&= \beta_i^4\mathbb{E}(r_p^4) + 4\beta_i^3\mathbb{E}(r_p^3 u_i) + 6\beta_i^2\mathbb{E}(r_p^2 u_i^2) + 4\beta_i\mathbb{E}(r_p u_i^3) + \mathbb{E}(u_i^4)) \\
&= \underbrace{\beta_i^3 cov(r_i, r_p^3) + 3\beta_i^3 cov(u_i, r_p^3)}_{COKURT} + \underbrace{6\beta_i^2\mathbb{E}(r_p^2 u_i^2)}_{VOLCOMV} + \underbrace{4\beta_i cov(u_i^3, r_p)}_{ICOKURT} + \underbrace{\mathbb{E}(u_i^4))}_{RESKURT} \qquad (8)
\end{aligned}$$

This decomposition displays four sources of fund kurtosis: cokurtosis (COKURT), comovements of volatility (VOLCOMV), idiosyncratic cokurtosis (ICOKURT), and residual kurtosis (RESKURT). COKURT, VOLCOMV, and ICOKURT are exposed to the market and are classified as systematic tail risks. The residual kurtosis is considered as idiosyncratic tail risk. The importance and validity of cokurtosis on asset returns are documented by Christie-David and Chaudhry (2001) and Dittmar (2002). Note that cokurtosis defined in this study contains the covariance between residual returns and market skewness, but it is assumed to be small, compared to the covariance between total returns and market skewness.

The cokurtosis of an asset can impact the total kurtosis of the fund. Investors dislike fat-tails in returns and thus demand a positive risk premium on an asset with large kurtosis. Such an asset will increase the total kurtosis of the fund. If a manager constantly adopts the strategy of buying positive cokurtosis assets, the fund will show a large weight on cokurtosis in the kurtosis decomposition. In addition, since cokurtosis reflects the covariance between market skewness and individual fund returns, a positively cokurtosised fund indicates a positive relation between the fund return and the skewness of the market returns.

The VOLCOMV term can be viewed as the comovement of volatility between the fund and market returns. The concept of comovement of volatility is often applied to the studies across international markets[20]. However, the comovement of volatility between the market and a fund can be interesting. Fund managers are known to use market-timing and market volatility timing strategies (eg. Treynor and Mazuy (1966), Henriksson and Merton (1981) and Busse (1999)). From the hedging perspective, if an investor's portfolio is exposed to the market, adding a fund which comoves with market volatility can be suboptimal due to dispersion to kurtosis. Since kurtosis is the variance of the variance, a fund manager can add assets with high volatility comovements with the market to increase the kurtosis of the fund. When a fund exhibits a large VOLCOMV component, it implies that using comovements of volatility is a common strategy for this fund.

Following Chabi-Yo (2009), I refer to the covariance between idiosyncratic skewness and market returns as idiosyncratic cokurtosis. Like idiosyncratic coskewness, idiosyncratic cokurtosis can be interpreted as a weighted average of individual security call and put betas. For a single factor model, market upswings imply positive option betas and thus positive idiosyncratic cokurtosis.

$cov(u_i^3, r_p)$ can be rewritten as $cov[\mathbb{E}(u_i^3|r_p), r_p]$ or $\mathbb{E}[\mathbb{E}(u_i^3|r_p)r_p]$. The idiosyncratic cokurtosis is implicitly embedded with a skewness-return relation and the magnitude of conditional heteroskewticity. Conditional heteroskewticity is a property of residual returns. If an asset has high (low) idiosyncratic skewness/conditional heteroskewticity and its skewness is negatively correlated with market returns, adding this asset will decrease fund kurtosis through a large (small) negative ICOKURT.

Chabi-Yo (2009) extends his analysis to higher moments and concludes that higher moment premium is driven by individual security call and put betas. Although idiosyncratic kurtosis premium is not well documented in the literature, a fund with a larger weight on idiosyncratic kurtosis in the decomposition implies that its manager has more flexibility in what and how to trade. For example, since HF managers constantly use higher leverage and dynamic strategies, and are able to invest in a wider class of assets, HFs should exhibit a larger weight on RESSKEW and RESKURT.

B.3 The GMM Estimation for Skewness and Kurtosis Decompositions

The error terms of the time-series regression in (6) may suffer from heteroscedasticity, autocorrelation, and non-normality, and thus result in inefficient β coefficients and biased standard errors. Furthermore, funds in the same group share commonalities in risk and strategies, and thus the error terms may be correlated across funds and subject to possible fixed effects and clustering. Hansen's (1982) generalized method of moments (GMM) is the most robust estimation technique to allow for heteroscedasticity, autocorrelation, non-normality, and cross-sectional correlation in error terms. Therefore, I adopt GMM methodology to estimate components of skewness and kurtosis decompositions.

The vector of unknown parameters for the skewness decomposition are β_i, μ_i, μ_p, $COSKEW_i$, $ICOSKEW_i$, and $RESSKEW_i$, for $i = 1...N$. N is the number of funds in the same fund style. μ_p is

[20]See, for example, Hamao, Masuli, and Ng (1990) and Susmel and Engle (1994).

the expected return for the portfolio of funds. μ_i is the expected return for fund i. Following equation (6) and (7), moment conditions for skewness are the following:

$$\begin{aligned}
r_{i,t} &= R_{i,t} - \mu_i \\
r_{p,t} &= R_{p,t} - \mu_p \\
u_{i,1t} &= (R_{p,t} - \mu_p)(u_{i,t}) \\
u_{i,2t} &= COSKEW_i - \beta_i^3 r_{p,t}^3 - 3\beta_i^2 (r_{p,t}^2 u_{i,t}) \\
u_{i,3t} &= ICOSKEW_i - 3\beta_i (r_{p,t} u_{i,t}^2) \\
u_{i,4t} &= RESSKEW_i - u_{i,t}^3
\end{aligned}$$

Similarly, the following moment conditions are used to estimate β_i, μ_i, μ_p, $COKURT_i$, $VOLCOMV_i$, $ICOKURT_i$, and $RESKURT_i$ in the kurtosis decomposition in equation (6) and (8).

$$\begin{aligned}
r_{i,t} &= R_{i,t} - \mu_i \\
r_{p,t} &= R_{p,t} - \mu_p \\
u_{i,1t} &= (R_{p,t} - \mu_p)(u_{i,t}) \\
u_{i,2t} &= COKURT_i - \beta_i^4 r_{p,t}^4 - 4\beta_i^3 (r_{p,t}^3 u_{i,t}) \\
u_{i,3t} &= VOLCOMV_i - 6\beta_i^2 (r_{p,t}^2 u_{i,t}^2) \\
u_{i,4t} &= ICOKURT_i - 4\beta_i (r_{p,t} u_{i,t}^3) \\
u_{i,5t} &= RESKURT_i - u_{i,t}^4
\end{aligned}$$

The decomposition (%) for skewness and kurtosis are reported in table III and IV, respectively.

VII Empirical Results

Table II presents the frequencies of tail returns exceeding 3 and 5 standard deviations across fund types. For the average fund, the frequencies of total tail returns range from 1.78% (CEFs) to 1.10% (OEFs) and 0.13% (CEFs) to 0.01% (ETFs) for the 3 and 5 standard deviations, respectively [21]. Both ranges exceed the probability under the normal distribution - 0.27% and less than 0.0001%, respectively. This result substantiates the existence of tail risks in managed portfolios.

The test statistics of four fund types fail to reject the 4% (1%) frequencies of tail returns at the 3

[21]The results for 2 standard deviations are also available upon request. Across fund types, the frequencies of total tail returns ranges from 4.74% and 5.6%; the frequency of both systematic and idiosyncratic tail returns is very close to 5%.

(5) standard deviations at the 1% significance level. This suggests that on a monthly basis, all four fund types are subject to returns above or below 3 (5) standard deviations with 4% (1%) probability. In view of economic significance, investors will face monthly returns 3 standard deviations from their means approximately every two years.

The range of the frequencies on idiosyncratic tail returns is narrower than those on systematic tail returns. Using the 3 standard deviations, CEFs have the highest frequencies of tail returns on both return components[22]. ETFs show higher frequencies of systematic tail returns, but the lowest frequencies of idiosyncratic tail returns. The frequencies for both systematic and idiosyncratic tail returns at the 5 standard deviations follow the same order as total tail returns. The classic portfolio theory suggests that idiosyncratic tail risks can be diversified away by increasing the number of assets. It is interesting to see that managed funds suffer from both systematic and idiosyncratic tail risks at similar frequencies.

The high frequencies of tail returns in CEFs and HFs imply that both fund types have higher tracking errors and their managers trade on individual assets to take higher idiosyncratic risks to increase performance. ETFs exhibit higher frequencies of systematic tail risks than HFs and OEFs since tracking errors and idiosyncratic risks should be minimized for ETFs. From an investor's perspective, investors suffer more systematic risks by investing in ETFs, but more idiosyncratic risks in HFs and OEFs.

The comparisons of frequencies of tail returns across fund types do not show strong statistical significance at 1% significance level, except for equity CEFs and ETFs for the 3 standard deviations. This indicates that investors should be aware of tail risks not only on HFs, but all four fund types. For fixed income funds, the frequencies of total tail returns and systematic tail returns is in the following order: CEFs, OEFs, and ETFs. ETFs have the highest frequencies of idiosyncratic tail returns at the 3 standard deviations, but the lowest frequencies at the 5 standard deviations. For equity funds, CEFs have the highest frequencies of total tail returns, systematic tail returns, and idiosyncratic tail returns.

The comparison of styles across fund types shows that fixed income global funds consistently have the higher frequencies of tail returns than the fixed income government funds[23]. This difference may be due to a more strict monitoring and control policy over U.S. fixed income instruments by the U.S. government agencies. Fixed income high yield funds are subject to high tail risks among fixed income styles. Currencies or foreign exchanges funds also show high frequencies in tail returns. The size seems matter in tail risks as well. Equity larger cap funds are subject to higher total tail risks and systematic tails risks, but lower idiosyncratic risks than the smaller cap funds. Table I also shows that the larger cap funds exhibit lower skewness and higher kurtosis than the smaller cap funds. On the hand, the book-to-market ratios (growth vs. value) do not seem to offer a consistent comparison of frequencies on tail returns.

I further break down the percentage of monthly tail returns by right and left tails. The striking finding is that most tail returns come from the left tails. There is very low frequency of right-tailed tail returns

[22]One concern is that the recording of the last return due to delisting varies across data vendors. One reason for CEFs to have higher frequencies may be due to traded price discounts. However, the order of frequencies still hold, if the last observation is removed for the analysis.

[23]The frequencies of tail returns exceeding 3 and 5 standard deviations at the individual fund level are available upon request.

(less than 0.45% (0.04%) at the 3 (5) standard deviations) across fund styles and types. All the statistical patterns observed from two-sided tail returns are induced by the left-tails. This evidence supports the importance of downside risk and the prevalence of negative skewness and leptokurtosis across fund types.

Table III reports the skewness decomposition across fund types. The first column (EW Portfolio Skewness) is the total skewness for the equal-weighted portfolios of funds. The second column (Individual Skewness) is the average of total skewness across all funds in a given style. The weight of each decomposed component is computed by dividing individual funds' coskewness, idiosyncratic coskewness, and residual skewness by their total fund skewness. I report the average across all funds within the same style in percentage as individual COSKEW (%), ICOSKEW (%), and RESSKEW (%), respectively.

The equal-weighted portfolio skewness and average skewness can be different. The only exception is fixed income funds, which have both values being close. Equal-weighted portfolios of funds are constructed by using all available observations in the same style on a given month, but number of funds has been changing from time to time. If the attrition rate is high through time, this can create more skewed distributions for the equal-weighted portfolios of funds. HFs are one example.

It is interesting to observe negative skewness and excess kurtosis (except ETFs) at both the aggregate and individual fund levels. The economic theory suggests that risk aversion with constant or decreasing absolute risk aversion implies preference to positive skewness and aversion to kurtosis. Therefore, managed portfolios showing negative skewness and excess kurtosis may be a result of agency costs and risk-taking induced from compensation schemes as suggested by the model. Another possible explanation is the diversification effects. Simkowitz and Beedles (1978) and Conine and Tamarkin (1981) show that diversification causes an undesirable increase in negative return skewness and this explains why investors hold limited number of stocks. However, the comparisons of skewness and kurtosis across fund *styles* suggests trade-offs between variance-skewness-kurtosis.

COSKEW is the most important source of skewness across fund types. CEFs allocate weights almost equally on the three components of skewness. The individual COSKEW, ICOSKEW, and RESSKEW are 40.48%, 33.32%, and 26.21%, respectively. ETFs have almost a 80% weight on COSKEW. OEFs' skewness mostly comes from COSKEW (75.05%) and shows a negative weight on ICOSKEW (-8.11%). HFs also have a negative weight on ICOSKEW (-10.20%) and the largest weight on COSKEW (65.93%). However, HFs' weight on RESSKEW (44.29%) is the largest among fund types. This may reflect the broad individual assets HFs can hold, and the leverage and dynamic strategies HFs can undertake. Overall, COSKEW contributes the most to investment funds' skewness.

COSKEW still stands out as the largest weight of skewness decomposition when comparing fixed income and equity funds across fund types. Fixed income OEFs have a relatively large negative weight on ICOSKEW, and a relatively large positive weight on RESSKEW relative to fixed income CEFs and ETFs. The result on ICOSKEW may suggest that fixed income assets in OEFs have volatility more sensitive to market returns and the relation between fund risk and market returns is positive. The larger weight on RESSKEW implies that the manager for a fixed income OEF manages skewness through individual assets. For instance, the turnover of assets for short-term and high yield funds can be high.

Equity ETFs and OEFs consistently have their largest shares in COSKEW. Equity CEFs' allocated weights on three components are close, with the largest weight on RESSKEW.

The comparison of the same style across fund types shows no consistency in the decomposition. For instance, the equity global funds have the largest weight in COSKEW for OEFs, but most of skewness of the same style for CEFs come from RESSKEW. This inconsistency shows that different types of investment funds rely on different patterns of trading strategies.

The sign and magnitude of each component in the skewness decomposition can be determined by multiplying individual COSKEW (%), ICOSKEW (%), and RESSKEW (%) by the average skewness. CEFs, ETFs, OEFs, and HFs all have negative coskewness and negative residual skewness. This result denotes that investment fund returns and the market volatility move in opposite directions and fund managers add individual assets with negative skewness. Investors will demand higher expected returns to compensate funds with negative coskewness and residual skewness.

The sign of ICOSKEW depends on the contemporary relation between idiosyncratic risk and market returns. The relation can be positive or negative. The negative and large idiosyncratic coskewness of a fund means that assets' idiosyncratic risks in the fund is negatively correlated with and more sensitive to market returns. Empirical studies show that small growth firms have high idiosyncratic volatility; large value firms are low idiosyncratic volatility stocks.

OEFs and HFs have a negative sign on ICOSKEW (%) (positive values of ICOSKEW), but CEFs and ETFs have a positive sign on ICOSKEW (%) (negative values of ICOSKEW). HFs and OEFs have posititive relations, but ETFs and CEFs have negative relations. The magnitude of idiosyncratic coskewness tells the asset characteristics a fund trades. The comparision implies that HFs and CEFs prefer small growth stocks and ETFs and OEFs prefer large value stocks.

Table IV presents the results from kurtosis decomposition. Similar to table III, the EW portfolio kurtosis and the individual kurtosis are the total excess kurtosis for portfolios of funds and the total excess kurtosis averaged across funds in the same style, respectively. In general, the excess kurtosis for the individual fund is lower than the kurtosis for portfolios of funds. The average ETF and OEF fund has excess kurtosis below 3 and CEFs and HFs exhibit large kurtosis. This result confirms with the analysis on the frequencies of tail returns. Across fund types, the kurtosis for fixed income funds is consistently larger than that of equity funds. In particular, equity ETFs and equity OEFs show less fat-tailedness than other fund types.

COKURT (41.4%) and VOLCOMV (35.62%) contribute the most to the kurtosis of CEFs, even for fixed income and equity CEFs. COKURT is the most important contributor to ETFs' kurtosis, both for fixed income and equity ETFs. OEFs have the largest weight in COKURT as well, for both fixed income and equity OEFs. HFs rely more on RESKURT (39.60%), and then VOLCOMV (33.81%). Across all fund styles and types, the influence from ICOKURT on total fund kurtosis tends to be the minimum.

Similar to skewness, fund managers can use COKURT, VOLCOMV, ICOKURT, and RESKURT to manage the total kurtosis of funds. Results show that managed portfolios have positive cokurtosis, positive volatility comovements, and positive residual kurtosis. Investors will demand higher risk premiums for such funds due to dispersion to kurtosis. Like the analysis on skewness, agency costs allow a manager to take tail risks (low skewness and high kurtosis) to generate risk-adjusted returns.

Similar to ICOSKEW, the sign of ICOKURT also depends on the contemporary relation between the idiosyncratic skewness of the fund and market returns. A positive sign for ICOKURT implies a positive relation, i.e. an increase in market returns will add kurtosis to the fund. A large negative ICOKURT implies that the relation between idiosyncratic skewness and market returns is negative and assets' idiosyncratic skewness is highly sensitive to market returns. Small growth firms are positively skewed; large value firms are negatively skewed.

CEFs and OEFs have negative values for ICOKURT, but ETFs and HFs exhibit positive values. Furthermore, the covariance between idiosyncratic skewness and market returns can be inferred from the sign of ICOKURT. Except HFs, other fund types have negative covariance relations. The comparison of the magnitude of ICOKURT across fund types suggests that HFs and CEFs tend to trade small stocks, but ETFs and OEFs trade larger stocks.

An interesting finding is that the magnitude of COSKEW and COKURT is ranked in reverse order across investment funds since investors demand higher risk premiums on assets with more negative coskewness or more positive cokurtosis. HFs have the lowest negative coskewness but the lowest positive cokurtosis. CEFs have the largest negative coskewness but the largest cokurtosis. A possible explanation is the trade-off between cokurtosis and volatility comovement or residual kurtosis. This trade-off further suggests the importance of coskewness, volatility comovement, and residual kurtosis in fund tail risks. Another possible explanation is diversification. Diversification across coskewed and cokurtosised assets can reduce coskewness and cokurtosis. HFs are more diversified than other fund types in this aspect.

The significance level of each component in the kurtosis decomposition is higher than that in the skewness decomposition. RESKURT and VOLCOMV are statistically significant at 5% for most fund styles and types. It seems that fund managers manage high kurtosis assets and assets comoving with the market volatility. On the other hand, three components of the skewness decomposition yield low statistical significance.

The decomposition of unconditional higher moments of funds can help understand the trading strategies commonly used by fund managers within the same group and priced risks across fund types. If a fund manager tends to add negatively coskewed assets to increase expected returns, one would observe negative coskewness in this fund. If a fund manager often chooses assets with high idiosyncratic volatility or negative idiosyncratic skewness, this fund will exhibit more weights on either component. If the skewness or kurtosis of a fund comes mostly from the idiosyncratic component of returns, one can conclude that this fund manager uses individual assets to increase fund expected returns. If a fund's common trading strategy is to rely on comovements in volatility between the assets and the market, the source of kurtosis of this fund will mostly come from the comovement of volatility component.

ETFs' compensation schemes are tied more to the systematic returns with no convexity, but the contract for fund managers who are rewarded to great stock-picking skills is tied more to the idiosyncratic returns. Based on model predictions, across fund types, HFs (ETFs) should be subject to the idiosyncratic risk the most (least). Some OEFs are subject to explicit incentive fees and their assets have been growing (Elton, Gruber, and Blake(2003)). Moreover, the fund-flow performance for OEFs is well documented in the literature. It suggests implicit convexity in their contracts. This implicit convexity might also exist in CEFs to a lesser degree due to no redemption. But the compensation for CEFs has more weight on idiosyncratic returns than ETFs, because of active management in CEFs and index-tracking in ETFs. The weight in percentage for idiosyncratic skewness risk for HFs, OEFs, CEFs, and ETFs are 44.29%, 26.21%, 33.06%, and 5.74%, respectly. This result conincides with model's prediction.

For the kurtosis decomposition, HFs, CEFs, OEFs, and ETFs have weights in idiosyncratic kurtosis risk as follows: 39.60%, 11.90%, 23.45%, and 10.30%. Although the model's predictions cannot clearly distinguish closed-end and OEFs, HFs and ETFs are still in line with the predictions.

The total fund skewness from low to high is HFs, OEFs, CEFs, and ETFs. This ranking is predicted by the model. The total fund kurtosis for CEFs is the highest, but only slightly above HFs. Figure 3 suggest that it is possible if the α (the return decomposition parameter) and g (the convexity parameter) for CEFs on average is close to 0. OEFs have the lowest kurtosis, but very close to ETFs. The model fails to predict this result, but it can be attributed to the assumed range of α and g for an average OEF. It is premature to verify the reasonings, given that no empirical studies document values for $alpha$ and g for various fund styles and types.

The order of weights in idiosyncratic skewness and kurtosis risk holds across fixed-income and equity funds. The weights for fixed-income funds across ETFs, CEFs, and OEFs are 7.62%, 11.33%, and 78.15%, respectively, for the skewness decomposition. The kurtosis decomposition also shows that fixed-income ETFs have the lowest weight (13.30%) on the idiosyncratic component. Equity ETFs have the lowest weights across fund types on idiosyncratic skewness and kurtosis risk - 4.48% and 8.29%, respectively. The order of skewness holds across different types of fixed-income funds, but the result for kurtosis is mixed across different types of equity funds.

The empirical results and model predictions are in line with Starks (1987). She concludes that the "symmetric" contract does not necessarily eliminate agency costs , but it better aligns the interests between investors and managers than the "bonus" contract. Since ETFs use a symmetric contract and HFs use a bonus contract, the alignment of interests is worse for HFs but agency costs still exist in both funds. This implication is reflected in the differences in skewness and kurtosis between these two types of funds. ETFs are less negatively skewed and fat-tailed. HFs are more negatively skewed and more leptokurtic. ETFs are subject to more systematic tail risks and HFs are subject to more idiosyncratic tail risks.

In addition to compensation schemes, the leverage effect by Black (1976) and volatility feedback may help understand each component of skewness and kurtosis decompositions across fund strategies. Both the leverage effect and volatility feedback suggest the negative relation between risks and return. The leverage effect means that a drop in price will increase leverage within the firm and thus increase future volatility. If a fund uses high leverage, the impact of the leverage effect is magnified. The volatility feedback theorizes that if volatility is persistent and priced, an increase in volatility today will incur an increase in future volatility and required rate of returns. Since shocks to market volatility have a longer memory in illiquid assets, illiquidity can amplify volatility feedback effect. Funds subject to the leverage effect and volatility feedback may exhibit long and left tails.

Another perspective on explaining differences in tail risks across investment funds is the level and type of risks the funds face. For example, high-yield bond funds face credit risk, which can cause large downside tails. Funds with large market exposure are less negatively skewed. A fund strategy may be subject to multiple sources of risk, such as market risk, interest rate risk, credit risk, and liquidity risk, etc. This type of fund will be more left-skewed and fat-tailed because the dependence of risks is multiplied during market downturns and its price tumbles.

Types of assets traded in a fund can also induce differences in skewness and kurtosis across fund strategies. For instance, longing a call or put can increase skewness and writing a call or put can reduce skewness. Since small cap and value stocks are positively skewed on average, adding them can increase the skewness of a fund.

The comparison of the same strategy across fund types show many puzzling findings. It is intuitive that fixed-income government funds has less negative coskewness (positive cokurtosis) and fixed-income corporate funds and mortgage funds show more negative coskewness (positive cokurtosis).

The duration risk would suggest that long-term funds have more negative coskewness and more positive cokurtosis than short-term funds. However, the coskewness of long-term ETFs is positive, but the coskewness of short-term ETFs is negative. One possible explanation is liquidity, i.e. long-term bonds that ETFs track are more liquid than the short-term bonds.

High yield bonds are subject to interest rate risk and credit risk. However, high yield bonds do not have the largest negative coskewness and the largest positive cokurtosis within the same fund type. It is possible that the high yield bonds held in investment funds have shorter durations close to short-term funds. More surprisingly, high yield ETFs and OEFs have positive coskewness. This result may reflect that the redemption requirement on both types of funds force fund managers to trade only liquid high yield bonds and use less leverage.

The fixed-income global and sector funds mainly concentrate on one country or sector and diversify assets within that country or sector. This trading strategy implies more weights on systematic tail risks but less weights on residual tail risks. However, global OEFs are one exception. They have around 80% in residaul skewness. This result indicates that the global funds traded by OEF managers are highly correlated with other funds in the same country and thus idiosyncratic tail risks are not diversified away. The magnitude of coskewness and cokurtosis is hard to interpret across and among investment funds because countries and sectors are not further subclassified according to their risks. Funds investing in developed countries and matured industries are less asymmetric and fat-tailed.

On the contrary, the equity global and sector funds across fund types do consistently show more weights on systematic tail risks and less weights on idiosyncratic tail risks. This result suggests that across fund types, diversification takes place within the same sector or country for equity funds. In addition, the correlation among equity assets within the same country or sector is lower than fixed-income funds.

Commodity funds include a wide variety of commodities: oil, gold, soy, corn, natural gas, etc. Some funds may only engage in commodity futures. A comparison of coskewness and cokurtosis across CEFs and OEFs show that commodity CEFs have lower coskewness and higher cokurtosis. This finding indicates that CEF managers tend to trade illiquid commodities due to privilege of no redemption.

Large risk premiums are associated with small cap stocks, implying negative coskewness and positive cokurtosis. However, empirical results do not reflect this implication uniformly. Small cap CEFs do have lower coskewness and higher cokurtosis than large cap CEFs, but small-cap and large-cap funds have similar coskewness and cokurtosis in ETFs and OEFs.

According to value risk premiums, value stocks generally perform better than growth stocks in the past decades. Therefore, similar to small cap stocks, value stocks would demand higher risk premiums. However, another argument is that growth stocks are growing firms and subject to more event risks, such as redemption, bankruptcy, etc., than stable firms. The empirical results on tail risks agree with both arguments. Cokurtosis is higher for value funds and coskewness is lower for value ETFs. This result coincides with the value premium hypothesis. However, coskewness is positive and higher for growth CEFs. This result matches with the latter argument.

The bear funds or funds with leverage and short strategies show improved coskewness and cokurtosis. Both strategies make profits from market downturns. The long put option dominates the leverage effect to induce higher coskewness and lower cokurtosis.

Agarwal and Naik (2004) show that event-driven and relative value strategies of HFs can be viewed as writing at the out-of-the-money put option and going long on small and value stocks and short on large and growth stocks. In addition, relative value strategies also show a negative loading on Carhart's momentum factor, indicating that these strategies buy losers and sell winners. Event-driven strategies include transactions, such as financial distress, mergers and acquisitions, restructuring, etc. These transactions incur huge losses when markets are down. Relative value strategies mainly bet on undervalued firms to turn around or overvalued firms to go south. These strategies will lose money during market downturns. Both strategies have implicit short position in put and thus show relatively low skewness and high kurtosis. However, the high residual skewness in relative value strategies show that their fund managers manage skewness through individual assets across HF strategies. This result is consistent with the fund strategies since relative value strategies search for mispriced assets with similar fundamental values.

Equity hedge strategies are shown by Agarwal and Naik (2004) to have a positive (negative) and statistically significant loading on Fama and French's size (value) factor. Equity hedge strategies involve both long and short positions in equity and equity derivative securities. Since small and high book-to-market stocks are likely to be distressed, longing small and growth stocks can offset skewness and kurtosis. Equity hedge strategies exhibit negative skewness close to zero and the lowest kurtosis. The lowest values for each component of the skewness and kurtosis decompositions across HF strategies are the result of hedged positions.

HFs classified under HFRI or HFRX are funds used to construct respective benchmark indexes, but are not classified under the five main HF strategies. Therefore, these funds represent their strategies and are shown to have large weights on coskewness. However, the exclusion from main categories indicate that these funds are subject to specific extreme event risks, such as credit risk, interest risk, etc. Therefore, these funds are more negatively skewed and fat-tailed, funds under the HFRX category in particular. The large magnitude of idiosyncratic coskewness implies high covariability between idiosyncratic skewness and market returns and their strategies are highly sensitive to extreme event risks.

Macro strategies invest in equity, fixed income, currency, and commodities based on predicted movements of economic variables. Therefore, funds with macro strategies use high-frequency trading and have liquidity in assets. This trading pattern is reflected in the positive skewness and low kurtosis of macro funds. Like fixed-income ETFs, macro funds are ideal candidates for investors. Since the addition of macro funds can improve investors' portfolio skewness and kurtosis, macro strategies can be viewed as longing options. In addition, the positive value and the largest weight of residual skewness and residual kurtosis in macro funds across HF strategies indicate that their fund managers add individual positively skewed assets with some kurtosis to improve total fund skewness and kurtosis.

Fund of funds have low skewness and mild kurtosis. Fund of funds invest in a pool of HFs and are supposed to diversify away idiosyncratic risks. By contrast, idiosyncratic skewness risks are relatively large. This conflicting result may be explained by multi-layer agency costs.

VIII Robustness Analysis

A An Application of the Model on Mutual Funds

All moments in the model in section IV are standardized. One set of parameters from mutual funds is applied to the model. Brown, Goetzmann, Ibbotson, and Ross (1992) simulate mutual fund returns by the following:

$$R_{i,j} = r_f + \beta_i(R_{p,j} - r_f) + \epsilon_{i,j} \tag{9}$$

where the risk free rate is 0.07 and the risk premium is assumed to be normal with mean 0.086 and standard deviation 0.208. β_i follows the normal distribution with mean 0.95 and standard deviation 0.25 cross-sectionally. The idiosyncratic term $\epsilon_{i,j}$ is assumed to be normal with mean 0 and standard deviation σ_i. The relationship between nonsystematic risk and β_i is approximated as:

$$\sigma_i^2 = k(1 - \beta_i)^2 \tag{10}$$

The value of k is 0.05349. Note that $\beta_i(R_{p,j} - r_f)$ and $\epsilon_{i,j}$ are equivalent to $r_{p,j}$ and $r_{BB,j}$ in the model, representing systematic and idiosyncratic components of returns. I implement these parameters into the model and the model predicts the same result on the relation between the return decomposition (convexity) effect and the optimal weight on the market portfolio and the big bet.

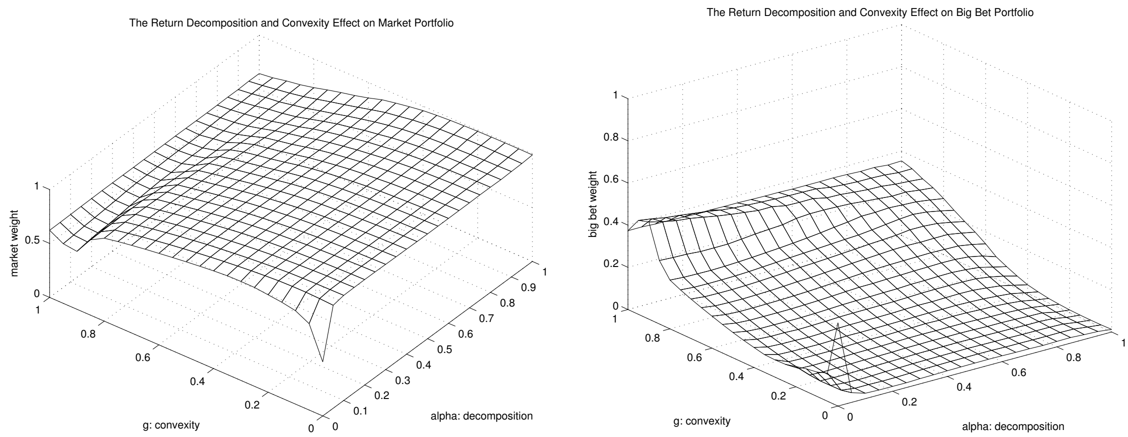


Figure 4: The Optimal Weight on the Market Portfolio and the big bet

The return decomposition parameter α and the convexity parameter g are the weight of systematic returns and the magnitude of convexity on the fund manager's compensation, respectively. z-axis is the optimal unconditional weight.

B Autocorrelation

Stale pricing or serial correlation of returns have the most significant impact on HFs than other fund types. Due to the unique characteristics of HFs, such as limited regulations and the lockup and notice periods, HF managers have more flexibility in trading illiquid assets. Since current prices may not be available for illiquid assets, HF managers commonly use past prices to estimate current prices. As a result, the presence of illiquid assets can lead to significant serial correlation on HF returns. This link is supported by Getmansky, Lo, and Makarov (2004), who conclude that illiquidity and smoothed returns are the main source of serial correlation in HFs. The existence of serial correlation in returns can affect HF performance and statistics (Lo (2002) and Jagannathan, Malakhov, and Novikov (2010)).

Following Asness, Krail, and Lieu (2001) and Getmansky, Lo, and Makarov (2004), let the true but unobserved demeaned return satisfy the following regression:

$$r^*_{i,t} = \beta^*_i r_{p,t} + u^*_{i,t},\ E(u^*_{i,t}) = 0,\ r_{p,t} \text{ and } u^*_{i,t} \text{ are } i.i.d.$$

I use three lags to model autocorrelations of the observed demeaned returns. The observed demeaned return $r_{i,t}$ is thus modeled as:

$$\begin{aligned} r_{i,t} &= \theta_0 r^*_{i,t} + \theta_1 r^*_{i,t-1} + \theta_2 r^*_{i,t-2} \\ &= \beta^*_i(\theta_0 r_{p,t} + \theta_1 r_{p,t-1} + \theta_2 r_{p,t-2}) + (\theta_0 u^*_{i,t} + \theta_1 u^*_{i,t-1} + \theta_2 u^*_{i,t-2}) \\ &= \beta_{0,i}\theta_0 r_{p,t} + \beta_{1,i}\theta_1 r_{p,t-1} + \beta_{2,i}\theta_2 r_{p,t-2}) + \eta_{i,t} \\ &= (\beta_{0,i} + \beta_{1,i} + \beta_{2,i})(R_{p,t} - \mu_p) + \tilde{u}_{i,t} \end{aligned}$$

The last equation is used by Asness, Krail, and Lieu (2001) to compute the "summed beta" Sharpe ratios for HFs. They estimate coefficients by the second to last equation and consider the summation of three coefficients as the true beta. They therefore compute the "summed beta" residuals as

$$\tilde{u}^*_{i,t} = r_{i,t} - \tilde{\beta}^*_i(R_{p,t} - \mu_p)$$

where $\tilde{\beta}^*_i$ is the true or "summed beta", i.e. $\tilde{\beta}^*_i = \beta_{0,i} + \beta_{1,i} + \beta_{2,i}$. I follow the same approach to construct moment conditions. After adjusted for stale prices, GMM moment conditions are modified as follows:

For skewness decomposition:

$$\begin{aligned} r_{i,t} &= R_{i,t} - \mu_i \\ r_{p,t} &= R_{p,t} - \mu_p \\ u_{i,1t} &= (R_{i,t} - \mu_i - \beta_{0,i}(R_{p,t} - \mu_p) - \beta_{1,i}(R_{p,t-1} - \mu_p) - \beta_{2,i}(R_{p,t-2} - \mu_p))(R_{p,t} - \mu_p) \\ u_{i,2t} &= (R_{i,t} - \mu_i - \beta_{0,i}(R_{p,t} - \mu_p) - \beta_{1,i}(R_{p,t-1} - \mu_p) - \beta_{2,i}(R_{p,t-2} - \mu_p))(R_{p,t-1} - \mu_p) \\ u_{i,3t} &= (R_{i,t} - \mu_i - \beta_{0,i}(R_{p,t} - \mu_p) - \beta_{1,i}(R_{p,t-1} - \mu_p) - \beta_{2,i}(R_{p,t-2} - \mu_p))(R_{p,t-2} - \mu_p) \\ u_{i,4t} &= COSKEW_i - \tilde{\beta}^{*3}_i r^3_{p,t} - 3\tilde{\beta}^{*2}_i(r^2_{p,t}\tilde{u}^*_{i,t}) \\ u_{i,5t} &= ICOSKEW_i - 3\tilde{\beta}^*_i(r_{p,t}\tilde{u}^{*2}_{i,t}) \\ u_{i,6t} &= RESSKEW_i - \tilde{u}^{*3}_{i,t} \end{aligned}$$

For kurtosis decomposition:

$$
\begin{aligned}
r_{i,t} &= R_{i,t} - \mu_i \\
r_{p,t} &= R_{p,t} - \mu_p \\
u_{i,1t} &= (R_{i,t} - \mu_i - \beta_{0,i}(R_{p,t} - \mu_p) - \beta_{1,i}(R_{p,t-1} - \mu_p) - \beta_{2,i}(R_{p,t-2} - \mu_p))(R_{p,t} - \mu_p) \\
u_{i,2t} &= (R_{i,t} - \mu_i - \beta_{0,i}(R_{p,t} - \mu_p) - \beta_{1,i}(R_{p,t-1} - \mu_p) - \beta_{2,i}(R_{p,t-2} - \mu_p))(R_{p,t-1} - \mu_p) \\
u_{i,3t} &= (R_{i,t} - \mu_i - \beta_{0,i}(R_{p,t} - \mu_p) - \beta_{1,i}(R_{p,t-1} - \mu_p) - \beta_{2,i}(R_{p,t-2} - \mu_p))(R_{p,t-2} - \mu_p) \\
u_{i,4t} &= COKURT_i - \tilde{\beta_i^*}^4 r_{p,t}^4 - 4\tilde{\beta_i^*}^3 (r_{p,t}^3 \tilde{u}_{i,t}^*) \\
u_{i,5t} &= VOLCOMV_i - 6\tilde{\beta_i^*}^2 (r_{p,t}^2 \tilde{u}_{i,t}^{*2}) \\
u_{i,6t} &= CONSKT_i - 4\tilde{\beta_i^*}(r_{p,t} \tilde{u}_{i,t}^{*3}) \\
u_{i,7t} &= RESKURT_i - \tilde{u}_{i,t}^{*4}
\end{aligned}
$$

The decomposition (%) for skewness and kurtosis are reported in table VI. Overall, results for tail risk decomposition are robust to autocorrelation. The weight on RESSKEW increases slightly and the weight on RESKURT stays almost the same. COSKEW and RESSKEW are still the top two contributors on skewness decomposition. The components of VOLCOMV and RESKURT occupy the most weights in total fund kurtosis.

C Exogenous Systematic Factors

Different fund types are subject to different exogenous systematic factors due to differences in risk characteristics. ETFs are passive and index-tracking, and therefore returns are highly correlated with market factors. The premiums on CEFs are related to market risk, small-firm risk, and book-to-market risk (Lee, Shleifer, and Thaler (1991), Swaminathan (1996), Pontiff (1997)). Carhart (1994) shows that momentum plays an important role in mutual fund performance. Non-linearities in HF returns may suggest some systematic factors representing option-like payoffs (Fung and Hsieh (2001) and Agarwal and Naik (2004)).

Following the literature, I use Fama-French 3-factor model for equity ETFs and CEFs, Carhart 4-factor model for equity OEFs and Fung and Hsieh 7 factor model for HFs. For bond fonds, I add two more Barclay bond indexes - the Barclay U.S. government/credit index and corporation bond index. Fama-French 3 factors are value-weighted market excess returns, and two factor-mimicking portfolios SMB and HML. SMB and HML measure the observed excess returns of small caps over big caps and of value stocks over growth stocks. Carhart adds the momentum factor on top of Fama-French 3 factors. The momentum factor is constructed by the monthly return difference between one-year prior high over low momentum stocks. Fung and Hsieh 7 factors include the equity and bond market factor, the size spread factor [24], the credit spread factors [25], and three lookback straddles on bond futures, currency futures, and commodity futures.

For simplicity, this paper adopts the single-factor model to illustrate economic intuitions on components of skewness and kurtosis decompositions. I construct beta-weighted time series of aforementioned factors to decompose systematic and idiosyncratic tail risks. Table VI and VII show the results. [26]

First, COSKEW contributes the most to total fund skewness, except HFs. COKURT is the most contributing source to total fund kurtosis for ETFs and OEFs. In addition, HFs (ETFs) have the largest (smallest) weight on RESSKEW and RESKURT. Second, RESSKEW and RESKURT tend to be higher for fixed income funds when beta-weighted exogenous factors are used. This spurious result may be induced by missing bond factors, such as a high-yield index or a global bond index.

D Year 1996-2008

The starting period of four fund types differs in this study. However, the time-variation of economic states, such as changes in yields and business cycles, may impose differential impacts of "economy-wide" shocks on funds. Using the same time intervals for all four fund types can ascertain that all funds are subject to the same economic shocks at any time. If the pattern of skewness and kurtosis decomposition in section III and IV holds, the weight of each component should be robust to the same starting period. Therefore, I restrict all investment funds to have the same starting date as HFs and perform GMM on this subsample of data.

The results hold, when I restrict the dataset for all funds between the period from 1996 to 2008 only. Note that this period also excludes the 1987 stock market crash. COSKEW contributes the most to the skewness of all fund types. COKURT and VOLCOMV have the largest two shares in kurtosis decomposition for CEFs, ETFs, and OEFs. HFs' kurtosis comes mostly from the VOLCOMV and RESKURT. However, at the style level of each fund type, few fund styles have different allocated weights in skewness and kurtosis decompositions. It may imply that each component is time-varying at the style level. But at the aggregate fund type level, the weight on each component stays the same. In addition, HFs (ETFs) have the largest (least) weights on idiosyncratic tail risks.

[24] Wilshire Small Cap 1750 - Wilshire Large Cap 750 return.

[25] month-end to month-end change in the difference between Moody's Baa yield and the Federal Reserve's 10-year constant-maturity yield.

[26] I also use equal-weighted exogenous factors but across all fund types and styles, RESSKEW and RESKURT consistently have the largest weights among all components in both skewness and kurtosis decompositions. This spurious result reflects that equal-weighted exogenous factors do not appropriately capture time-variation in systematic tail risks. A further analysis on the correlation between equal-weighted portfolios of funds and equal-weighted exogenous factors shows that the decomposition of the systematic and idiosyncratic tail risks is sensitive to the chosen benchmarks, i.e. low correlation between the endogenous and exogenous benchmarks implies the increased weights on RESSKEW and RESKURT. All results are available upon request.

IX Conclusion

Different styles and types of managed portfolios execute different strategies and objectives. Traditional fund managers can make investment decisions based on returns and volatility of different individual assets. They can also adjust exposures to systematic factors or asset classes, such as size, book-to-market, or momentum. However, many stylized facts on financial asset returns refute the validity of the mean-variance framework and market-timing and stock-picking strategies can induce systematic and idiosyncratic tail risks.

This study shows that managed portfolios are subject to tail risks. The frequencies of tail returns shows that CEFs and HFs are subject to more total tail risks. ETFs show a disparity in the frequencies between the systematic and idiosyncratic tail returns. Therefore, fund managers may manage systematic and idiosyncratic tail risks through investing in assets with desired properties and tail risks. For instance, a manager can generate abnormal returns by adding assets with negative coskewness or positive cokurtosis or selecting negatively skewed or positively kurtosised assets. The skewness and kurtosis decompositions show the mechanisms fund managers may use to manage tail risks.

Skewness and kurtosis decompositions introduce important economic components. Skewness is decomposed into coskewness, idiosyncratic coskewness, and residual skewness. Coskewness and idiosyncratic coskewness are relatively important in the total fund skewness, but all three components do not show statistical significance. Likewise, kurtosis can be decomposed into four components - cokurtosis, volatility comovement, idiosyncratic cokurtosis, and residual kurtosis. The volatility comovement and residual kurtosis contribute the most to the total fund kurtosis at a statistically significant level. Results of the skewness and kurtosis decompositions are robust to benchmarks used.

The fund tail risks are linked to compensation structure across fund types through a simple model. There are two main determinants of compensation schemes - the decomposition between the systematic and idiosyncratic returns (the return decomposition effect), and the convexity or degree of option-like payoffs (the convexity effect). The model predicts that the increased weight on systematic returns can increase market exposures, and in turn increase total skewness and decrease total kurtosis. In addition, increased convexity can increase idiosyncratic tail risks, and thus reduce asymmetry and raise fat-tailedness. Empirical results confirm both predictions.

A Appendix

A The Numerical Procedure for the Optimization Problem

Fund managers observe returns up to time t and solve for the optimal unconditional weight based on those returns. Steps are the following:

(a) Generate 10,000 jointly independent random variables (U,V) from the T-Copula.

(b) Use the inverse method to generate time-series of returns for the market portfolio and the big bet, i.e. $F_p^{-1}(U)$ and $F_{BB}^{-1}(V)$, where F_p^{-1} and F_{BB}^{-1} are inverse CDFs for the normal and skewed t-distribution, respectively.

(c) Solve for the optimal weight:

$$w_{uncond,t} \equiv argmax \frac{1}{t} \sum_{j=1}^{j=t} U(W_j) \quad (11)$$

(d) Simulate step (a) to (c) 1000 times.

B Open-ended Fund Styles

I consider funds with the following style codes are fixed income funds - POLICY in B&P, Bonds, Flex,GS, or I-S; WB_OBJ in I, S, I-S, S-I, I-G-S, I-S-G, S-G-I, CBD, CHY, GOV, IFL, MTG, BQ, BY, GM, or GS; SI_OBJ in BGG, BGN, BGS, CGN, CHQ, CHY, CIM, CMQ, CPR, CSI, CSM, GBS, GGN, GIM, GMA, GMB, GSM, or IMX; , Lipper Class in 'TX' or 'MB'; Lipper_OBJ in EMD, GLI, INI, SID, SUS, SUT, USO, GNM, GUS, GUT, IUG, IUS, ARM, USM, A, BBB, or HY ; and TR_OBJ in AAG, BAG, GLI, BDS, GVA, GVL, GVS, UST, MTG, CIG, or CHY. I further screen out funds with holdings in bonds and cash less than 70% at the end of the previous year.

Fixed income funds (FI) are classified as Index, Global, Short Term, Government, Mortgage, Corporate, and High Yield. Index funds (FI Index) are selected by matching the string "index" with the fund name. Global funds are coded as SI_OBJ in BGG or BGN, Lipper_OBJ in EMD, GLI, or INI, or TR_OBJ in AAG, BAG, or GLI.

Short term funds are coded as SI_OBJ in CSM, CPR, BGS, GMA, GBS, or GSM, Lipper_OBJ in SID, SUS, SUT, USO, or TR_OBJ in BDS. Government funds are codes as POLICY in GS, WB_OBJ in GOV or GS, SI_OBJ in GIM or GGN, or Lipper_OBJ in GNM, GUS, GUT, IUG, or IUS, or TR_OBJ in GVA, GVL, GVS, or UST. Mortgage funds are coded as POLICY WB_OBJ in MTG, GM, SI_OBJ in GMB, Lipper_OBJ in ARM or USM, or TR_OBJ in MTG. Corporate funds are coded as POLICY in B&P, WB_OBJ in CBD,BQ, SI_OBJ in CHQ, CIM, CGN, CMQ, Lipper_OBJ in A, BBB, or TR_OBJ in CIG. High Yield funds are coded as POLICY in Bonds, WB_OBJ in I-G-S, I-S-G, S-G-I, BY, CHY, SI_OBJ in CHY, Lipper_OBJ in HY, TR_OBJ in CHY. Other funds are funds that I classify as bond funds but do not meet the criteria above.

Similarly, I use the following codes to screen out equity funds - POLICY in Bal, C & I, CS, Hedge, or Spec; WB_OBJ in G, G-I, I-G, AAL, BAL, ENR, FIN, GCI, GPM, HLT, IEQ, INT, LTG, MCG, SCG, TCH, UTL, AG, AGG, BL, GE, GI, IE, LG, OI, PM, SF, or UT; SI_OBJ AGG, BAL, CVR, ECH, ECN, EGG, EGS, EGT, EGX, EID, EIG, EIS, EIT, EJP, ELT, EPC, EPR, EPX, ERP, FIN, FLG, FLX, GLD, GLE, GMC, GRI, GRO, HLT, ING, JPN, OPI, PAC, SCG, SEC, TEC, or UTI; Lipper Class in EQ; Lipper_OBJ in SP, SPSP, AU, BM, CMD, NR, FS, H, ID, S, TK, TL, UT, CH, CN, CV, DM, EM,

EU, FLX, GFS, GH, GL, GLCC, GLCG, GLCV, GMLC, GMLG, GMLV, GS, GSMC, GSME, GSMG, GSMV, GNR, GTK, IF, ILCC, ILCG, ILCV, IMLC, IMLG, IMLV, IS, ISMC, ISMG, ISMV, JA, LT, PC, XJ, B, BT, CA, DL, DSB, ELCC, LSE, SESE, MC, MCCE, MCGE, MCVE, MR, SCCE, SCGE, SCVE, SG, G, GI, EI, EIEI; and TR_OBJ in AAD, AAG, AGG, BAD, BAG, CVT, EME, ENR, EQI, FIN, FOR, GCI, GLE, GPM, GRD, HLT, MID, OTH, SMC, SPI, TCH, UTL. I further screen out funds with holdings in bonds and cash less than 70% at the end of the previous year.

Equity funds (EF) are classified as Index, commodities, Sector, Global, Balanced, Leverage and Short, Long Short, Mid Cap, Small Cap, Aggressive Growth, Growth, Growth and Income, Equity Income, and Others. Index funds (EF Index) are identified by finding the match of the string “index” within the fund name or funds with Lipper_OBJ in SP or SPSP, or TR_OBJ in SPI.

Commodities funds are coded as WB_OBJ in ENR, GPM, PM, SI_OBJ in GLD Lipper_OBJ in AU, BM, CMD, NR, or TR_OBJ in ENR, GPM. Sector funds are codes as POLICY in Spec, WB_OBJ in FIN, HLT, TCH, UTL, SF, UT, SI_OBJ in FIN,HLT, Lipper_OBJ in FS, H, ID, S, TK, TL, UT, or TR_OBJ in FIN, HLT, OTH, TCH, UTL. Global funds are coded as POLICY in C & I, WB_OBJ in INT, GE, IE, SI_OBJ in ECH, ECN, EGG, EGS, EGT, EGX, EID, EIG, EIS, EIT, EJP, ELT, EPC, EPX, ERP, FLG, GLE, JPN, PAC, Lipper_OBJ CH, CN, DM, EM, EU, GFS, GH, GL, GLCC, GLCG, GLCV, GMLC, GMLG, GMLV, GS, GSMC, GSME, GSMG, GSMV, GNR, GTK, IF, ILCC, ILCG, ILCV, IMLC, IMLG, IMLV, IS, ISMC, ISMG, ISMV, JA, LT, PC, XJ, TR_OBJ in EME, FOR, GLE. Balanced funds are coded as POLICY in Bal, WB_OBJ in AAL, BAL, BL, SI_OBJ in BAL, CVR, FLX, Lipper_OBJ in B, BT, CV, FLX, or TR_OBJ in AAD, BAD, AAG, BAG, CVT. Leverage and short funds are coded as POLICY in Hedge, WB_OBJ in OI, SI_OBJ in OPI, or Lipper_OBJ in CA, DL, DSB, ELCC, SESE. Long short funds are coded as Lipper_OBJ in LSE. Mid cap funds are coded as WB_OBJ in GMC, Lipper_OBJ in MC, MCCE, MCGE, MCVE, TR_OBJ in MID. Small cap funds are coded as WB_OBJ in SCG, Lipper_OBJ in MR, SCCE, SCGE, SCVE, SG, or TR_OBJ in SMC. Aggressive growth funds are coded as WB_OBJ in GI, GCI, SI_OBJ in AGG, or TR_OBJ in AGG. Growth funds are coded as WB_OBJ in G,LG, SI_OBJ in GRO, Lipper_OBJ in G, or TR_OBJ in GRD. Growth and income funds are coded as WB_OBJ in GI, GCI, SI_OBJ in GRI, Lipper_OBJ in GI, or TR_OBJ in GCI. Equity income funds are coded as WB_OBJ in EI, IEQ, Lipper_OBJ in EI, EIEI, or TR_OBJ in EQI. Other funds are funds that I classify as equity funds but do not meet the criteria above.

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Table I: Summary Statistics

This table reports summary statistics for average funds across fund styles and types. Nofunds is the total number of funds. Nobs is the average number of nonmissing time series observations of average funds. Each statistic for a style is reported as the cross-sectional average of statistics of individual funds in the same style. Mean is the average mean, std is the average standard deviation, skewness is the average skewness, kurtosis is the average excess kurtosis, ρ_1 is the average first order sample autocorrelation, ρ_2 is the average second order sample autocorrelation, and ρ_3 is the average third order sample autocorrelation. Reported statistics are in percentage per month. JB is the Jarque Bera p-value for the test for normality. JB test statistic is $\frac{Nobs}{6}(Skewness^2 + \frac{Kurtosis^2}{4})$. LQ is the Ljung-Box q statistics for the test of lag-3 autocorrelation. LQ test statistic is $Nobs(Nobs+2)\sum_{j=1}^{3}\frac{\rho_j}{Nobs-j}$. *FI Average* is the average of statistics across fixed-income fund styles. *EF Average* is the average of statistics across equity fund styles. *Group Average* is the average of statistics across all fund styles.

Style	Nofunds	Nobs	Mean	Std	Skewness	Kurtosis	Min	Max	JB	ρ_1	ρ_2	ρ_3	LQ
Panel A: Closed-End Funds													
FI Global	26	133	0.185	5.953	−0.602	6.080	−26.00	20.33	<0.05	−0.043	−0.002	−0.122	0.2713
FI Sector	29	151	0.309	6.214	−0.399	4.611	−22.48	22.33	<0.05	−0.033	0.028	−0.057	0.4299
FI Long Term	26	129	−0.580	7.356	−1.224	8.322	−31.50	19.77	<0.05	−0.065	0.091	−0.020	0.1992
FI Intermediate Term	25	259	0.803	5.759	0.203	5.443	−19.15	26.50	<0.05	−0.097	−0.025	−0.045	0.145
FI Short Term	6	114	0.584	3.777	−0.912	4.361	−15.76	10.52	<0.001	−0.061	−0.002	0.058	0.1801
FI Government	13	120	0.451	2.963	−0.185	2.305	−9.37	9.78	0.0679	−0.067	−0.012	0.028	0.3736
FI High Yield	47	142	−0.377	6.545	−0.620	3.708	−24.05	19.95	<0.05	0.075	0.048	−0.003	0.357
FI Others	23	73	−0.685	4.672	−1.656	6.415	−19.71	10.70	<0.001	0.259	0.186	0.013	0.0643
FI Average	24	140	0.086	5.405	−0.675	5.156	−21.00	17.49	<0.05	−0.004	0.039	−0.019	0.2526
EF Balanced	46	110	−0.695	7.329	−0.780	4.193	−24.99	20.72	0.0693	0.112	0.021	−0.058	0.3177
EF Global	92	122	−0.145	9.955	−0.059	2.725	−29.53	31.94	0.1199	0.060	0.017	−0.031	0.4727
EF Sector	17	157	0.153	7.142	−0.162	4.424	−23.74	28.19	<0.05	0.064	−0.002	−0.035	0.2411
EF Commodities	20	125	−1.214	9.109	−1.136	4.279	−32.94	18.95	<0.05	0.056	0.188	0.010	0.2806
EF Large Cap	59	145	−0.272	6.438	−0.698	5.530	−23.44	20.71	0.0828	0.104	0.001	−0.024	0.361
EF Mid Cap	11	152	0.169	7.198	−0.258	4.565	−22.40	20.36	<0.05	0.038	−0.071	−0.056	0.3546
EF Small Cap	6	161	0.611	12.124	−0.138	3.321	−31.95	51.28	<0.05	0.110	0.017	−0.019	0.4631
EF Growth	18	97	0.200	8.482	−0.480	4.707	−24.89	28.51	<0.05	0.101	−0.030	−0.042	0.3682
EF value	19	63	−0.584	6.251	−0.996	3.886	−21.98	14.63	0.053	0.099	0.025	−0.073	0.4109
EF Others	32	65	−1.318	10.111	−1.426	5.649	−38.08	20.11	0.1106	0.164	−0.050	−0.004	0.3635
EF Average	32	120	−0.310	8.414	−0.613	4.328	−27.39	25.54	0.0645	0.091	0.011	−0.033	0.3633
Group Average	29	129	−0.134	7.077	−0.640	4.696	−24.55	21.96	<0.05	0.049	0.024	−0.027	0.3141

Style	Nofunds	Nobs	Mean	Std	Skewness	Kurtosis	Min	Max	JB	ρ_1	ρ_2	ρ_3	LQ
Panel B: ETFs													
FI Global	2	14	−0.218	6.383	−0.314	2.910	−15.61	12.82	0.2702	0.084	−0.341	−0.209	0.1995
FI Sector	3	22	0.677	1.680	0.826	1.841	−2.61	4.98	0.1073	0.360	−0.367	−0.287	0.0708
FI Long Term	2	49	0.631	3.407	0.945	7.720	−8.81	13.33	<0.001	0.223	−0.475	−0.297	<0.01
FI Intermediate Term	6	28	0.464	2.001	0.585	3.537	−4.08	6.13	<0.05	0.227	−0.392	−0.183	0.1196
FI Short Term	3	21	0.437	0.969	−0.252	2.156	−2.00	2.66	0.1579	0.163	−0.207	−0.062	0.2098
FI Government	12	44	0.927	3.990	0.526	1.444	−8.12	11.55	0.4384	0.115	−0.050	0.024	0.2719
FI High Yield	2	17	−1.562	6.988	0.654	2.636	−13.97	16.36	0.2087	0.051	−0.233	−0.504	0.0681
FI Others	2	40	0.409	2.477	−1.078	3.699	−7.78	5.74	<0.01	0.176	−0.239	−0.130	0.2464
FI Average	4	29	0.221	3.487	0.236	3.243	−7.87	9.20	0.1517	0.175	−0.288	−0.206	0.1484
EF Balanced	5.000	14	−1.728	4.575	−0.215	1.988	−10.87	7.97	0.1928	0.150	−0.351	−0.284	0.0631
EF Global	108.000	56	−1.117	7.917	−0.733	2.404	−24.24	15.27	0.192	0.268	−0.046	−0.059	0.2524
EF Sector	111.000	42	−0.939	6.346	−0.726	1.687	−18.51	11.23	0.2064	0.161	−0.148	−0.093	0.2482
EF Commodities	47.000	38	−0.939	10.759	−0.892	1.430	−29.54	16.56	0.1325	0.253	0.129	−0.003	0.2758
EF Large Cap	82.000	51	−0.956	5.537	−1.310	2.842	−18.78	7.67	<0.05	0.284	−0.116	−0.028	0.1816
EF Mid Cap	55.000	40	−1.496	7.450	−1.194	2.648	−23.77	10.13	0.1149	0.298	−0.116	−0.077	0.1537
EF Small Cap	35.000	50	−1.269	6.874	−1.327	2.731	−24.21	8.64	<0.05	0.231	−0.138	−0.175	0.1783
EF Growth	46.000	47	−1.457	7.245	−1.068	1.884	−22.61	10.35	0.1382	0.290	−0.017	−0.099	0.2181
EF value	46.000	51	−0.843	5.699	−1.413	3.579	−20.47	8.19	<0.05	0.239	−0.189	−0.050	0.1512
EF Bear Market	40.000	22	1.624	10.706	0.676	1.142	−15.53	26.78	0.2369	0.170	−0.288	−0.206	0.1844
EF Currency	10.000	29	0.197	3.486	−0.670	3.786	−10.02	7.36	0.0801	0.284	0.091	0.016	0.3396
EF Others	82.000	48	−1.555	8.767	−0.737	1.749	−24.44	16.49	0.1675	0.162	−0.172	−0.118	0.2887
EF Average	55.583	41	−0.873	7.113	−0.801	2.323	−20.25	12.22	0.1294	0.233	−0.113	−0.098	0.2113
Group Average	34.95	36	−0.436	5.663	−0.386	2.691	−15.30	11.01	0.1383	0.209	−0.183	−0.141	0.1861
Panel C: Open-Ended Funds													
FI Index	32	95	0.508	1.252	−0.034	1.378	−3.14	4.21	0.2657	0.136	−0.096	0.065	0.2406
FI Global	303	87	0.381	2.367	−0.556	3.739	−8.00	6.47	0.1495	0.181	−0.114	−0.038	0.1798
FI Short Term	645	76	0.287	0.763	−0.890	5.023	−2.07	2.28	0.2501	0.242	0.084	0.124	0.1684
FI Government	727	93	0.464	1.124	−0.138	1.311	−2.88	3.60	0.1831	0.210	0.016	0.117	0.2543

Style	Nofunds	Nobs	Mean	Std	Skewness	Kurtosis	Min	Max	JB	ρ_1	ρ_2	ρ_3	LQ
FI Mortgage	219	81	0.399	0.898	−0.420	2.018	−2.33	2.69	0.2976	0.191	0.002	0.138	0.2589
FI Corporate	798	74	0.421	1.285	−0.580	2.578	−3.81	3.63	0.2704	0.142	−0.090	0.043	0.2166
FI High Yield	944	87	0.361	2.338	−1.174	5.553	−9.41	6.04	0.1161	0.224	−0.112	−0.094	0.1069
FI Others	619	79	0.623	1.006	0.286	3.412	−2.32	3.60	0.2316	0.425	0.378	0.334	0.1669
FI Average	536	84	0.431	1.379	−0.438	3.126	−4.24	4.07	0.2205	0.219	0.009	0.086	0.199
EF Index	838	79	−0.177	5.149	−0.966	2.850	−17.75	10.37	0.1072	0.199	−0.066	−0.013	0.2642
EF commodities	238	78	0.340	8.826	−0.516	1.585	−27.06	20.58	0.1587	0.085	0.050	0.065	0.2728
EF Sector	1331	69	−0.322	6.933	−0.371	1.268	−18.82	15.72	0.2876	0.137	−0.051	−0.059	0.3842
EF Global	3373	78	−0.115	5.884	−0.796	2.245	−19.52	12.36	0.1489	0.237	0.024	0.008	0.2393
EF Balanced	988	80	0.134	3.096	−1.098	3.332	−11.16	6.03	0.1121	0.192	−0.065	0.003	0.274
EF Leverage and Short	675	62	−0.099	6.231	−0.287	1.597	−16.50	14.93	0.2483	0.119	−0.051	−0.059	0.336
EF Long Short	80	22	−1.774	4.877	−0.980	1.439	−14.30	5.24	0.1843	0.293	−0.061	−0.109	0.2205
EF Mid Cap	1331	63	−0.335	5.942	−0.919	2.579	−19.61	11.80	0.1253	0.229	−0.050	−0.051	0.2213
EF Small Cap	1970	68	−0.183	6.207	−0.741	1.930	−19.66	13.03	0.1336	0.170	−0.053	−0.132	0.2247
EF Aggressive Growth	247	46	1.493	6.072	−0.734	2.067	−17.52	13.05	0.1803	0.059	−0.094	−0.036	0.5208
EF Growth	4586	73	−0.141	5.145	−0.812	2.114	−16.50	10.24	0.1826	0.186	−0.047	−0.023	0.3083
EF Growth and Income	2459	70	−0.160	4.494	−0.883	2.169	−14.83	8.48	0.1484	0.165	−0.073	−0.027	0.3286
EF Equity Income	509	55	−0.208	4.233	−0.782	2.041	−13.09	8.05	0.2366	0.140	−0.095	−0.026	0.327
EF Others	1758	65	1.267	5.362	−0.498	1.994	−15.42	12.90	0.2147	0.062	−0.044	−0.093	0.4216
EF Average	1456	65	−0.020	5.604	−0.742	2.086	−17.27	11.63	0.1763	0.163	−0.048	−0.039	0.3102
Group Average	1121	72	0.144	4.067	−0.631	2.465	−12.53	8.88	0.1924	0.183	−0.028	0.006	0.2698
Panel D: Hedge Funds													
Equity Hedge	2367	48	0.399	5.051	−0.299	2.001	−12.87	12.30	0.2928	0.102	0.015	−0.019	0.3381
Event-Driven	585	56	0.381	3.241	−0.618	4.071	−9.32	8.23	0.1682	0.262	0.102	0.057	0.209
Fund of Funds	1194	46	0.091	2.625	−0.981	2.951	−7.83	4.82	0.2097	0.272	0.159	0.064	0.2403
HFRI	75	137	0.612	2.925	−1.115	6.471	−11.69	9.49	<0.05	0.302	0.148	0.073	0.1028
HFRX	27	46	−0.425	2.337	−1.709	6.048	−9.27	2.80	0.1688	0.273	0.182	0.049	0.1318
Macro	810	45	0.470	4.562	0.012	2.006	−10.38	11.74	0.3267	0.054	−0.052	−0.044	0.3471
Relative Value	786	46	0.241	2.991	−1.208	7.001	−10.18	5.84	0.146	0.265	0.100	0.073	0.2289
Group Average	835	60	0.253	3.390	−0.845	4.364	−10.22	7.89	0.1945	0.219	0.093	0.036	0.2283

Table II: Frequency of Tail Returns across Fund Types

Tail returns are defined as monthly returns exceeding $(+/-)5$ and $(+/-)3$ standard deviations from their means. The frequency of tail returns of a fund is calculated by the count of tail returns divided by its total number of monthly returns. The test statistics is calculated by assuming the distribution of the counts of tail returns to be Bernoulli and i.i.d. Total fund returns are further decomposed into systematic and idiosyncratic components to calculate the frequency of systematic and idiosyncratic tail returns. Results are reported in three rows for each fund type. The first row is the frequency of total tail returns. The second row is the frequency of systematic tail returns. The third row is the frequency of idiosyncratic tail returns. The cross cell by the same fund type represents the average frequency of tail returns across funds in that fund type. The cross cell of two different fund types is the difference in frequency of tail returns between two fund types. T-values are in the parenthesis based on the test hypothesis of zero frequency. CEFs/ETFs/OEFs/HFs refer to closed-end funds/exchange-traded funds/open-ended funds/hedge funds, respectively.

Panel A: All Funds

	CEFs		ETFs		OEFs		HFs	
	$5std$	$3std$	$5std$	$3std$	$5std$	$3std$	$5std$	$3std$
	0.132(-0.47)	1.775(-1.54)	0.123(0.21)	0.617(1.33)	0.086(0.04)	0.672(0.45)	0.055(0.03)	0.609(0.50)
CEFs	0.139(-0.47)	1.885(-1.46)	0.137(0.23)	0.462(0.99)	0.109(0.06)	0.814(0.55)	0.093(0.06)	0.788(0.64)
	0.095(-0.49)	1.076(-2.02)	0.087(0.15)	0.426(0.92)	0.035(0.02)	0.212(0.14)	0.032(0.02)	0.156(0.13)
			0.009(-0.34)	1.158(-1.25)	-0.037(-0.06)	0.056(0.10)	-0.068(-0.04)	-0.008(-0.01)
ETFs			0.002(-0.34)	1.423(-1.13)	-0.028(-0.05)	0.352(0.72)	-0.044(-0.02)	0.326(0.22)
			0.007(-0.34)	0.650(-1.47)	-0.052(-0.09)	-0.214(-0.45)	-0.055(-0.03)	-0.270(-0.18)
					0.046(-0.39)	1.102(-1.53)	-0.031(-0.08)	-0.063(-0.21)
OEFs					0.030(-0.40)	1.071(-1.55)	-0.016(-0.03)	-0.026(-0.01)
					0.059(-0.39)	0.864(-1.66)	-0.003(-0.00)	-0.056(-0.22)
							0.077(-0.50)	1.165(-1.95)
HFs							0.046(-0.51)	1.097(-2.00)
							0.063(-0.50)	0.920(-2.12)

Panel B: Fixed Income Funds

	CEFs		ETFs		OEFs	
	$5std$	$3std$	$5std$	$3std$	$5std$	$3std$
	0.199(-0.49)	1.967(-1.59)	0.159(0.05)	1.173(0.48)	0.052(0.02)	0.867(0.36)
CEFs	0.234(-0.47)	2.054(-1.53)	0.193(0.06)	1.715(0.70)	0.127(0.04)	0.930(0.38)
	0.146(-0.52)	1.265(-2.14)	0.106(0.03)	-0.288(-0.12)	-0.016(-0.01)	-0.034(-0.01)
			0.041(-0.28)	0.793(-1.21)	-0.107(-0.03)	-0.306(-0.13)
ETFs			0.041(-0.28)	0.339(-1.38)	-0.066(-0.02)	-0.785(-0.33)
			0.041(-0.28)	1.553(-0.92)	-0.122(-0.04)	0.254(0.11)
					0.147(-0.26)	1.099(-1.13)
OEFs					0.106(-0.27)	1.124(-1.12)
					0.162(-0.26)	1.299(-1.05)

Panel C: Equity Funds

	CEFs		ETFs		OEFs	
	$5std$	$3std$	$5std$	$3std$	$5std$	$3std$
	0.085(-0.41)	1.642(-1.35)	0.078(0.40)	0.464(3.06)	0.065(0.04)	0.552(0.48)
CEFs	0.074(-0.42)	1.769(-1.28)	0.074(0.38)	0.285(1.88)	0.064(0.04)	0.724(0.64)
	0.059(-0.42)	0.946(-1.75)	0.053(0.28)	0.346(2.28)	0.026(0.02)	0.191(0.17)
			0.007(-0.34)	1.178(-1.22)	-0.013(-0.01)	0.088(0.13)
ETFs			0.000(-0.34)	1.484(-1.09)	-0.010(-0.01)	0.439(0.54)
			0.006(-0.34)	0.600(-1.47)	-0.028(-0.03)	-0.156(-0.20)
					0.020(-0.36)	1.091(-1.35)
OEFs					0.010(-0.36)	1.044(-1.37)
					0.033(-0.35)	0.756(-1.51)

Table III:
Skewness Decomposition by the Equal-weighted Portfolios across Fund Styles and Types

This table summarizes the skewness decomposition by using the equal-weighted portfolio of funds as market portfolio. EW portfolio skewness is the skewness for equal-weighted portfolios of funds formed by funds in the same styles. Individual skewness is the cross-sectional average of skewness of individual funds in each style. Skewness is the third central moment about the mean and computed as $\mathbb{E}[r_i^3]/\sigma_i^3$. r_i and σ_i are the demeaned return and standard deviation of fund i. COSKEW, ICOSKEW, and RESSKEW refer to the following components in the skewness decomposition:

$$\mathbb{E}(r_i^3) \quad = \quad \underbrace{\beta_i^2 cov(r_i, r_p^2) + 2\beta_i^2 cov(u_i, r_p^2)}_{COSKEW} + \underbrace{3\beta_i cov(u_i^2, r_p)}_{ICOSKEW} + \underbrace{\mathbb{E}(u_i^3)}_{RESSKEW}$$

where r_p is the demeaned return for the market portfolio. Individual COSKEW, ICOSKEW, and RESSKEW are the average of estimated values from the above equation by GMM across individual funds and reported as percentages of the skewness of demeaned fund returns $\mathbb{E}[r_i^3]$. FI and EF stand for fixed income and equity funds, respectively. Numbers in parentheses are t-values for COSKEW, ICOSKEW, and RESSKEW against the hypothesis of zero weight. *FI Average* is the average of statistics across fixed-income fund styles. *EF Average* is the average of statistics across equity fund styles. *Group Average* is the average of statistics across all fund styles.

Styles	EW Port Skewness	Individual Skewness	Individual COSKEW (%)	Individual ICOSKEW (%)	Individual RESSKEW (%)
Panel A: Closed-End Funds					
FI Global	−1.512	−0.602	122.89	−12.21	−10.67
			(−0.65)	(−0.29)	(0.32)
FI Sector	−0.754	−0.399	105.95	−6.07	0.12
			(−0.60)	(−0.41)	(−0.10)
FI Long Term	−0.339	−1.224	57.37	40.49	2.14
			(−0.33)	(−0.61)	(0.19)
FI Intermediate Term	0.749	0.203	−6.31	116.74	−10.43
			(0.43)	(0.32)	(−0.22)
FI Short Term	−0.419	−0.912	27.74	63.65	8.61
			(−0.73)	(−1.20)	(−0.03)
FI Government	−0.262	−0.185	32.15	36.76	31.09
			(−0.14)	(−0.31)	(−0.59)
FI High Yield	0.296	−0.620	70.36	4.62	25.01
			(−0.88)	(−0.16)	(−0.49)
FI Others	−2.273	−1.656	43.16	12.03	44.81
			(−1.16)	(−0.65)	(−0.10)
FI Average	−0.564	−0.675	56.66	32.00	11.33
			(−0.51)	(−0.41)	(−0.13)
EF Balanced	−0.157	−0.780	72.21	25.29	2.49
			(−0.99)	(−0.45)	(0.22)
EF Global	0.598	−0.059	16.66	70.76	12.59
			(−0.74)	(0.61)	(0.36)
EF Sector	−0.896	−0.162	53.60	19.99	26.41
			(−0.99)	(0.30)	(−0.24)
EF Commodities	0.508	−1.136	50.18	66.73	−16.90
			(−0.69)	(−0.38)	(0.01)
EF Large Cap	2.306	−0.698	3.07	−28.21	125.15

Styles	EW Port Skewness	Individual Skewness	Individual COSKEW (%)	Individual ICOSKEW (%)	Individual RESSKEW (%)
			(−1.01)	(−0.25)	(−0.14)
EF Mid Cap	0.247	−0.258	−67.72	77.61	90.10
			(−0.41)	(−0.25)	(−0.47)
EF Small Cap	0.833	−0.138	68.26	9.26	22.48
			(−1.26)	(1.39)	(−0.89)
EF Growth	0.789	−0.480	51.55	−19.30	67.76
			(−1.11)	(0.26)	(−0.67)
EF Value	−0.834	−0.996	−13.76	97.39	16.37
			(−1.11)	(−0.50)	(−0.47)
EF Others	−1.830	−1.426	41.24	24.17	34.59
			(−1.07)	(−0.33)	(0.18)
EF Average	0.156	−0.613	27.53	34.37	38.10
			(−0.94)	(0.04)	(−0.21)
Group Average	−0.164	−0.640	40.48	33.32	26.21
			(−0.75)	(−0.16)	(−0.17)
Panel B: ETFs					
FI Global	−1.016	−0.314	59.64	39.26	1.10
			(−0.55)	(0.93)	(0.00)
FI Sector	0.924	0.826	103.91	−5.69	1.79
			(1.20)	(−0.47)	(−0.32)
FI Long Term	1.178	0.945	122.79	−20.81	−1.98
			(0.94)	(−0.97)	(0.21)
FI Intermediate Term	0.650	0.585	85.66	5.04	9.30
			(0.75)	(−0.86)	(0.37)
FI Short Term	0.445	−0.252	46.24	25.57	28.20
			(0.27)	(−1.18)	(−0.34)
FI Government	0.024	0.526	−45.66	123.15	22.51
			(−0.01)	(0.83)	(0.20)
FI High Yield	0.531	0.654	106.86	−6.95	0.09
			(0.66)	(−1.15)	(0.48)
FI Others	−1.143	−1.078	101.51	−1.50	−0.01
			(−1.33)	(1.54)	(0.49)
FI Average	0.199	0.236	72.62	19.76	7.62
			(0.24)	(−0.17)	(0.14)
EF Balanced	−0.041	−0.215	76.95	12.18	10.87
			(−0.48)	(0.52)	(0.54)
EF Global	−0.967	−0.733	87.30	4.00	8.70
			(−1.33)	(0.34)	(0.38)
EF Sector	−0.716	−0.726	71.30	27.25	1.45
			(−1.07)	(−0.50)	(0.19)
EF Commodities	−0.751	−0.892	81.85	18.00	0.15
			(−1.61)	(−0.40)	(−0.08)
EF Large Cap	−0.743	−1.310	87.54	12.13	0.33
			(−1.55)	(−1.11)	(0.07)
EF Mid Cap	−1.071	−1.194	88.21	10.39	1.41
			(−1.46)	(−1.07)	(0.06)
EF Small Cap	−1.023	−1.327	94.84	5.52	−0.36

Styles	EW Port Skewness	Individual Skewness	Individual COSKEW (%)	Individual ICOSKEW (%)	Individual RESSKEW (%)
			(−1.53)	(−1.23)	(−0.13)
EF Growth	−0.121	−1.068	94.54	5.37	0.09
			(−1.72)	(−0.78)	(−0.09)
EF Value	−0.560	−1.413	93.09	6.51	0.40
			(−1.57)	(−0.77)	(0.03)
EF Bear Market	0.917	0.676	62.21	17.30	20.50
			(1.00)	(0.88)	(0.46)
EF Currency	−1.362	−0.670	105.81	−11.26	5.45
			(−0.60)	(0.10)	(−0.35)
EF Others	−0.321	−0.737	75.58	19.59	4.82
			(−1.16)	(−0.47)	(0.01)
EF Average	−0.563	−0.801	84.93	10.58	4.48
			(−1.09)	(−0.37)	(0.09)
Group Average	−0.258	−0.386	80.01	14.25	5.74
			(−0.56)	(−0.29)	(0.11)
Panel C: Open-Ended Funds					
FI Index	−0.167	−0.035	100.30	3.62	−3.92
			(−0.16)	(0.04)	(−0.19)
FI Global	−0.849	−0.556	85.77	−66.27	80.50
			(0.06)	(−1.13)	(0.13)
FI Short Term	−0.333	−0.890	45.00	−142.57	197.57
			(−0.51)	(−0.35)	(−0.38)
FI Government	−0.158	−0.138	69.42	8.48	22.10
			(−0.67)	(0.24)	(−0.01)
FI Mortgage	−0.315	−0.420	80.90	2.53	16.57
			(−0.58)	(−0.29)	(−0.04)
FI Corporate	−0.963	−0.580	113.87	−33.19	19.32
			(−0.69)	(−0.11)	(0.07)
FI High Yield	−0.776	−1.174	−32.05	−7.75	139.80
			(−1.00)	(−0.51)	(0.06)
FI Others	−0.095	0.286	48.69	−62.56	113.86
			(0.00)	(0.06)	(0.41)
FI Average	−0.457	−0.439	63.99	−37.22	73.23
			(−0.44)	(−0.25)	(0.01)
EF Index	5.493	−0.966	95.55	2.39	2.05
			(−1.45)	(0.01)	(−0.33)
EF commodities	0.155	−0.516	87.41	23.22	−10.63
			(−1.07)	(0.07)	(−0.15)
EF Sector	−0.569	−0.371	83.74	3.99	12.27
			(−0.73)	(−0.20)	(0.04)
EF Global	−0.918	−0.796	83.73	9.82	6.45
			(−1.24)	(−0.01)	(−0.00)
EF Balanced	−0.472	−1.098	88.85	17.72	−6.57
			(−1.23)	(−0.40)	(−0.13)
EF Leverage and Short	2.351	−0.287	19.62	29.08	51.30
			(−0.48)	(−0.06)	(−0.26)
EF Long Short	−1.658	−0.980	76.09	−1.42	25.33

Styles	EW Port Skewness	Individual Skewness	Individual COSKEW (%)	Individual ICOSKEW (%)	Individual RESSKEW (%)
			(−1.69)	(−0.72)	(−0.26)
EF Mid Cap	−0.494	−0.919	84.11	11.02	4.87
			(−1.13)	(−0.56)	(0.06)
EF Small Cap	−0.490	−0.741	103.62	−7.17	3.54
			(−1.07)	(−0.41)	(0.07)
EF Aggressive Growth	−0.405	−0.734	101.10	−5.18	4.08
			(−1.05)	(0.68)	(0.07)
EF Growth	−0.695	−0.812	81.57	14.60	3.83
			(−1.30)	(−0.31)	(−0.00)
EF Growth and Income	−0.997	−0.883	96.89	0.93	2.18
			(−1.30)	(−0.31)	(−0.14)
EF Equity Income	−0.944	−0.782	91.69	1.25	7.07
			(−0.93)	(−0.79)	(0.06)
EF Others	−0.567	−0.498	−40.20	143.89	−3.70
			(−0.85)	(0.73)	(0.07)
EF Average	−0.015	−0.742	75.27	17.44	7.29
			(−1.11)	(−0.16)	(−0.07)
Group Average	−0.176	−0.631	71.17	−2.44	31.27
			(−0.87)	(−0.20)	(−0.04)
Panel D: Hedge Funds					
Equity Hedge	−0.302	−0.299	46.67	17.42	35.91
			(−0.36)	(−0.25)	(0.04)
Event-Driven	−1.899	−0.618	53.84	21.50	24.67
			(−0.63)	(−0.60)	(0.06)
Fund of Funds	−1.000	−0.981	42.13	10.99	46.88
			(−0.93)	(−0.92)	(−0.32)
HFRI	−1.074	−1.115	157.06	−95.69	38.63
			(−0.64)	(−0.79)	(−0.17)
HFRX	−2.257	−1.709	110.83	−23.03	12.20
			(−0.57)	(−1.70)	(−0.71)
Macro	0.378	0.012	19.74	−20.42	100.68
			(0.14)	(0.14)	(0.04)
Relative Value	−4.219	−1.208	31.24	17.85	51.04
			(−0.45)	(−0.62)	(−0.23)
Group Average	−1.482	−0.845	65.93	−10.20	44.29
			(−0.49)	(−0.68)	(−0.18)

Table IV:
Kurtosis Decomposition by the Equal-weighted Portfolios across Fund Styles and Types

This table summarizes the kurtosis decomposition by using the equal-weighted portfolio of funds as market portfolio. EW portfolio kurtosis is the kurtosis for equal-weighted portfolios of funds formed by funds in the same styles. Individual kurtosis is the cross-sectional average of kurtosis of individual funds in each style. Kurtosis is the fourth central moment about the mean and computed as $\mathbb{E}[r_i^4]/\sigma_i^4 - 3$. r_i and σ_i are the demeaned return and standard deviation of fund i. COKURT, VOLCOMV, ICOKURT, and RESKURT refer to the following components in the kurtosis decomposition:

$$\mathbb{E}(r_i^4) = \underbrace{\beta_i^3 cov(r_i, r_p^3) + 3\beta_i^3 cov(u_i, r_p^3)}_{COKURT} + \underbrace{6\beta_i^2 \mathbb{E}(r_p^2 u_i^2)}_{VOLCOMV} + \underbrace{4\beta_i cov(u_i^3, r_p)}_{ICOKURT} + \underbrace{\mathbb{E}(u_i^4))}_{RESKURT}$$

where r_p is the demeaned return for the market portfolio. Individual COKURT, VOLCOMV, ICOKURT, and RESKURT are the average of estimated values from the above equation by GMM across individual funds and reported as percentages of the kurtosis of demeaned fund returns $\mathbb{E}[r_i^4]$. FI and EF stand for fixed income and equity funds, respectively. Numbers in parentheses are t-values for COSKEW, ICOSKEW, and RESSKEW against the hypothesis of zero weight. *FI Average* is the average of statistics across fixed-income fund styles. *EF Average* is the average of statistics across equity fund styles. *Group Average* is the average of statistics across all fund styles.

Styles	EW Port Kurtosis	Individual Kurtosis	Individual COKURT (%)	Individual VOLCOMV (%)	Individual ICOKURT (%)	Individual RESKURT (%)
Panel A: Closed-End Funds						
FI Global	11.897	6.080	52.09	37.14	−3.27	14.04
			(1.12)	(2.10)	(0.19)	(2.60)
FI Sector	3.395	4.611	19.84	41.68	5.24	33.24
			(0.90)	(1.77)	(0.63)	(2.86)
FI Long Term	7.365	8.322	43.68	37.20	−2.08	21.20
			(0.66)	(1.88)	(0.05)	(2.06)
FI Intermediate Term	5.568	5.443	29.75	44.91	2.92	22.42
			(1.12)	(2.21)	(0.76)	(3.24)
FI Short Term	1.814	4.361	12.36	54.30	3.88	29.47
			(0.35)	(1.58)	(0.39)	(2.35)
FI Government	2.390	2.305	14.97	38.31	8.46	38.25
			(1.20)	(2.13)	(0.83)	(2.51)
FI High Yield	5.445	3.708	47.57	36.53	−5.41	21.32
			(1.56)	(2.27)	(−0.04)	(2.59)
FI Others	11.743	6.415	67.79	22.50	−0.54	10.25
			(1.36)	(1.73)	(0.21)	(2.20)
FI Average	6.202	5.156	36.01	39.07	1.15	23.77
			(1.03)	(1.96)	(0.38)	(2.55)
EF Balanced	5.747	4.193	51.43	34.53	−1.24	15.29
			(1.40)	(1.96)	(0.29)	(2.50)
EF Commodities	5.801	2.725	30.94	40.01	3.98	25.07
			(1.33)	(2.21)	(0.48)	(2.84)
EF Global	4.882	4.424	18.35	41.89	3.87	35.89
			(0.96)	(2.04)	(0.21)	(2.40)
EF Sector	5.754	4.279	34.19	43.47	−6.02	28.36
			(1.19)	(1.82)	(−0.41)	(2.27)
EF Large Cap	27.479	5.530	45.49	39.45	−0.17	15.23

Styles	EW Port Kurtosis	Individual Kurtosis	Individual COKURT (%)	Individual VOLCOMV (%)	Individual ICOKURT (%)	Individual RESKURT (%)
			(1.30)	(1.85)	(0.27)	(2.62)
EF Mid Cap	2.958	4.565	29.65	36.43	5.81	28.10
			(0.99)	(1.92)	(0.52)	(2.51)
EF Small Cap	5.238	3.321	5.27	76.14	−16.61	35.21
			(−0.43)	(1.89)	(−0.47)	(3.32)
EF Growth	6.635	4.707	22.20	50.27	−5.23	32.76
			(0.39)	(1.64)	(0.01)	(2.77)
EF Value	4.680	3.886	56.87	37.22	−1.57	7.48
			(1.38)	(1.91)	(−0.13)	(2.06)
EF Others	7.017	5.649	58.66	33.23	−0.44	8.55
			(1.18)	(1.92)	(0.51)	(2.24)
EF Average	7.619	4.328	35.30	43.26	−1.76	23.19
			(0.97)	(1.92)	(0.13)	(2.55)
Group Average	6.989	4.696	35.62	41.40	−0.47	23.45
			(1.00)	(1.94)	(0.24)	(2.55)
Panel B: ETFs						
FI Global	3.555	2.910	52.77	31.84	8.92	6.47
			(0.89)	(1.27)	(0.15)	(2.18)
FI Sector	2.002	1.841	92.65	8.34	−1.43	0.45
			(1.77)	(2.01)	(0.03)	(1.97)
FI Long Term	9.208	7.720	82.56	16.75	0.16	0.54
			(1.35)	(1.47)	(0.25)	(1.60)
FI Intermediate Term	4.283	3.537	66.89	30.30	−0.64	3.46
			(1.29)	(1.61)	(−0.35)	(2.16)
FI Short Term	0.890	2.156	36.00	34.02	−1.95	31.93
			(0.80)	(1.14)	(0.12)	(2.26)
FI Government	0.123	1.444	7.41	28.26	0.77	63.56
			(0.65)	(1.16)	(0.35)	(2.47)
FI High Yield	2.787	2.636	94.35	5.68	−0.05	0.02
			(1.39)	(2.51)	(−0.13)	(2.00)
FI Others	4.516	3.699	98.79	1.20	0.01	0.01
			(1.57)	(2.14)	(−0.22)	(1.87)
FI Average	3.421	3.243	66.43	19.55	0.72	13.30
			(1.21)	(1.66)	(0.03)	(2.06)
EF Balanced	1.408	1.988	61.75	28.67	0.07	9.50
			(1.24)	(2.09)	(0.17)	(1.73)
EF Global	2.524	2.404	69.21	22.32	1.84	6.63
			(1.45)	(2.27)	(0.15)	(2.60)
EF Sector	2.259	1.687	48.06	33.30	−0.38	19.01
			(1.16)	(2.02)	(0.04)	(2.42)
EF Commodities	3.222	1.430	69.22	23.32	1.37	6.10
			(1.56)	(2.03)	(0.07)	(2.23)
EF Large Cap	1.559	2.842	79.38	17.94	−0.28	2.96
			(1.50)	(2.31)	(−0.28)	(2.36)
EF Mid Cap	3.267	2.648	79.32	15.20	−0.51	5.98
			(1.35)	(1.96)	(0.05)	(2.31)
EF Small Cap	2.240	2.731	90.59	9.41	−0.56	0.56

Styles	EW Port Kurtosis	Individual Kurtosis	Individual COKURT (%)	Individual VOLCOMV (%)	Individual ICOKURT (%)	Individual RESKURT (%)
			(1.51)	(2.29)	(−0.09)	(2.47)
EF Growth	1.453	1.884	81.83	15.01	−0.03	3.19
			(1.70)	(2.28)	(0.21)	(2.62)
EF Value	2.537	3.579	79.72	17.24	−0.44	3.48
			(1.40)	(2.24)	(0.16)	(2.43)
EF Bear Market	0.970	1.142	48.28	38.85	−1.11	13.99
			(1.26)	(1.83)	(−0.01)	(2.24)
EF Currency	3.894	3.786	55.12	26.71	0.19	17.99
			(0.94)	(1.60)	(0.31)	(2.24)
EF Others	0.489	1.749	55.47	32.84	1.62	10.08
			(1.45)	(2.27)	(0.04)	(2.63)
EF Average	2.152	2.323	68.16	23.40	0.15	8.29
			(1.38)	(2.10)	(0.07)	(2.36)
Group Average	2.659	2.691	67.47	21.86	0.38	10.30
			(1.31)	(1.93)	(0.05)	(2.24)
Panel C: Open-Ended Funds						
FI Index	0.545	1.412	75.50	20.03	−1.91	6.38
			(2.17)	(2.30)	(−0.13)	(2.42)
FI Global	5.778	3.739	35.55	52.03	−4.35	16.76
			(1.11)	(2.29)	(0.10)	(2.56)
FI Short Term	1.911	5.023	16.24	71.25	−20.75	33.20
			(0.47)	(1.94)	(−0.33)	(2.20)
FI Government	0.430	1.311	56.88	26.83	−1.82	18.10
			(1.97)	(2.18)	(0.18)	(2.65)
FI Mortgage	0.966	2.018	60.27	27.10	0.48	12.15
			(1.99)	(2.38)	(0.13)	(2.17)
FI Corporate	4.220	2.578	69.02	25.31	−1.93	7.60
			(1.79)	(2.54)	(−0.15)	(2.17)
FI High Yield	4.850	5.553	72.90	21.01	−0.03	6.12
			(1.58)	(2.28)	(0.27)	(2.34)
FI Others	2.824	3.412	18.32	21.92	−0.95	60.71
			(0.56)	(1.36)	(0.14)	(2.84)
FI Average	2.690	3.131	50.59	33.18	−3.91	20.13
			(1.45)	(2.16)	(0.03)	(2.42)
EF Index	87.572	2.850	77.95	18.13	−0.77	4.69
			(1.69)	(2.57)	(−0.14)	(2.44)
EF Commodities	4.114	1.585	66.37	25.43	−0.66	8.86
			(1.57)	(2.62)	(0.05)	(2.52)
EF Sector	2.142	1.268	44.65	37.35	1.03	16.97
			(1.70)	(2.32)	(0.25)	(2.68)
EF Global	3.287	2.245	73.89	20.49	0.54	5.08
			(1.69)	(2.75)	(0.15)	(2.79)
EF Balanced	2.151	3.332	73.09	21.10	−0.83	6.64
			(1.55)	(2.49)	(0.25)	(2.56)
EF Leverage and Short	23.537	1.597	44.92	38.01	−0.47	17.54
			(1.39)	(2.12)	(0.34)	(2.33)
EF Long Short	2.791	1.439	67.59	24.49	2.43	5.48

Styles	EW Port Kurtosis	Individual Kurtosis	Individual COKURT (%)	Individual VOLCOMV (%)	Individual ICOKURT (%)	Individual RESKURT (%)
			(1.36)	(2.09)	(0.07)	(2.49)
EF Mid Cap	1.336	2.579	76.03	21.74	−1.06	3.28
			(1.65)	(2.43)	(0.10)	(2.55)
EF Small Cap	1.097	1.930	73.92	24.35	−1.25	2.98
			(1.70)	(2.55)	(−0.03)	(2.56)
EF Aggressive Growth	0.730	2.067	71.61	19.73	0.58	8.08
			(1.39)	(2.54)	(0.04)	(2.55)
EF Growth	2.198	2.114	73.00	21.60	0.11	5.30
			(1.86)	(2.62)	(0.16)	(2.61)
EF Growth and Income	2.785	2.169	82.80	14.39	−0.06	2.87
			(1.80)	(2.69)	(0.07)	(2.55)
EF Equity Income	3.010	2.041	79.60	17.44	−0.21	3.17
			(1.74)	(2.52)	(0.09)	(2.57)
EF Others	1.857	1.994	66.75	23.17	0.11	9.97
			(1.41)	(2.54)	(0.08)	(2.58)
EF Average	9.901	2.086	69.44	23.39	−0.04	7.21
			(1.61)	(2.49)	(0.11)	(2.56)
Group Average	7.279	2.466	62.59	26.95	−1.45	11.91
			(1.55)	(2.37)	(0.08)	(2.50)
Panel D: Hedge Funds						
Equity Hedge	2.004	2.001	17.56	34.18	1.08	47.17
			(0.64)	(1.50)	(0.29)	(2.45)
Event-Driven	6.907	4.071	23.59	31.03	3.75	41.64
			(0.73)	(1.58)	(0.49)	(2.25)
Fund of Funds	4.186	2.951	44.53	33.21	2.35	19.91
			(1.17)	(1.95)	(0.37)	(2.31)
HFRI	4.018	6.471	33.21	42.58	−0.29	24.50
			(0.98)	(2.14)	(0.70)	(2.90)
HFRX	8.220	6.048	50.56	27.05	1.26	21.13
			(0.69)	(1.88)	(0.65)	(2.27)
Macro	0.134	2.006	7.28	22.82	2.96	66.95
			(0.61)	(1.21)	(0.29)	(2.32)
Relative Value	25.845	7.001	7.27	45.82	−8.80	55.89
			(0.42)	(1.07)	(0.20)	(1.96)
Group Average	7.330	4.364	26.28	33.81	0.33	39.60
			(0.75)	(1.62)	(0.43)	(2.35)

Table V: Autocorrelation-adjusted Skewness Decomposition of Hedge Funds

Identify the 3-lag autocorrelated observed return process as $r_{i,t} = (\beta_{0,i} + \beta_{1,i} + \beta_{2,i})r_{p,t} + u_{i,t}$. $r_{i,t}$ and $r_{p,t}$ are demeaned return for fund i and market portfolio. Substitute the true $\tilde{\beta}_i$ (=$\beta_{0,i} + \beta_{1,i} + \beta_{2,i}$) in the equation of $r_{i,t} = \tilde{\beta}_i r_{p,t}$ to derive and compute the skewness decomposition. *Group Average* is the average of statistics across all fund styles.

Panel A: Skewness Decomposition

Styles	*Individual* $COSKEW(\%)$	*Individual* $ICOSKEW(\%)$	*Individual* $RESSKEW(\%)$
Equity Hedge	23.66	36.20	43.21
	(-0.32)	(-0.28)	(0.04)
Event-Driven	50.84	21.25	27.54
	(-0.54)	(-0.59)	(0.08)
Fund of Funds	44.63	21.19	35.23
	(-0.95)	(-0.79)	(-0.30)
HFRI	141.69	-49.19	8.05
	(-0.75)	(-0.40)	(-0.26)
HFRX	66.09	-15.20	52.80
	(-0.83)	(-1.36)	(-0.25)
Macro	42.53	-99.38	157.81
	(0.11)	(0.12)	(0.05)
Relative Value	32.20	22.77	45.39
	(-0.37)	(-0.60)	(-0.18)
Group Average	57.38	-8.91	52.86
	(-0.52)	(-0.56)	(-0.12)

Panel B: Kurtosis Decomposition

Styles	*Individual* $COKURT(\%)$	*Individual* $VOLCOMV(\%)$	*Individual* $ICOKURT(\%)$	*Individual* $RESKURT(\%)$
Equity Hedge	9.77	48.98	-11.54	52.88
	(0.50)	(1.20)	(0.22)	(2.15)
Event-Driven	10.18	51.51	-6.23	44.51
	(0.50)	(1.26)	(0.25)	(2.06)
Fund of Funds	37.69	43.03	-2.42	21.82
	(1.04)	(1.66)	(0.33)	(2.04)
HFRI	36.99	34.96	4.50	23.57
	(1.07)	(1.91)	(0.69)	(2.80)
HFRX	52.37	21.01	1.58	25.76
	(0.90)	(1.53)	(0.25)	(2.25)
Macro	-9.27	60.95	-35.47	84.24
	(0.27)	(0.82)	(0.14)	(1.95)
Relative Value	-5.57	67.05	-21.31	60.21
	(0.27)	(0.95)	(0.07)	(1.82)
Group Average	18.88	46.79	-10.13	44.71
	(0.65)	(1.33)	(0.28)	(2.15)

Table VI:
Skewness Decomposition by the Beta-weighted Exogenous Factors

Beta-weighted factors are constructed from Fama-French 3 factors, Carhart 4 factors, Fung-Hsieh 7 factors, and 2 bond factors. Equity CEFs and ETFs use the beta-weighted Fama-French 3 factors. Equity open-ended funds and hedge funds use the beta-weighted Carhart 4 factors, and Fung-Hsieh 7 factors, respectively. Bond CEFs, ETFs, and open-ended funds use two more bond indexes in addition to the factors used in their equity counterparts - the Barclay U.S. government/credit index and corporation bond index. The weights to construct beta-weighted factors depend on the respective betas on each factor. Betas are estimated by regressing fund excess returns on factor excess returns. EW portfolio skewness is the cross-sectional average of skewness of beta-weighted factors. Individual skewness is the cross-sectional average of skewness of individual funds in each style. Skewness is the third central moment about the mean and computed as $\mathbb{E}[r_i^3]/\sigma_i^3$. r_i and σ_i are the demeaned return and standard deviation of fund i. COSKEW, ICOSKEW, and RESSKEW refer to the following components in the skewness decomposition:

$$\mathbb{E}(r_i^3) = \underbrace{\beta_i^2 cov(r_i, r_p^2) + 2\beta_i^2 cov(u_i, r_p^2)}_{COSKEW} + \underbrace{3\beta_i cov(u_i^2, r_p)}_{ICOSKEW} + \underbrace{\mathbb{E}(u_i^3)}_{RESSKEW}$$

where r_p is the demeaned return for the market portfolio. Individual COSKEW, ICOSKEW, and RESSKEW are the average of estimated values from the above equation by GMM across individual funds and reported as percentages of the skewness of demeaned fund returns $\mathbb{E}[r_i^3]$. FI and EF stand for fixed income and equity funds, respectively. Numbers in parentheses are t-values for COSKEW, ICOSKEW, and RESSKEW against the hypothesis of zero weight. *FI Average* is the average of statistics across fixed-income fund styles. *EF Average* is the average of statistics across equity fund styles. *Group Average* is the average of statistics across all fund styles.

Styles	EW Port Skewness	Individual Skewness	Individual COSKEW (%)	Individual ICOSKEW (%)	Individual RESSKEW (%)
Panel A: Closed-End Funds					
FI Global	−0.574	−0.602	41.59	43.16	22.61
			(−0.58)	(−0.93)	(−0.55)
FI Sector	−0.953	−0.399	17.23	50.57	30.62
			(−0.52)	(−0.58)	(−0.14)
FI Long Term	−1.046	−1.224	24.06	40.45	37.31
			(−0.10)	(−0.57)	(−0.38)
FI Intermediate Term	−0.346	0.203	33.08	21.62	38.87
			(0.52)	(0.27)	(−0.14)
FI Short Term	−0.644	−0.912	27.61	31.06	41.33
			(−0.15)	(−0.62)	(−0.62)
FI Government	−0.002	−0.185	−10.10	31.90	73.75
			(0.28)	(−0.35)	(−0.66)
FI High Yield	−0.892	−0.620	35.88	43.72	23.16
			(−1.17)	(−0.85)	(−0.19)
FI Others	−1.718	−1.656	27.92	45.98	26.33
			(−1.10)	(−1.11)	(−1.07)
FI Average	−0.772	−0.675	24.66	38.56	36.75
			(−0.35)	(−0.59)	(−0.47)
EF Balanced	−1.411	−0.780	56.15	37.73	1.82
			(−1.16)	(−1.08)	(0.20)
EF Commodities	−1.050	−0.059	13.74	36.45	48.92
			(−1.21)	(−0.02)	(0.92)
EF Global	−1.261	−0.162	42.24	35.65	18.19

Styles	EW Port Skewness	Individual Skewness	Individual COSKEW (%)	Individual ICOSKEW (%)	Individual RESSKEW (%)
			(−0.70)	(−0.43)	(0.26)
EF Sector	−1.256	−1.136	34.77	36.87	26.89
			(−0.67)	(−0.96)	(−0.47)
EF Large Cap	−1.301	−0.698	44.38	28.93	24.39
			(−0.99)	(−0.55)	(0.13)
EF Mid Cap	−0.738	−0.258	38.64	44.45	19.48
			(−0.72)	(−0.35)	(0.50)
EF Small Cap	−1.190	−0.138	60.32	15.79	23.89
			(−1.16)	(−0.17)	(0.65)
EF Growth	−1.276	−0.480	56.45	24.12	15.49
			(−0.92)	(−0.72)	(0.48)
EF Value	−1.732	−0.996	37.16	49.86	43.53
			(−1.01)	(−0.87)	(−0.17)
EF Others	−1.521	−1.426	71.28	19.91	−1.25
			(−1.12)	(−1.31)	(0.26)
EF Average	−1.274	−0.613	45.51	32.98	22.14
			(−0.96)	(−0.64)	(0.28)
Group Average	−1.051	−0.640	36.24	35.46	28.63
			(−0.69)	(−0.62)	(−0.05)
Panel B: ETFs					
FI Global	1.047	−0.314	135.92	−37.93	2.01
			(0.08)	(−0.99)	(0.41)
FI Sector	0.442	0.826	74.44	−24.43	49.99
			(0.82)	(−0.79)	(2.22)
FI Long Term	0.521	0.945	46.15	27.52	26.33
			(0.59)	(0.30)	(0.85)
FI Intermediate Term	0.350	0.585	61.15	−15.91	54.76
			(0.36)	(−0.28)	(1.32)
FI Short Term	0.032	−0.252	11.22	79.71	9.08
			(−0.05)	(−0.75)	(0.77)
FI Government	−0.352	0.526	−39.38	97.85	19.69
			(−0.41)	(0.99)	(0.64)
FI High Yield	0.444	0.654	144.24	−46.88	2.64
			(0.75)	(−0.49)	(0.58)
FI Others	4.09	−1.078	43.27	43.25	13.49
			(−0.91)	(−1.07)	(−0.20)
FI Average	0.162	0.236	59.63	15.40	22.25
			(0.15)	(−0.39)	(0.82)
EF Balanced	−0.495	−0.215	28.13	51.83	20.04
			(−0.93)	(0.02)	(1.13)
EF Global	−1.158	−0.733	88.37	2.47	8.92
			(−1.42)	(0.58)	(0.41)
EF Sector	−1.120	−0.726	74.80	20.61	0.27
			(−1.15)	(−0.30)	(0.29)
EF Commodities	−0.884	−0.892	89.40	13.56	−0.32
			(−1.42)	(−0.46)	(0.38)
EF Large Cap	−1.494	−1.310	95.59	4.35	0.18

Styles	EW Port Skewness	Individual Skewness	Individual COSKEW (%)	Individual ICOSKEW (%)	Individual RESSKEW (%)
			(−1.67)	(−0.57)	(−0.10)
EF Mid Cap	−1.354	−1.194	97.48	2.74	−0.62
			(−1.49)	(−0.41)	(0.44)
EF Small Cap	−1.367	−1.327	99.31	0.74	−0.16
			(−1.61)	(−0.27)	(0.02)
EF Growth	−1.143	−1.068	98.63	1.72	−0.45
			(−1.67)	(−0.47)	(−0.12)
EF Value	−1.673	−1.413	90.50	6.64	1.52
			(−1.53)	(−0.75)	(0.08)
EF Bear Market	−0.859	0.676	68.43	25.77	5.16
			(1.04)	(0.94)	(−0.43)
EF Currency	−1.328	−0.670	68.62	20.14	12.68
			(−0.47)	(−0.80)	(0.28)
EF Others	−1.159	−0.737	91.31	7.37	−1.07
			(−1.30)	(−0.11)	(0.30)
EF Average	−1.170	−0.801	82.55	13.16	3.85
			(−1.14)	(−0.22)	(0.22)
Group Average	−0.637	−0.386	73.38	14.06	11.21
			(−0.62)	(−0.28)	(0.46)
Panel C: Open-Ended Funds					
FI Index	0.166	−0.035	19.27	69.24	11.49
			(0.18)	(0.02)	(−0.50)
FI Global	−0.799	−0.556	10.45	13.12	74.46
			(−0.39)	(−0.30)	(0.10)
FI Short Term	−0.235	−0.890	25.12	28.16	47.71
			(−0.20)	(−0.45)	(−0.74)
FI Government	−0.208	−0.138	6.38	37.52	63.02
			(0.22)	(−0.38)	(−0.34)
FI Mortgage	−0.078	−0.420	13.81	37.08	57.28
			(−0.15)	(−0.54)	(−0.35)
FI Corporate	−0.471	−0.580	17.70	28.37	59.14
			(−0.06)	(−0.57)	(−0.68)
FI High Yield	−0.881	−1.174	54.63	13.86	33.40
			(−0.47)	(−0.70)	(−1.02)
FI Others	−0.308	0.286	33.13	9.97	55.44
			(−0.07)	(−0.09)	(0.60)
FI Average	−0.352	−0.439	22.56	29.67	50.24
			(−0.12)	(−0.38)	(−0.37)
EF Index	−1.068	−0.966	95.98	2.51	0.57
			(−1.43)	(−0.49)	(0.37)
EF commodities	−0.768	−0.516	53.30	16.87	34.83
			(−1.14)	(−0.73)	(0.34)
EF Sector	−0.642	−0.371	86.37	12.00	1.64
			(−0.71)	(−0.20)	(0.19)
EF Global	−0.958	−0.796	88.93	6.46	4.64
			(−1.23)	(0.03)	(0.00)
EF Balanced	−1.103	−1.098	89.70	6.38	3.60

Styles	EW Port Skewness	Individual Skewness	Individual COSKEW (%)	Individual ICOSKEW (%)	Individual RESSKEW (%)
			(−1.24)	(−0.52)	(0.10)
EF Leverage and Short	−0.669	−0.287	83.87	13.29	2.68
			(−0.40)	(−0.04)	(−0.09)
EF Long Short	−1.074	−0.980	98.29	6.13	−4.30
			(−1.69)	(−0.51)	(−0.55)
EF Mid Cap	−0.959	−0.919	95.43	4.80	−0.13
			(−1.15)	(−0.31)	(0.08)
EF Small Cap	−0.853	−0.741	94.79	5.05	0.15
			(−1.09)	(−0.20)	(0.14)
EF Aggressive Growth	−1.139	−0.734	96.85	−1.35	3.82
			(−1.06)	(0.80)	(0.19)
EF Growth	−0.963	−0.812	95.01	2.79	1.97
			(−1.28)	(−0.33)	(0.13)
EF Growth and Income	−0.970	−0.883	97.86	2.22	−0.23
			(−1.32)	(−0.21)	(0.25)
EF Equity Income	−0.876	−0.782	98.07	1.68	0.61
			(−1.02)	(−0.57)	(0.24)
EF Others	−0.837	−0.498	92.97	0.77	4.13
			(−0.76)	(0.56)	(0.12)
EF Average	−0.919	−0.742	90.53	5.69	3.85
			(−1.11)	(−0.19)	(0.11)
Group Average	−0.712	−0.631	65.81	14.41	20.72
			(−0.75)	(−0.26)	(−0.06)
Panel D: Hedge Funds					
Equity Hedge	0.458	−0.299	25.50	35.17	39.09
			(−0.23)	(−0.35)	(−0.07)
Event-Driven	0.823	−0.618	35.04	33.95	31.73
			(−0.53)	(−0.57)	(−0.18)
Fund of Funds	0.875	−0.981	24.86	41.13	32.78
			(−0.60)	(−0.96)	(−0.69)
HFRI	1.683	−1.115	52.08	32.13	17.61
			(−1.07)	(−0.84)	(−0.25)
HFRX	1.788	−1.709	−7.77	−29.76	137.54
			(−0.43)	(−1.32)	(−0.39)
Macro	0.202	0.012	33.18	19.93	41.59
			(0.15)	(0.04)	(0.01)
Relative Value	0.668	−1.208	31.81	34.61	34.24
			(−0.43)	(−0.77)	(−0.47)
Group Average	0.928	−0.845	27.81	23.88	47.80
			(−0.45)	(−0.68)	(−0.29)

Table VII:
Kurtosis Decomposition by the Beta-weighted Exogenous Factors

Beta-weighted factors are constructed from Fama-French 3 factors, Carhart 4 factors, Fung-Hsieh 7 factors, and 2 bond factors. Equity CEFs and ETFs use the beta-weighted Fama-French 3 factors. Equity open-ended funds and hedge funds use the beta-weighted Carhart 4 factors, and Fung-Hsieh 7 factors, respectively. Bond CEFs, ETFs, and open-ended funds use two more bond indexes in addition to the factors used in their equity counterparts - the Barclay U.S. government/credit index and corporation bond index. The weights to construct beta-weighted factors depend on the respective betas on each factor. Betas are estimated by regressing fund excess returns on factor excess returns. EW portfolio kurtosis is the cross-sectional average of kurtosis of beta-weighted factors. Individual kurtosis is the cross-sectional average of kurtosis of individual funds in each style. Kurtosis is the fourth central moment about the mean and computed as $\mathbb{E}[r_i^4]/\sigma_i^4 - 3$. r_i and σ_i are the demeaned return and standard deviation of fund i. COKURT, VOLCOMV, ICOKURT, and RESKURT refer to the following components in the kurtosis decomposition:

$$\mathbb{E}(r_i^4) = \underbrace{\beta_i^3 cov(r_i, r_p^3) + 3\beta_i^3 cov(u_i, r_p^3)}_{COKURT} + \underbrace{6\beta_i^2 \mathbb{E}(r_p^2 u_i^2)}_{VOLCOMV} + \underbrace{4\beta_i cov(u_i^3, r_p)}_{ICOKURT} + \underbrace{\mathbb{E}(u_i^4))}_{RESKURT}$$

where r_p is the demeaned return for the beta-weighted factors. Individual COKURT, VOLCOMV, ICOKURT, and RESKURT are the average of estimated values from the above equation by GMM across individual funds and reported as percentages of the kurtosis of demeaned fund returns $\mathbb{E}[r_i^4]$. FI and EF stand for fixed income and equity funds, respectively. Numbers in parentheses are t-values for COSKEW, ICOSKEW, and RESSKEW against the hypothesis of zero weight. *FI Average* is the average of statistics across fixed-income fund styles. *EF Average* is the average of statistics across equity fund styles. *Group Average* is the average of statistics across all fund styles.

Styles	EW Port Kurtosis	Individual Kurtosis	Individual COKURT (%)	Individual VOLCOMV (%)	Individual ICOKURT (%)	Individual RESKURT (%)
Panel A: Closed-End Funds						
FI Global	2.746	6.080	14.40	27.69	18.79	36.80
			(0.92)	(1.44)	(1.06)	(2.67)
FI Sector	3.270	4.611	5.23	26.79	15.40	51.98
			(0.70)	(1.39)	(1.00)	(2.68)
FI Long Term	5.264	8.322	11.30	19.77	14.87	54.04
			(0.54)	(1.38)	(0.98)	(2.12)
FI Intermediate Term	3.594	5.443	3.46	20.80	15.67	60.89
			(0.79)	(1.61)	(1.29)	(2.74)
FI Short Term	2.044	4.361	9.81	18.24	13.01	58.94
			(−0.14)	(1.40)	(1.05)	(2.67)
FI Government	0.750	2.305	0.57	10.51	5.81	82.79
			(0.28)	(1.32)	(0.65)	(2.51)
FI High Yield	2.621	3.708	8.99	30.42	14.85	44.63
			(1.21)	(1.67)	(1.24)	(2.65)
FI Others	8.538	6.415	8.91	41.37	19.53	29.81
			(0.71)	(1.21)	(1.42)	(1.84)
FI Average	3.603	5.156	7.83	24.45	14.74	52.48
			(0.62)	(1.43)	(1.09)	(2.48)
EF Balanced	4.621	4.193	20.13	37.79	8.76	32.81
			(1.19)	(1.68)	(0.82)	(2.17)
EF Commodities	2.748	2.725	17.71	35.60	4.72	39.76
			(1.20)	(2.14)	(0.62)	(2.55)
EF Global	4.518	4.424	17.42	32.38	9.61	40.91

Styles	EW Port Kurtosis	Individual Kurtosis	Individual COKURT (%)	Individual VOLCOMV (%)	Individual ICOKURT (%)	Individual RESKURT (%)
			(0.86)	(1.81)	(0.88)	(2.74)
EF Sector	4.861	4.279	19.55	39.53	7.99	31.30
			(0.62)	(1.44)	(0.70)	(2.55)
EF Large Cap	5.141	5.530	25.55	41.39	8.17	21.42
			(1.09)	(1.59)	(0.90)	(2.45)
EF Mid Cap	3.140	4.565	22.54	38.02	8.98	23.25
			(1.04)	(1.81)	(0.68)	(2.82)
EF Small Cap	3.346	3.321	33.94	25.32	2.18	38.55
			(1.40)	(2.03)	(0.55)	(3.10)
EF Growth	3.710	4.707	28.12	31.77	7.24	29.89
			(0.98)	(1.67)	(0.63)	(2.52)
EF Value	5.606	3.886	13.76	53.38	6.21	23.54
			(0.73)	(1.42)	(0.79)	(2.15)
EF Others	4.585	5.649	40.51	33.07	6.33	17.54
			(1.00)	(1.91)	(0.80)	(2.40)
EF Average	4.228	4.328	23.92	36.83	7.02	29.90
			(1.01)	(1.75)	(0.74)	(2.54)
Group Average	3.950	4.696	16.77	31.33	10.45	39.94
			(0.84)	(1.61)	(0.89)	(2.52)
Panel B: ETFs						
FI Global	1.354	2.910	33.42	42.41	6.63	17.54
			(0.76)	(1.40)	(1.00)	(2.42)
FI Sector	1.820	1.841	20.78	62.23	−20.61	37.60
			(0.56)	(1.36)	(−0.55)	(2.15)
FI Long Term	2.156	7.720	16.85	22.49	15.72	44.94
			(0.49)	(1.00)	(0.56)	(2.14)
FI Intermediate Term	1.805	3.537	18.03	39.49	−1.36	43.85
			(0.52)	(1.12)	(0.05)	(1.96)
FI Short Term	1.432	2.156	14.42	36.50	−4.77	53.85
			(0.94)	(1.13)	(−0.09)	(1.82)
FI Government	1.583	1.444	1.57	38.33	4.27	56.37
			(0.16)	(1.23)	(0.31)	(2.29)
FI High Yield	0.991	2.636	72.62	26.28	−0.63	1.74
			(1.12)	(2.27)	(−0.19)	(2.14)
FI Others	3.516	3.699	26.57	47.05	0.80	25.58
			(0.68)	(1.36)	(0.09)	(2.07)
FI Average	1.832	3.243	25.53	39.35	0.01	35.18
			(0.65)	(1.36)	(0.15)	(2.12)
EF Balanced	−0.293	1.988	46.27	31.39	11.01	11.33
			(1.21)	(1.35)	(2.03)	(2.20)
EF Global	2.252	2.404	67.05	21.44	2.57	8.68
			(1.43)	(2.32)	(0.40)	(2.58)
EF Sector	2.475	1.687	55.01	29.01	−0.25	16.49
			(1.36)	(2.15)	(0.13)	(2.44)
EF Commodities	2.052	1.430	61.38	27.92	−3.39	14.13
			(1.36)	(2.35)	(−0.38)	(2.43)
EF Large Cap	3.501	2.842	88.41	9.75	0.28	0.57

Styles	EW Port Kurtosis	Individual Kurtosis	Individual COKURT (%)	Individual VOLCOMV (%)	Individual ICOKURT (%)	Individual RESKURT (%)
			(1.60)	(2.25)	(−0.01)	(2.47)
EF Mid Cap	2.627	2.648	87.58	10.54	0.49	1.66
			(1.49)	(2.36)	(0.22)	(2.51)
EF Small Cap	2.781	2.731	93.75	5.88	0.05	0.22
			(1.55)	(2.43)	(−0.25)	(2.53)
EF Growth	1.961	1.884	88.07	11.39	0.13	0.76
			(1.79)	(2.61)	(0.03)	(2.56)
EF Value	4.289	3.579	81.71	11.59	2.61	2.85
			(1.40)	(2.06)	(0.30)	(2.36)
EF Bear Market	1.356	1.142	56.81	31.56	3.70	7.84
			(1.25)	(1.91)	(0.19)	(2.25)
EF Currency	2.791	3.786	37.36	34.30	4.05	24.77
			(0.73)	(1.65)	(0.27)	(2.32)
EF Others	2.158	1.749	63.24	27.58	1.25	4.44
			(1.58)	(2.21)	(0.31)	(2.61)
EF Average	2.329	2.323	68.89	21.03	1.88	7.81
			(1.40)	(2.14)	(0.27)	(2.44)
Group Average	2.130	2.691	51.55	28.36	1.13	18.76
			(1.10)	(1.82)	(0.22)	(2.31)
Panel C: Open-Ended Funds						
FI Index	1.733	1.412	1.80	31.32	1.30	65.57
			(0.05)	(1.52)	(0.29)	(2.63)
FI Global	3.549	3.739	20.32	29.09	6.65	43.96
			(0.75)	(1.45)	(0.70)	(2.88)
FI Short Term	3.699	5.023	12.68	28.73	3.11	56.08
			(0.62)	(1.47)	(0.44)	(2.51)
FI Government	2.232	1.311	3.82	26.34	−1.65	72.39
			(0.03)	(1.43)	(0.12)	(2.92)
FI Mortgage	2.061	2.018	9.05	27.42	2.03	61.33
			(0.39)	(1.52)	(0.43)	(2.84)
FI Corporate	2.674	2.578	12.86	29.27	4.46	53.43
			(0.58)	(1.51)	(0.57)	(2.58)
FI High Yield	4.426	5.553	36.92	32.94	3.21	27.33
			(0.95)	(2.09)	(0.57)	(2.66)
FI Others	2.070	3.412	15.20	19.88	−0.84	66.49
			(0.43)	(1.29)	(−0.04)	(2.85)
FI Average	2.806	3.131	14.08	28.12	2.28	55.82
			(0.47)	(1.53)	(0.39)	(2.73)
EF Index	2.484	2.850	87.34	10.00	0.01	1.90
			(1.87)	(2.79)	(0.18)	(2.83)
EF Commodities	1.800	1.585	34.93	34.79	−0.98	31.00
			(1.03)	(2.16)	(−0.02)	(2.83)
EF Sector	1.559	1.268	57.22	31.86	0.40	10.43
			(1.78)	(2.48)	(0.15)	(2.93)
EF Global	2.023	2.245	66.39	25.07	0.18	7.95
			(1.57)	(2.72)	(0.00)	(2.84)
EF Balanced	2.643	3.332	76.37	17.82	0.42	4.54

Styles	EW Port Kurtosis	Individual Kurtosis	Individual COKURT (%)	Individual VOLCOMV (%)	Individual ICOKURT (%)	Individual RESKURT (%)
			(1.60)	(2.65)	(0.31)	(2.63)
EF Leverage and Short	1.511	1.597	63.23	26.77	0.81	8.70
			(1.74)	(2.36)	(0.23)	(2.59)
EF Long Short	1.739	1.439	75.20	19.82	1.72	3.17
			(1.48)	(2.01)	(0.37)	(2.45)
EF Mid Cap	2.032	2.579	82.92	15.60	0.30	1.00
			(1.71)	(2.67)	(0.25)	(2.72)
EF Small Cap	1.881	1.930	84.21	14.58	0.02	1.05
			(1.80)	(2.77)	(0.01)	(2.71)
EF Aggressive Growth	2.797	2.067	74.67	17.15	1.04	6.71
			(1.43)	(2.55)	(0.17)	(2.61)
EF Growth	2.172	2.114	80.98	15.26	0.16	2.63
			(1.93)	(2.71)	(0.14)	(2.70)
EF Growth and Income	2.285	2.169	86.95	11.60	0.19	0.97
			(1.87)	(2.69)	(0.19)	(2.66)
EF Equity Income	2.488	2.041	81.92	16.17	0.27	1.38
			(1.79)	(2.45)	(0.00)	(2.70)
EF Others	2.725	1.994	72.46	20.63	0.51	5.78
			(1.47)	(2.56)	(0.12)	(2.62)
EF Average	2.153	2.086	73.20	19.80	0.36	6.23
			(1.65)	(2.54)	(0.15)	(2.70)
Group Average	2.390	2.466	51.70	22.82	1.06	24.26
			(1.22)	(2.17)	(0.23)	(2.71)
Panel D: Hedge Funds						
Equity Hedge	2.316	2.001	10.75	32.73	−0.82	57.31
			(0.41)	(1.25)	(0.22)	(2.50)
Event-Driven	3.158	4.071	19.04	33.37	3.82	44.35
			(0.57)	(1.42)	(0.54)	(2.45)
Fund of Funds	3.030	2.951	14.08	40.21	3.48	42.06
			(0.50)	(1.33)	(0.50)	(2.39)
HFRI	6.654	6.471	17.96	27.41	10.30	44.30
			(0.93)	(1.64)	(1.27)	(2.90)
HFRX	5.915	6.048	28.63	47.71	−10.42	34.08
			(0.43)	(1.34)	(0.01)	(2.25)
Macro	1.449	2.006	9.42	31.69	−1.27	60.01
			(0.42)	(1.26)	(0.16)	(2.44)
Relative Value	3.122	7.001	19.63	29.62	5.14	45.70
			(0.58)	(1.32)	(0.60)	(2.27)
Group Average	3.664	4.364	17.07	34.68	1.46	46.83
			(0.55)	(1.36)	(0.47)	(2.46)