Do Hedge Funds Exploit Rare Disaster Concerns?*

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Abstract

We investigate whether hedge fund managers with better skills of exploiting market *ex ante* rare disaster concerns, which may not realize as disaster shocks *ex post*, deliver superior future fund performance. We propose a measure of the fund skills on exploiting disaster concerns (SED) based on the covariation between fund returns and a disaster concern index we develop through out-of-the-money puts on various economic sector indices. Funds earning higher returns when the index is high possess better skills of exploiting market disaster concerns. We document substantial heterogeneity as well as strong persistence in SED. Our main result shows that high-SED funds on average outperform low-SED by more than 0.9% per month and even more during stressful market times. High-SED funds are also shown to have less disaster risk exposure.

Keywords: Rare disaster concern; hedge fund; skill

JEL classifications: G11; G12; G23

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1 Introduction

Prior research on the performance of hedge funds regarding disaster risk focuses on covariance of fund returns and *ex post* realized disaster shocks. In time series, a number of hedge fund investment styles, characterized as *de facto* sellers of put options, incur huge losses when market goes south (Mitchell and Pulvino (2001) and Agarwal and Naik (2004)). In cross sections, individual hedge funds have heterogeneous disaster risk exposure, and funds with higher exposure to disaster shocks usually earn higher returns during normal time, followed by losses during stressful time (Agarwal, Bakshi, and Huij (2010); Jiang and Kelly (2012)). At its face value, the evidence suggests that hedge funds are much like conventional assets: they earn higher returns simply by being more exposed to disaster risk.

We provide novel evidence that some hedge fund managers with skills of exploiting *ex ante* market disaster concerns, which may not realize as *ex post* disaster shocks, deliver superior future fund performance, yet being less exposed to disaster risk. Key to our study is to differentiate *ex ante* disaster concerns and *ex post* realized shocks. Figure 1 plots monthly time-series of a rare disaster concern (RIX) index we construct using out-of-the-money put options on various economic sector indices. The index value essentially equals to an insurance price against extreme downside movements of the financial market in the future (see Section 2 for details). Two salient features emerge from Figure 1. First, the market disaster concerns spike when the market *fears* future disaster events such as the peak of Nasdaq, the "quant crisis" in 2007, the "flash crash" in 2011, and the market rally in October 2011 that are not followed by market losses. Second, though many peaks of disaster concerns happen when the financial market experiences realized shocks such as the LTCM collapse, the crash of Nasdaq, and the recent financial crisis, magnitudes of disaster concern increase seem to be enormous relative to the subsequent realized losses. Such a startling difference hints the possibility that investors may be paying a "fear premium" beyond the compensation for realized shocks, which could be consistent with behaviors of non-expected utility agents who are averse to the tail event (Quiggin (1993); Barberis and Huang (2008); Caballero and Krishnamurthy (2008); Baberis (2013)), or with market mispricing or sentiment (Bondarenko (2003); Han (2008)). Under such circumstances, hedge fund managers with better skills of exploiting such disaster concerns or "fear premium" could deliver superior future fund performance.

How do certain hedge funds exploit such *ex-ante* disaster concerns better than others while being less exposed to disaster shocks? First of all, some fund managers may be better than others in identifying market concerns that are fears with no subsequent disaster shocks. By supplying the disaster insurance to investors with high disaster concerns, they profit more than others who do not possess such skills and who are unable to take advantage of such opportunities.[1] Second, even when disaster concerns subsequently realized as disaster shocks, some fund managers may be better than others in identifying whether there is a "fear premium" beyond the compensation for realized shocks. Extracting such "fear premium", they profit more than others who do not possess such skills. Third, "difficulty in inference regarding...severity of disasters...can effectively lead to significant disagreements among investors about disaster risk" (Chen, Joslin, and Tran (2012)). As a result, different investors can have different disaster concerns with different levels of "fear premium" when the market disaster concern is high, regardless of whether it is followed by a realized disaster shock or not. Some hedge fund managers may have better skills of identifying the investors who are willing to pay higher premium for disaster insurance. From an operational perspective, many of the standard financial insurance contracts, including options on fixed-income securities, currencies, and certain equities, are traded on the over-the-counter (OTC) market. Thus funds with different networks have different ability to locate investors paying high premiums. In summary, skills of exploiting disaster concerns can contribute to higher returns of certain hedge funds and not necessarily make them more exposed to disaster shocks.

While covariance between hedge fund returns and *ex post* realized shocks helps us to understand hedge fund risk profiles, it is the covariance between hedge fund returns and *ex ante* disaster concerns that helps to identify skillful hedge fund managers. In principal, funds with better skills should earn higher contemporaneous returns than those with no such skills when the market concern is high. Empirically, we measure fund skills on exploiting rare disaster concerns (SED) by the covariation of fund returns and the disaster concern index we construct.[2] Consistent with the view that hedge funds exhibit different skills in exploiting rare disaster concerns, we document

[1] "Supplying the disaster insurance" here does not literally mean hedge funds write a disaster insurance contract to investors. As argued by Stulz (2007), hedge funds, as a group of sophisticated and skillful investors who frequently use short sales, leverage, and derivatives, are capable of supplying earthquake-type rare disaster insurance through dynamic trading strategies, market timing, and asset allocations.

[2] In the same vein, Sialm, Sun, and Zheng (2012) use fund of funds' return loadings on some local/non-local factors to measure the fund's local bias, different from the conventional β interpretation.

substantial heterogeneity across hedge funds as well as significant persistence in SED.

Our main tests focus on the relation between the SED measures and future fund performance. Among the sample of funds in our study, funds in the highest SED decile on average outperform funds in the lowest SED decile by 0.96% per month (t-statistic of 3.7).[3] Moreover, the better performance of higher SED funds is not short-lived. The return spread of the high-minus-low SED deciles ranges from 0.84% per month (t-statistic of 3.6) for a three-month holding horizon, to 0.44% per month (t-statistic of 2.2) for a 12-month holding horizon. We also show that the outperformance of high SED funds is pervasive across almost all hedge fund investment styles. These results are inconsistent with the view that hedge funds earn higher returns on average simply by being more exposed to disaster risk. If the SED measure, as the covariation between fund returns and disaster concern index, were interpreted as measuring disaster risk exposure, then the better SED funds should earn lower returns (rather than higher returns we documented) on average because they are better hedges against disaster risk.

However, it is still possible that high SED funds may have more disaster risk exposure in exploiting disaster concerns, and the higher average returns they earn over the full sample are just a result of better performance during normal times and (hypothetically) worse performance during stressful times that are too short in our sample between 1996 and 2010. To address this concern, we carefully study the performance of all SED fund deciles in both stressful and normal times under a variety of definitions of market states. We find that although all fund deciles incur losses during market downturns, high SED funds significantly outperform low SED funds. In other words, high SED funds lose less than low SED funds because of their better skills in exploiting disaster concerns rather than simply taking more disaster risk exposure. Moreover, we study the exposure of SED-based fund deciles to realized disaster risk measures such as default risk factor and various liquidity risk factors. We find that higher SED funds have less disaster risk exposure, further collaborating our conclusion that hedge fund managers with better skills of exploiting *ex-ante* market disaster concerns deliver superior future fund performance, yet being less exposed to disaster risk. Finally,

[3] We also perform time series analysis on dozens of hedge fund indices from Hedge Fund Research Inc. (HFRI). In estimating regressions of hedge fund index monthly excess returns on market excess return and $\mathbb{RIX}$, we find negative and statistically significant $\mathbb{RIX}$ loadings for the majority of HFRI investment strategies. These results confirm the points made elsewhere that the payoffs of hedge fund strategies resemble a payoff from a written put, and hence these strategies are sensitive to extreme downside market movements (Lo (2001); Goetzmann et al. (2002); Agarwal and Naik (2004)).

we also confirm that high SED funds exhibit significantly higher survival rates.

Throughout the paper, we compute risk-adjusted abnormal returns using the Fung and Hsieh (2001, 2004) seven-factor model (and also the Fama-French (1993) three-factor model augmented with the Carhart (1997) momentum factor and the Pastor-Stambaugh (2003) liquidity factor). The return difference between the high and low SED funds remains highly significant (both economically and statistically) relative to the Fung-Hsieh model. We also conduct portfolio analysis and Fama-MacBeth (1973) regressions to control for hedge fund characteristic effects and to verify the less exposure of higher SED funds to other risk factors in the hedge fund literature, including market risk, downside market risk, and volatility risk (Ang, Chen, and Xing (2006); Ang et al. (2006)), market liquidity risk (Pastor and Stambaugh (2003); Acharya and Pedersen (2005); Sadka (2006)), funding liquidity risk (Mitchell, Pedersen, and Pulvino (2007); Brunnermeier and Pedersen (2009); Hu, Pan, and Wang (2012); Mitchell and Pulvino (2012)), and macroeconomic risk (Bali, Brown, and Caglayan (2011)), and hedge fund total variance risk by Bali, Brown, and Caglayan (2012).

Our paper contributes to the literature of cross-sectional hedge fund skills and performance, including Agarwal, Daniel, and Naik (2009), Aggarwal and Jorion (2010), Aragon (2007), Cao, Chen, Liang, and Lo (2012), Fung, Hsieh, Naik, and Ramadorai (2008), Liang and Park (2008), Li, Zhang, and Zhao (2011), Sun, Wang and Zheng (2012, 2013), and Titman and Tiu (2011). We investigate the distinctiveness of the SED in predicting fund performance from other fund skill measures, such as the fund skill of hedging away of systematic risk measured by R-squared of fund returns on the Fung-Hsieh seven factors (Titman and Tiu, 2011), the skill of adopting innovative strategies captured by correlation with peer funds (Sun, Wang, Zheng, 2012), and the skill of timing market liquidity (Cao, Chen, Liang, and Lo, 2012). We also show that VIX has no power in explaining cross-sectional hedge fund returns.

Our results are robust to alternative ways of measuring *ex-ante* disaster concerns such as the measure by Bollerslev and Todorov (2011) based on intraday returns and short-maturity OTM options and an average price of certain OTM puts.[4] Our results also persist according to a battery of robustness checks such as portfolio weights, fund size, fund delisting returns, and different benchmark models.

[4] The methodology of Bollerslev and Todorov (2011) requires the option maturiy to coverge to zero, and hence is only applicable to closest-to-maturity options. In contrast, the $\mathbb{RIX}$ construction works for any fixed maturities and.

The remainder of the paper is organized as follows. Section 2 describes the construction of our disaster concern index. Sections presents the SED measure and its properties across the pool of hedge funds. Section 4 reports cross-sectional analysis of fund performance based on SED. Section 5 shows the uniqueness of SED in predicting cross-sectional fund performance from other documented fund skills in the literature. We perform robustness checks in Section 6 and conclude in Section 7.

2 Quantifying Rare Disaster Concerns

In this section, we develop a rare disaster concern index ($\mathbb{RIX}$) to quantify the *ex-ante* market expectation about disaster events in the future. In particular, the value of $\mathbb{RIX}$ depends on the price difference between two option-based replication portfolios of variance swap contracts. The first portfolio accounts for mild market volatility shocks, and the second for extreme volatility shocks induced by market jumps associated with rare event risk. By construction, the $\mathbb{RIX}$ equals the insurance price against extreme downside movements of the financial market in the future.

2.1 Construction of $\mathbb{RIX}$

Consider an underlying asset whose time-t price is S_t. We assume for simplicity that the asset does not pay dividends. An investor holding this security is concerned about its price fluctuations over a time period $[t, T]$. One way to protect herself against price changes is to buy a contract that delivers payments equal to the extent of price variations over $[t, T]$, minus a prearranged price. Such a contract is called a "variance" swap contract as the price variations are essentially about the stochastic variance of the price process.[5] The standard variance swap contract in practice pays

$$\left(\ln \frac{S_{t+\Delta}}{S_t}\right)^2 + \left(\ln \frac{S_{t+2\Delta}}{S_{t+\Delta}}\right)^2 + \cdots + \left(\ln \frac{S_T}{S_{T-\Delta}}\right)^2$$

minus the prearranged price $\mathbb{VP}$. That is, the variance swap contract uses the sum of squared log returns to measure price variations, which is a standard practice in the finance literature (Singleton (2006)).[6]

[5] The variance here refers to stochastic changes of the asset price, and hence is different from (more general than) the seond-order central moment of the asset return distribution (see Equation (5)).

[6] Martin (2012) recently proposes a simple variance swap contract with payments in the form of simple returns rather than log returns.

In principle, replication portfolios consisting of out-of-the-money (OTM) options written on S_t can be used to replicate the time-varying payoff associated with the variance swap contract and hence to determine the price $\mathbb{VP}$. We now introduce two replication portfolios and their implied prices for the variance swap contract. The first, which underlies the construction of VIX by the CBOE, focuses on the limit of the discrete sum of squared log returns, determines $\mathbb{VP}$ as

$$\mathbb{IV} \equiv \frac{2e^{r\tau}}{\tau} \left\{ \int_{K>S_t} \frac{1}{K^2} C(S_t; K, T) dK + \int_{K<S_t} \frac{1}{K^2} P(S_t; K, T) dK \right\}, \tag{1}$$

where r is the constant risk-free rate, $\tau \equiv T - t$ is the time-to-maturity, and $C(S_t; K, T)$ and $P(S_t; K, T)$ are prices of call and put options with strike K and maturity date T, respectively. As observed from equation (1), this replication portfolio contains positions in OTM calls and puts with a weight inversely proportional to their squared strikes. $\mathbb{IV}$ has been employed in the literature to construct measures of variance risk premiums (Bollerslev, Tauchen, and Zhou (2009), Carr and Wu (2009), and Drechsler and Yaron (2011)).

The second replication portfolio relies on $Var_t^{\mathbb{Q}}(\ln S_T/S_t)$ that avoids the discrete sum approximation, and determines $\mathbb{VP}$ as

$$\mathbb{V} \equiv \frac{2e^{r\tau}}{\tau} \left\{ \int_{K>S_t} \frac{1 - \ln(K/S_t)}{K^2} C(S_t; K, T) dK + \int_{K<S_t} \frac{1 - \ln(K/S_t)}{K^2} P(S_t; K, T) dK \right\}. \tag{2}$$

This replication portfolio differs from the first in equation (1) by assigning larger (smaller) weights to more deeply OTM put (call) options. As strike price K declines (increases), i.e., put (call) options become more out of the money, $1 - \ln(K/S_t)$ becomes larger (smaller). Since more deeply OTM options protect investors against larger price changes, it is intuitive that the difference between $\mathbb{IV}$ and $\mathbb{V}$ captures investors' expectation about the distribution of large price variations.

Our $\mathbb{RIX}$ is equal to the difference between $\mathbb{V}$ and $\mathbb{IV}$ essentially, which is due to extreme deviations of S_T from S_t. However, both upside and downside price jumps contribute to this difference. Given the results of many recent studies that investors are more concerned about downside price swings (Ang, Chen and Xing (2006); Barro (2006); Gabaix (2012); Liu, Pan, and Wang (2005); Watcher (2012)), we focus on downside rare events associated with unlikely but extreme negative price jumps. In particular, we consider the downside versions of both $\mathbb{IV}$ and $\mathbb{V}$:

$$
\begin{aligned}
\mathbb{IV}^- &\equiv \frac{2e^{r\tau}}{\tau}\int_{K<S_t}\frac{1}{K^2}P(S_t;K,T)dK, \\
\mathbb{V}^- &\equiv \frac{2e^{r\tau}}{\tau}\int_{K<S_t}\frac{1-\ln\left(K/S_t\right)}{K^2}P(S_t;K,T)dK,
\end{aligned} \tag{3}
$$

where only OTM put options that protect investors against negative price jumps are used. We then define our disaster concern index as

$$
\mathbb{RIX} \equiv \mathbb{V}^- - \mathbb{IV}^- = \frac{2e^{r\tau}}{\tau}\int_{K<S_t}\frac{\ln\left(S_t/K\right)}{K^2}P(S_t;K,T)dK. \tag{4}
$$

Assume the price process follows the Merton (1976) jump-diffusion model with $dS_t/S_t = (r-\lambda\mu_J)\,dt + \sigma dW_t + dJ_t$,where r is the constant risk-free rate, σ is the volatility, W_t is a standard Brownian motion, J_t is a compound Poisson process with jump intensity λ, and the compensator for the Poisson random measure $\omega\left[dx,dt\right]$ is equal to $\lambda\frac{1}{\sqrt{2\pi}\sigma_J}\exp\left(-\left(x-\mu_J\right)^2/2\right)$. We can show that

$$
\mathbb{RIX} \equiv 2\mathbb{E}_t^{\mathbb{Q}}\int_t^T\int_{R_0}\left(1+x+x^2/2-e^x\right)\omega^-\left[dx,dt\right], \tag{5}
$$

where $\omega^-\left[dx,dt\right]$ is the Poisson random measure associated with negative price jumps. Therefore, our $\mathbb{RIX}$ captures all the high-order (≥ 3) moments of the jump distribution with negative sizes given that $e^x-(1+x+x^2/2) = x^3/3 + x^4/4 + \cdots$.

Motivated by the fact that hedge funds invest in different sectors of the economy, we make one further extension particularly relevant for analyzing hedge fund performance. Namely, we measure market concerns about future rare disaster events associated with various economic sectors, instead of relying on the S&P 500 index exclusively. In particular, we employ liquid index options on six sectors: KBW banking sector (BKX), PHLX semiconductor sector (SOX), PHLX gold and silver sector (XAU), PHLX housing sector (HGX), PHLX oil service sector (OSX), and PHLX utility sector (UTY). This allows us to avoid the caveat that the perceived disastrous outcome of one economic sector may be offset by a euphoric outlook in another sector so that disaster concerns estimated using a single market index may miss those of certain sectors some hedge funds concentrate in. Specifically, we first use OTM puts on each sector index to calculate sector-level disaster concern indices, and then take a simple average across them to obtain a market-level $\mathbb{RIX}$. Such a construction is likely to incorporate disaster concerns on various economic sectors, which is particularly important for investigating hedge fund performance.

2.2 Options data and empirical estimation

We obtain daily options data from OptionMetrics from 1996 through 2011. For both European calls and puts on the six sector indices we consider, the dataset includes daily best closing bid and ask prices, in addition to implied volatility and option Greeks (delta, gamma, vega, and theta). Following the literature, we clean the data as follows: (1) We exclude options with non-standard expiration dates, with missing implied volatility, with zero open interest, and with either zero bid price or negative bid–ask spread; (2) We discard observations with bid or ask price less than 0.05 to mitigate the effect of price recording errors; and (3) We remove observations where option prices violate no-arbitrage bounds. Because there is no closing price in OptionMetrics, we use the mid-quote price (i.e., the average of best bid and ask prices) as the option price.[7] Finally, we consider only options with maturities longer than 7 days and shorter than 180 days for liquidity reasons.

We focus on the 30-day horizon to illustrate the construction of $\mathbb{RIX}$, i.e., $T-t=30$. On a daily basis, we choose options with exactly 30 days to expiration, if they are available. Otherwise, we choose two contracts with the nearest maturities to 30 days, with one longer and the other one shorter than 30 days. We keep only out-of-the-money put options and exclude days with fewer than two option quotes of different moneyness levels for each chosen maturity. As observed from (4), the computation of $\mathbb{RIX}$ relies on a continuum of moneyness levels. Following Carr and Wu (2009), and Du and Kapadia (2012), we interpolate implied volatilities across the range of observed moneyness levels. For moneyness levels outside the available range, we use the implied volatility of the lowest (highest) moneyness contract for moneyness levels below (above) it.

In total, we generate 2,000 implied volatility points equally spaced over a strike range of zero to three times the current spot price for each chosen maturity on each date. We then obtain a 30-day implied volatility curve either exactly or by interpolating the two implied volatility curves of the two chosen maturities. Finally, we use the generated 30-day implied volatility curve to

[7] Using the mid-quote price makes it possible that two put options with the same maturity but different strikes end up having the same option price. In this case, we discard the one that is further away from at-the-money (ATM).

compute the OTM option prices using the Black–Scholes (1973) formula and then $\mathbb{RIX}$ according to a discretization of equation (4) for each day. After obtaining those daily estimates, we take the daily average over the month to deliver a monthly time series of $\mathbb{RIX}$, extending from January 1996 through December 2011. Similar to Du and Kapadia (2012), we divide $\mathbb{RIX}$ by $\mathbb{V}^{-}$ as a normalization to mitigate the effect of different volatility levels across different economy sectors.

Table 1 reports average daily open interest of sector-level index put options with maturities between 14 and 60 days, which provide a sufficient number of contracts to interpolate a 30-day option. We categorize the puts into groups according to their moneyness. Although the number of option contracts varies across different sector indices, we observe a substantial amount of daily open interest for OTM put options (e.g., moneyness $K/S \leq 0.90$). Therefore, the sector-level OTM index puts we use are generally liquid, and thus the liquidity effect of these OTM puts on $\mathbb{RIX}$ is expected to be minor.

2.3 Descriptive statistics

Table 2 presents descriptive statistics of disaster concern indices. Panel A shows a mean of 0.063 for the monthly aggregated $\mathbb{RIX}$, with standard deviation equal to 0.02. Among sector-level disaster concern indices, the semiconductor sector has the highest mean and median (0.076 and 0.070, respectively), whereas the utility sector has the lowest mean and median (0.029 and 0.027, respectively). Interestingly, the banking sector has the highest standard deviation, probably as a result of the 2007-2008 financial crisis. Figure 1 presents a time-series plot of the aggregated $\mathbb{RIX}$ that illustrates how the market's perception on future disaster events varies over time. As discussed in the introduction, we observe that disaster concerns can peak without being followed by market losses, and frequently spike up much more than the subsequent realized market losses.

Panel B of Table 2 further reports correlations between $\mathbb{RIX}$ and a set of risk factors related to market, size, book-to-market equity, momentum, trend following, market liquidity, funding liquidity, term spread, default spread, and volatility. We find that $\mathbb{RIX}$ is only mildly correlated with the usual equity risk factors (-0.17 -0.12 for book-to-market and momentum factors, respectively) and hedge fund risk factors (0.25 and 0.18 for the Fung-Hsieh trend-following factors $PTFSBD$ of bond and $PTFSIR$ of short-term interest rate, respectively). More important, $\mathbb{RIX}$ is weakly correlated with risk factors that can proxy for market disaster shocks, e.g., between 0.20 and 0.31 with market liquidity (Pastor and Stambaugh, 2003; Sadka, 2006), around 0.22 with change of default spread, and only -0.10 with change of VIX for volatility risk. These low correlations further collaborate our finding that *ex-ante* disaster concerns are quite distinct from realized disaster shocks *ex post* even though they often spike up simultaneously.

3 Skills on Exploiting Disaster Concerns (SED)

In this section, we describe our sample of hedge funds, explain our measure of hedge fund skills on exploiting disaster concerns (SED), and present various properties of SED.

3.1 Hedge fund data

The data on hedge fund monthly returns are obtained from the Lipper TASS database. The database also provides fund characteristics, including assets under management (AUM), net asset value (NAV), and management and incentive fees, among others. There are two types of funds covered in the database: "Live" and "Graveyard" funds. The "Live" funds are active ones that continue reporting monthly returns to the database as of the snapshot date (July 2010 in our case); and the "Graveyard" funds are inactive ones that are "delisted" from the database because fund managers do not report their funds' performance for a variety of reasons such as liquidation, no longer reporting, merger, or closed to new investment. Following recent studies (Sadka (2010); Bali, Brown, and Caglayan (2011); Hu, Pan, and Wang (2012)), we choose a sample period starting in 1994 to mitigate the impact of survivorship bias. Because our measure of rare disaster concerns begins in 1996 when the OptionMetrics data become available, the full sample period of hedge funds in our study is from January 1996 through July 2010.

Table 3 presents descriptive statistics for our sample of hedge funds. We require funds to report returns net of fees in US dollars, to have at least 18 months of return history in the TASS database, and to have at least $10 million AUM (Cao, et al. (2010); Hu, Pan, and Wang (2012)). Panel A reports summary statistics by year. Overall, during the time period 01/1996-07/2010, there are 5864 funds reporting returns and 3674 funds removed from the TASS database. An equal-weight hedge fund portfolio on average earns 0.8% per month with standard deviation 1.9%; it earned the highest (lowest) mean return of 2.2% (-1.4%) per month for the year of 1999 (2008).

Panel B reports summary statistics by investment style over the full sample period. The fund of funds investment style accounts for the most funds both reporting returns and being deleted in the database. It also has a substantially lower incentive fee than other investment styles (8.6% vs. 16.3%-19.6%). In terms of average monthly return, the emerging markets investment style earns the highest mean return (1.2% with a standard deviation of 4.3%), and the dedicated short bias investment style earns the lowest return (0.1% with a standard deviation of 5.4%).

3.2 The SED Measure

We measure hedge fund skills on exploiting disaster concerns (SED) through the covariation between fund returns and our measure of rare disaster concerns ($\mathbb{RIX}$). At the end of each month from June 1997 through June 2010, for each hedge fund, we first perform 24-month rolling-window regressions of a fund's monthly excess returns on the CRSP value-weighted market excess return and $\mathbb{RIX}$. Then, we measure the fund's SED using the estimated regression coefficient on $\mathbb{RIX}$. To ensure we have a reasonable number of observations in the estimation, we require funds to have at least 18 months of returns.

Table 4 presents characteristics of SED sorted hedge fund portfolios. Panel A presents evidence that high SED funds on average demand higher incentive fees and minimal investment than low SED funds; high SED funds also have fewer assets under management, shorter redemption notice periods, and longer reporting histories. In addition, high SED funds have stronger fund flow, less liquidation and non-reporting rate, and better hedging away systematic risk with respect to the Fund and Hsieh (2001) seven factors. These results are consistent with our claim that high SED funds have better skills on exploiting disaster concerns (and hence deliver superior return performance).

In Panel B, within each investment style we report the distribution of hedge funds into ten SED deciles. On average we see 23.7% of the hedge funds following the emerging markets investment style appear in the low SED decile; we also see that 26.7% and 22.9% of the hedge funds following the managed futures and dedicated short bias investment styles, respectively, show up in the high SED decile. For other investment styles, the allocations of hedge funds into top and bottom deciles are less extreme.

3.3 Properties of SED

If a hedge fund can exploit market rare disaster concerns through trading strategies and managerial skills, the fund should display relatively persistent SED over time. To examine whether there exists such persistence, we monthly sort our sample of hedge funds into SED decile portfolios and then compute the average SED for each decile during the subsequent portfolio holding periods of one month, one quarter, and up to three years. A decile's SED is the cross-sectional average of funds' SED. A hedge fund stays in a decile unless it becomes a "graveyard" fund that exits the database. Each fund's monthly SED during portfolio holding periods is always estimated from 24-month rolling-window regression using the data updated through time.

Table 5 presents the time-series mean SED of each decile portfolio, both at the portfolio formation month and during the subsequent holding months. We also report the difference between high and low SED deciles. The future skills on exploiting disaster concerns of the high SED decile remains higher than those of the low SED decile for all portfolio holding horizons. The difference in skills on exploiting disaster concerns between high and low SED deciles decreases over time. For example, the differences are 3.48, 2.18, and 1.11, at one-month, one-year, and three-year holding horizons, respectively, all are highly significant. These results suggest a strong persistence in the SED measure.

In Table 6, we investigate the cross-sectional determinants of hedge fund skills on exploiting disaster concerns by performing both Fama-MacBeth and panel regressions of SED on lagged fund characteristics. We use the estimated SED in each June from 1997 through 2010 for dependent variable and use fund characteristics as of June for explanatory variables. Overall, funds with higher skills on exploiting disaster concerns require higher minimal investment and incentive fee, require longer redemption notice period, have smaller assets under management, and have positive return skewness in past two years. We also find a strong negative relation between Fung-Hsieh 7-factor alpha and SED. This result is not surprising for the following reason. On average, a hedge fund with high alpha has high loadings on the Fung and Hsieh (2001) trend-following factors because these factors are constructed through lookback straddles and earn negative mean returns.[8] In another

[8] During the sample period from January 1994 through June 2011, the monthly mean returns of three trend-following factors PTFSBD, PTFSSTK, and PTFSCOM are -1.7%, -5.1%, and -0.4%, respectively; the median returns are -5.2%, -6.6%, and -3.0%, respectively.

word, the high Fung-Hsieh alpha fund behaves more like demanding disaster insurance (and less like supplying disaster insurance). Thus, this fund tends to have low SED (i.e., low loading on the $\mathbb{RIX}$) because our measure of disaster concerns is essentially a disaster insurance price and the SED captures the extent to which funds supply insurance. Last, the heterogeneity of hedge fund SED is attributed more to fund-specific characteristics than to year-to-year variations (the adjusted R-squared increases from 2.8% to 17.4% when fund fixed effects are only included, and it increases from 2.8% to 9.6% when year fixed effects are only included).

4 SED and Hedge Fund Performance

In this section we test our main hypothesis that hedge fund skills on exploiting disaster concerns determine future fund performance. We first examine the cross-sectional relation between SED and future fund returns. Then we study SED and hedge fund performance across different fund investment styles and size categories. We also look into how SED affect hedge fund performance during normal and stressful market times. Finally, we probe funds' exploiting disaster concern skills by investigating their exposure to disaster risk.

4.1 Hedge fund portfolios sorted on SED

After selecting the sample of funds that reports monthly returns net of fees in US dollars and has at least \$10 million assets under management, we rank these funds into 10 deciles according to their SED. Decile 1 (10) consists of funds with the lowest (highest) SED, and the high-minus-low SED portfolio is constructed by going long on funds in decile 10 and going short on funds in decile 1. We hold portfolios for different horizons (1, 3, 6, 12, and 18 months) and calculate equal-weighted monthly portfolio returns. For holding horizons longer than one month, we follow the independently managed portfolio approach in Jegadeesh and Titman (1993) and calculate average monthly returns. To measure portfolio-level risk-adjusted abnormal returns (alphas), we use the Fung-Hsieh (2001) seven-factor model, which includes the market factor, the size factor, three primitive trend-following factors, and two non-return-based factors (the change in term spread and the change in credit spread) that are replaced by tradable bond portfolio returns based on the 7-10-year Treasury Index and the Corporate Bond Baa Index from Barclays Capital (Sadka

(2010)).

Table 7 shows our baseline results of SED sorted hedge fund portfolio returns. Each decile has about 148 hedge funds on average and is well diversified. We report mean excess returns (in percent) and the Fung-Hsieh seven-factor alphas for different portfolio holding periods. At one-month holding horizon, we observe a near monotonically increasing relation between SED and average excess return. High-skill funds (SED decile 10) outperform low-skill funds (SED decile 1) by more than 0.96% per month (with a highly significant t-statistic of 3.7). Indeed, the return performance of the bottom two SED deciles are not statistically different from T-bill rates, and the top two SED deciles earn 0.57% and 0.91% per month (both are at least three standard errors from zero). The alpha of high-minus-low SED decile is above 1.1% (with a t-statistic of 4.7), indicating that the outperformance of high-skill funds is not simply attributed to option-based strategies.

We observe similar results at longer holding horizons. High-skill funds on average outperform low-skill funds by 0.84% per month for a holding horizon of three months, 0.74% for a holding horizon of six months, and 0.44% for a holding horizon of one year, all are statistically significant. The Fung-Hsieh alphas of high-minus-low SED portfolios are even larger and at least three standard errors from zero.

Overall, our baseline results suggest that fund skills on exploiting disaster concerns play an important role in explaining future fund performance. High SED funds (with better skills of exploiting disaster concerns) do not simply earn high returns as compensation for being more exposed to disaster risk. If SED, as a traditional beta measure that only captures the covariance between fund returns and disaster shocks, then we expect that high SED funds earn low returns on average because they are good hedges against disaster risk, which is exactly opposite to our basic finding above.

4.2 Pervasiveness of SED in hedge fund performance

Are hedge fund skills of exploiting disaster concerns confined to particular types of hedge funds? We examine returns from SED sorted portfolios across different hedge fund investment styles, and across different size groups.

Table 8 presents results in detail. In Panel A, we sort all hedge funds into five SED quintiles within each of 13 TASS investment styles. For the majority of investment styles, we observe a strong and positive relation between SED and portfolio mean returns. In nine investment styles high-skill funds outperform low-skill funds; for the other four we find insignificant but positive return differences between high and low SED quintiles. The strongest outperformance by high-skill funds, 0.95% per month with a t-statistic of 2.3, is for the emerging markets investment style. The weakest outperformance, 0.39% per month with a t-statistic of 2.9, is for the fund of funds investment style. A closer look at return patterns shows that high SED quintiles have earned significantly positive returns for all investment styles except dedicated short bias, and low SED quintiles have earned monthly excess returns not statistically different from zero for all investment styles except other.

Panel B shows the strong relation between SED and fund performance across different fund size groups (measured by net asset value, NAV). The high-minus-low SED portfolio earns 0.96% and 0.75% per month, respectively, for funds within low and high NAV groups, both at least three standard errors from zero.[9] The Fung-Hsieh alphas are large and highly significant. In addition, all high SED quintiles earn significantly positive returns, and none of the low SED quintiles earns monthly excess returns different from zero.

In sum, the return results in Table 8 suggest that hedge fund skills on exploiting disaster concerns are pervasive. For a variety of investment styles and different size groups, our evidence suggests that high SED funds earn high returns with their better skills of exploiting disaster concerns and providing disaster insurance.

4.3 Fund performance: Normal vs. stressful times

If some hedge fund managers have better skills than others, these skills should become extremely important when the market is stressful. During the sample period of calculating returns (July 1997 through July 2010), we classify stressful market times in four different ways: (1) months during which the CRSP value-weighted market excess returns lose 10% or more; (2) months in the lowest quintile when we rank all months into five groups based on the market excess returns in these months; (3) NBER recessions (28 months in total: March 2001 through November 2001, and December 2007 through June 2009); and (4) months in the lowest decile when we rank all months

[9] Our results are robust to measuring fund size by assets under management (AUM). For example, mean returns of the high-minus-low SED portfolios within low and high AUM groups are 0.72% (with a t-statistic of 3.0) and 0.48% (with a t-statistic of 2.7), respectively.

into ten groups based on the market excess returns in these months. In specifications (1)-(3) above, we define normal market times as non-stressful months; and in specification (4), we define normal market times as months in the highest decile when we rank all months into ten groups based on the market excess returns in these months.

Table 9 presents results of SED decile returns during normal and stressful market times. During normal market times, high SED funds earn higher returns than low SED funds. During stressful market times, all funds lose, which is consistent with the view that hedge funds as suppliers of insurance earn profits overall but incur losses during market downturns. Funds with better skills on exploiting disaster concerns, however, lose much less. For example, in months when the market lost 10% or more, high SED funds outperform low SED funds by 6.5% per month (with a t-statistic of 2.1).

4.4 Disaster risk exposure

Table 10 reports factor loadings of SED sorted hedge fund deciles. In Panel A, we consider a set of macroeconomic and liquidity risk factors; and in Panel B, we consider the classic Fung-Hsieh seven factors.

We have two observations on the disaster risk exposure of SED portfolios. First, low-skill funds are high exposed to macroeconomic and liquidity shocks. Factor loadings are highly significant. Second, high-skill funds are not significantly exposed to macroeconomic and liquidity shocks.

5 Distinctiveness of SED from Other Fund Skills

In this section, we explore the distinctiveness of SED in explaining cross-sectional hedge fund performance in the presence of other known factors identified in the recent literature. We first apply a series of two-way portfolio sorts, and then perform Fama-MacBeth (1973) cross-sectional regressions.

5.1 SED vs Skills of Exploiting Volatility Concerns

In our construction of $\mathbb{RIX}$, the second component $\mathbb{IV}$ underlies construction of the CBOE VIX, a well-known fear gauge associated with volatility risk. In theory, $\mathbb{RIX}$ is fundamentally different from

VIX because it captures high-order (≥ 3) moments of the jump measure associated with disaster risk that is missing from VIX. Empirically, however, there can be a strong correlation between $\mathbb{RIX}$ and VIX since jump and volatility risks are closely related to each other. Therefore, it is imperative to ask whether our SED is driven by the skills of hedge funds in exploiting concerns about volatility risk based on VIX analogously.

The answer is unequivocally no. First, in untabulated analysis we rank hedge funds into ten deciles according to the fund skills to exploit volatility concerns (SEV), computed as the covariation between fund returns and VIX similar to SED. We find no significant return difference between funds with high and low SEV. The spread is 0.33% per month, with a t-statistic of 1.1. Second, in a more direct and powerful test, we perform sequential sorts and rank hedge funds into 25 portfolios according to the SEV and SED. We report equal-weighted portfolio returns in Table 11.

Panel A shows that SED, in the presence of volatility concern skills, well explains cross-sectional hedge fund returns. On average, high SED funds outperform low SED funds by 0.64% per month (t-statistic = 4.4). In fact, we observe an almost monotonically increasing relation between SED and hedge fund returns within quintiles of SEV: The return spreads of high-minus-low SED portfolios range from 0.43% to 1.1% per month (all are statistically significant at the 1% level).

In sharp contrast, Panel B of Table 11 finds no systematic relation between SEV and hedge fund returns in the presence of SED. On average, the return difference between funds of high and low SEV is 0.11% and it is less than one standard error from zero. Moreover, the SEV has no power to explain hedge fund returns within each SED quintile (all return spreads are economically small and statistically insignificant). These results show that fund skills of exploiting disaster concerns rather than volatility concerns explain cross-sectional hedge fund performance.

5.2 Other fund skills and hedge fund performance [To be added]

We control for the fund skill of hedging away systematic risk by Titman and Tiu (2011), the skill of adopting innovative strategies by Sun, Wang, Zheng (2012), and the skill of timing market liquidity by Cao, Chen, Liang, and Lo (2012).

5.3 Fama-MacBeth cross-sectional regressions

The portfolio analysis so far suggests that the fund skills of exploiting disaster concerns is distinct from other documented fund skills in the literature in explaining cross-sectional hedge fund performance. In this section, we further differentiate the SED from other fund skills using the Fama-MacBeth (1973) regression that can control for multiple skill measures simultaneously. Furthermore, our investigation of the characteristics of hedge funds in forming SED deciles (see Panel A of Table 4 for details) indicates that certain characteristics of hedge fund may be related to SED. To account for the impact of hedge fund characteristics on future performance, we include fund characteristics as explanatory variables in the regression. In addition, we also include different types of betas with respect to documented hedge fund risk factors.

Table 12 presents the results of regression coefficients and Newey-West (1987) t-statistics when we regress funds' monthly excess returns on SED and various subsets of the explanatory variables. In all six specifications, the coefficients on SED are positive and significant, showing that the explanatory power of the fund skills of exploiting disaster concerns on cross-sectional hedge fund performance is not subsumed by market beta, liquidity beta, default premium beta, inflation beta, total variance, or other fund characteristics including assets under management (AUM), age, lagged returns, management fees, incentive fees, high water mark, personal capital invested, leverage, lockup, and redemption notice period.

6 Robustness Checks

6.1 SED Portfolios and other risk factors

We first present portfolio sorting results showing that SED-based fund performance is not driven by risk exposure, collaborating our evidence in Section 4 about the risk exposure analysis of SED-based fund portfolios. Because SED focuses on the *extreme* downside jump embedded in the variance swap contract, it is also natural to ask whether SED is related to the downside risk and volatility risk documented in prior studies (Ang, Chen, and Xing (2006); Ang et al. (2006)). As a result, we conduct double portfolio sorts to examine whether the market beta, particularly the downside market beta, and the volatility risk beta can explain our results.[10]

At the end of each month we rank hedge funds independently into 25 portfolios according to their SED and market betas. We consider two types of market beta: regular market beta and downside market beta estimated by using only fund returns in months when the market excess return is below its sample mean (Ang, Chen, and Xing (2006)). To measure volatility risk, we first obtain the monthly time series of VIX from the CBOE, and then calculate the month-to-month change in VIX (Ang et al. (2006)). We estimate funds' volatility risk beta using 24-month rolling-window regressions (see Table 13 in detail).

Table 13 reports mean excess returns, alphas, and t-statistics of portfolios formed on market beta and SED (Panel A), and downside market beta and SED (Panel B). The conclusions are similar. First, except for funds ranked in the bottom market-beta quintile, we find strong return spreads associated with SED. Second, the effect of SED on future fund performance is strongest for funds ranked in the top market-beta quintile. The high-minus-low SED portfolio yields a monthly return of more than 0.8% that is at least three standard errors from zero. The abnormal returns (the Fung-Hsieh seven-factor alphas) are even greater. Finally, there are no systematic return patterns associated with market beta. Within each SED quintile, we find insignificant returns of high-minus-low market-beta portfolios, using either regular market beta or downside market beta. Panel C of Table 13 reports mean excess returns, alphas, and t-statistics of portfolios formed on volatility risk beta and SED. Across volatility-risk-beta quintiles, the return spreads of high-minus-low SED portfolios are both statistically and economically significant, ranging from 0.57% to 0.92% per month. In sharp contrast, we find no significant returns of high-minus-low volatility-risk-beta portfolios across SED quintiles. These results indicate that fund performance associated with SED is not driven by volatility risk.

Recent studies document that market liquidity risk (Sadka (2010)), funding liquidity risk (Hu, Pan, and Wang (2012)), macroeconomic risk (Bali, Brown, and Caglayan (2011)), and total variance (Bali, Brown, and Caglayan (2012)) are important factors determining cross-sectional variations of hedge fund returns. To investigate whether the fund skill of exploiting disaster concerns is just

[10] Throughout the paper we have constructed $\mathbb{RIX}$ using out-of-the-money puts on sector indices. One question is whether a simple equal-weighted aggregated factor based on these sector-level index returns would be sufficient in capturing market expectation on future disaster and hence drives cross-sectional fund performance. The answer is no. Using this sector-index-return-based factor to estimate hedge funds' beta and sort funds into portfolios, we find these betas have no power to explain future fund returns (full results are available upon request).

a manifestation of exposures to these risk factors, we further conduct several sequential portfolio sorts.

In Panel D of Table 13, we first rank funds into five quintiles according to their total variances, and then within each total-variance quintile we sort funds into additional five quintiles based on the basis of SED. Each fund's total variance is estimated as the sample variance of its excess returns within the past 36 months (see Bali, Brown, and Caglayan (2012)). After controlling for the total variance effect, we find that the average returns of SED portfolios increase monotonically from 0.14% (the bottom SED quintile) to 0.61% (the top SED quintile). In addition, the return difference between top and bottom quintiles is 0.47% per month, highly significant with a t-statistic of 3.6.

In Panel E of Table 13, we perform a similar portfolio exercise by sequential sorts first on funding liquidity beta based on the "noise" measure (Hu, Pan, and Wang (2012)), and then on SED. Within noise-beta quintiles, the return spreads of high-minus-low SED portfolios range from 0.4% to 0.96%, and all are statistically significant. Conditional on funding liquidity risk, the average return spread associated with SED is 0.58% per month, more than three standard errors from zero.

In the remaining panels of Table 13, we present double-sorted portfolio results after controlling for two macroeconomic risk factors of default risk and inflation risk (Bali, Brown, and Caglayan (2011)). The average returns of SED portfolios monotonically increase. The monthly mean return spreads of high-minus-low SED portfolios are 0.50% (Panel F) and 0.57% (Panel G), after we control for default beta and inflation beta, respectively. Both of these high-minus-low SED portfolios' spreads are at least three standard errors from zero. In untabulated analyses, we also use the set of global value and momentum factors (Asness, Moskowitz, and Pedersen (2013)) to measure abnormal returns of high-minus-low SED portfolios. The alpha remains highly significant, 0.92% per month (t-statistic = 3.7). Overall, these portfolio results further confirm that fund performance based on SED is not driven by exposure to risk factors proposed in the literature.

6.2 Fund size, return smoothing, and delisting

We have focused on equal-weighted hedge fund portfolio returns throughout the paper. We obtain similar results using value-weighted portfolio returns where weights are determined by funds' monthly assets under management (AUM). The mean excess return and the Fung-Hsieh alpha of high-minus-low SED portfolio are above 1% per month (t-statistic = 3.4). From an institutional investment and market impact perspective, funds with AUM of less than \$10 million are of less economic importance and we exclude them in our main analysis (Cao, et al. (2010); Hu, Pan, and Wang (2012)). When we impose no AUM restrictions in selecting hedge funds in the construction of decile portfolios, the return spread of high-minus-low SED portfolio is 0.89% per month (t-statistic = 3.6), a return very close to the 0.96% reported in our baseline specification (see Panel A of Table 5). Repeating the analysis with different AUM cutoffs such as \$5 million and \$50 million, we find similar results.

Prior studies document significant serial auto-correlation of hedge fund returns because of illiquidity and return smoothing (e.g., Getmansky, Lo, and Makarov (2004)). To better measure funds' skills of exploiting disaster concerns, we regress funds' monthly excess returns on a contemporaneous as well as lagged $\mathbb{RIX}$ factor. As reported in columns six and seven of Table 14, there is a further increase of return spreads on the high-minus-low SED portfolios, 1.15% for monthly excess return and 1.3% for the Fung-Hsieh alpha, and both are at least four standard errors away from zero.

The Lipper TASS database doesn't report "delisted" hedge fund returns. We address this issue by assuming a large negative return (such as -100%) in the month immediately after a hedge fund exits the database for reasons such as liquidation, no longer reporting, or unable to contact fund. The last two columns of Table 14 shows similar return patterns of SED deciles to those exhibited in our main result. In fact, a strong return spread of high-minus-low SED portfolio remains, 1.3% per month (t-statistic = 4.5). Results are similar for different negative numbers for hedge fund delisting returns.

7 Conclusions

Contrary to the prior research that mostly attributes higher fund returns as simply compensations for larger to disaster risk, we provide novel evidence that hedge fund managers with better skills of exploiting disaster concerns deliver superior future fund performance, yet being less exposed to disaster risk. The key to our finding is the differentiation between *ex-ante* market disaster concerns and *ex-post* disaster shocks. The former can peak without being followed by market losses, and may contain a "fear premium" beyond compensations for subsequent realized market losses. Consequently, fund managers with better skills in identifying the shoot-up of *ex-ante* disaster concerns as just a fear with no subsequent disaster shocks or identifying the investors who pay higher fear premiums can deliver superior future fund performance.

Based on the disaster concern index we develop that equals the price of a disaster insurance contract, we measure the fund skill of exploiting rare disaster concerns by the covariation of fund returns and disaster concern index. We document substantial heterogeneity across hedge funds as well as significant persistence in SED. We show that funds in the highest SED decile outperform funds in the lowest decile by 0.9% per month on average and even more during stressful market times. Higher-SED funds are also shown to have less exposure to disaster risks. Overall, our results present strong evidence that hedge fund managers with better skills of exploiting disaster concerns deliver superior future fund performance, different from the popular view that hedge funds earn higher returns on average simply by being more exposed to disaster risk.

Appendix: Technical Details of $\mathbb{RIX}$

Our rare disaster concern index quantifies *ex-ante* market expectations of rare disaster events in the future. In particular, the value of $\mathbb{RIX}$ depends on the price difference between two option-based replication portfolios of variance swap contracts. The first portfolio accounts for mild market volatility shocks, and the second for extreme volatility shocks induced by market jumps associated with rare event risks. By construction, the $\mathbb{RIX}$ is essentially the price for an insurance contract against extreme downside movements of the financial market in the future.

Consider an underlying asset whose time-t price is S_t. We assume for simplicity that the asset does not pay dividends. An investor holding this security is concerned about its price fluctuations over a time period $[t, T]$. One way to protect herself against price changes is to buy a contract that delivers payments equal to the extent of price variations over $[t, T]$, minus a prearranged price. Such a contract is called a "variance" swap contract as the price variations are essentially about the stochastic variance of the price process. The standard variance swap contract in practice pays

$$\left(\ln \frac{S_{t+\Delta}}{S_t}\right)^2 + \left(\ln \frac{S_{t+2\Delta}}{S_{t+\Delta}}\right)^2 + \cdots + \left(\ln \frac{S_T}{S_{T-\Delta}}\right)^2 - \mathbb{VP} \tag{A.1}$$

at time T, where $\mathbb{VP}$ is the prearranged price of the contract. That is, the variance swap contract uses the sum of squared log returns to measure price variations, which is a standard practice in the finance literature (Singleton (2006)).

For the convenience of pricing, a continuous-time setup is usually employed with $\Delta \to 0$. Then the fair price $\mathbb{VP}$ is

$$\mathbb{VP} = \mathbb{E}_t^{\mathbb{Q}} \left\{ \lim_{\Delta \to 0} \left[\left(\ln \frac{S_{t+\Delta}}{S_t}\right)^2 + \left(\ln \frac{S_{t+2\Delta}}{S_{t+\Delta}}\right)^2 + \cdots + \left(\ln \frac{S_T}{S_{T-\Delta}}\right)^2 \right] \right\},$$

where $\mathbb{Q}$ is the risk-neutral measure. The limit inside the expectation is called quadratic variation of the log price process, denoted as $[\ln S, \ln S]_t^T$, which is the continuous-time sum of squared log returns.

In principle, replication portfolios consisting of out-of-the-money (OTM) options written on S_t can be used to replicate the time-varying payoff associated with the variance swap contract and hence to determine the price $\mathbb{VP}$. We now introduce two replication portfolios and their implied prices for the variance swap contract. The first replication portfolio, which underlies the construction of VIX by the Chicago Board Options Exchange (CBOE), focuses on the limit of the discrete sum of squared log returns, determining $\mathbb{VP}$ as

$$\mathbb{IV} \equiv \frac{2e^{r\tau}}{\tau}\left\{\int_{K>S_t}\frac{1}{K^2}C(S_t;K,T)dK + \int_{K<S_t}\frac{1}{K^2}P(S_t;K,T)dK\right\}, \tag{A.2}$$

where r is the constant risk-free rate, $\tau \equiv T-t$ is the time-to-maturity, and $C(S_t;K,T)$ and $P(S_t;K,T)$ are prices of call and put options with strike K and maturity date T, respectively. As seen in equation (A.2), this replication portfolio holds positions in OTM calls and puts with a weight inversely proportional to their squared strikes. $\mathbb{IV}$ has been employed in the literature to construct measures of variance risk premiums (Bollerslev, Tauchen, and Zhou (2009), Carr and Wu (2009), and Drechsler and Yaron (2011)).

The intuition behind the construction of the second replication portfolio is that $\mathbb{VP}$ is equal to the variance of the holding period log return, i.e., $\mathbb{VP} = Var_t^{\mathbb{Q}}(\ln S_T/S_t)$, as shown in Du and Kapadia (2012).[11] This replication portfolio relies on $Var_t^{\mathbb{Q}}(\ln S_T/S_t)$, which avoids the discrete sum approximation, and determines $\mathbb{VP}$ as

$$\mathbb{V} \equiv \frac{2e^{r\tau}}{\tau}\left\{\int_{K>S_t}\frac{1-\ln(K/S_t)}{K^2}C(S_t;K,T)dK + \int_{K<S_t}\frac{1-\ln(K/S_t)}{K^2}P(S_t;K,T)dK\right\} \tag{A.3}$$

The second replication portfolio described in equation (A.3) differs from the first replication portfolio in equation (A.2) by assigning greater (lesser) weights to more deeply OTM put (call) options. As the strike price K declines (increases), i.e., put (call) options become more out of the money, $1-\ln(K/S_t)$ becomes larger (smaller). As more deeply OTM options protect investors against greater price changes, it is intuitive that the difference between $\mathbb{IV}$ and $\mathbb{V}$ captures investors' expectation about the distribution of large price variations.

To quantify the difference more explicitly and obtain a measure of rare events, we assume the

[11] The equality $\mathbb{VP} = Var_t^{\mathbb{Q}}(\ln S_T/S_t)$ holds exactly for processes with deterministic drift but approximately for processes with stochastic drift such as a stochastic volatility model. However, the approximation error is tiny for the stochastic drift case, shown by Du and Kapadia (2012) in simulations.

price process follows the Merton (1976) jump-diffusion model:

$$\frac{dS_t}{S_t} = (r - \lambda\mu_J)\, dt + \sigma dW_t + dJ_t, \tag{A.4}$$

where r is the constant risk-free rate, σ is the volatility, W_t is a standard Brownian motion, J_t is a compound Poisson process with jump intensity λ, and the compensator for the Poisson random measure $\omega\,[dx, dt]$ is equal to $\lambda \frac{1}{\sqrt{2\pi}\sigma_J} \exp\left(-\left(x - \mu_J\right)^2/2\right)$. The jump process J_t drives large price variations with an average size of μ_J. Rare event risks, however, are not likely to be captured by price jumps of average sizes within a range of the standard deviation σ_J. Instead, we focus on the high-order moments of the Poisson random measure $\omega\,[dx, dt]$, e.g., skewness and kurtosis, which are associated with unlikely but extreme price jumps, in capturing rare event risks.

We now quantify the difference between $\mathbb{IV}$ and $\mathbb{V}$ under the Merton (1976) framework. First, as shown by Carr and Madan (1998), Demeterfi et al. (1999), and Britten-Jones and Neuberger (2000), when the price process S_t does not have jumps, i.e., $dJ_t = 0$,

$$\mathbb{IV} = \mathbb{E}_t^{\mathbb{Q}}\left(\int_t^T \sigma^2 dt\right) = \mathbb{VP}.$$

That is, $\mathbb{IV}$ captures the price variation induced by the Brownian motion. However, for a price process with a jump term $dJ_t \neq 0$, it is no longer the case that $\mathbb{IV} = \mathbb{VP}$ because $\mathbb{VP}$ now contains price variations induced by jumps. Rather, as shown by Du and Kapadia (2012), $\mathbb{V} = \mathbb{VP}$ whether dJ_t is zero or not.

More important, the difference between $\mathbb{IV}$ and $\mathbb{V}$ under the Merton (1976) model is (see Du and Kapadia (2012) for a proof):

$$\mathbb{V} - \mathbb{IV} = 2\mathbb{E}_t^{\mathbb{Q}} \int_t^T \int_{R_0} \left(1 + x + x^2/2 - e^x\right) \omega\,[dx, dt]\,. \tag{A.5}$$

That is, $\mathbb{V} - \mathbb{IV}$ captures all the high-order (≥ 3) moments of the Poisson random measure $\omega\,[dx, dt]$ associated with unlikely but extreme price jumps. In fact, equation (A.5) holds for the entire class of Lévy processes, and approximately for stochastic volatility models with negligible errors, as shown by Du and Kapadia (2012).

We further focus on downside rare event risks associated with unlikely but extreme negative price jumps. In particular, we consider the downside versions of both $\mathbb{IV}$ and $\mathbb{V}$:

$$
\begin{aligned}
\mathbb{IV}^{-} &\equiv \frac{2e^{r\tau}}{\tau}\int_{K<S_t}\frac{1}{K^2}P(S_t;K,T)dK, \\
\mathbb{V}^{-} &\equiv \frac{2e^{r\tau}}{\tau}\int_{K<S_t}\frac{1-\ln\left(K/S_t\right)}{K^2}P(S_t;K,T)dK,
\end{aligned} \tag{A.6}
$$

where only OTM put options that protect investors against negative price jumps are used. We then define our rare disaster index as follows

$$
\mathbb{RIX} \equiv \mathbb{V}^{-} - \mathbb{IV}^{-} = 2\mathbb{E}_t^{\mathbb{Q}}\int_t^T\int_{R_0}\left(1+x+x^2/2-e^x\right)\omega^{-}\left[dx,dt\right], \tag{A.7}
$$

where the second equality can be shown as similar to equation (A.5), with $\omega^{-}\left[dx,dt\right]$ the Poisson random measure associated with negative price jumps.

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Table 1: Daily open interest of sector-level index put options

We select sector-level index put options with 14-60 days of maturity and divided them into six moneyness groups (i.e., K/S, the ratio between strike and underlying index level). Within a moneyness group we first calculate the average of daily open interest (in number of contracts) for each year from 1996 to 2011. The table reports the average of these numbers over years. The following daily options data come from OptionMetrics: BKX (1996/01-2011/12), SOX (1996/01-2011/12), XAU (1996/01-2011/12), HGX (2002/07-2011/12), OSX (1997/02-2011/12), and UTY (1996/01-2011/12). Options must all have non-zero open interest, standard expiration dates, non-missing implied volatility, and valid bid and ask prices (see Section 3.1 for details about cleaning data).

	$K/S \leq 0.90$	$0.90 < K/S \leq 0.95$	$0.95 < K/S \leq 1.00$	$1.00 < K/S \leq 1.05$	$1.05 < K/S \leq 1.10$	$K/S > 1.10$
KBW Banking Sector (BKX)	458	567	930	621	370	180
PHLX Semiconductor Sector (SOX)	131	203	231	178	107	59
PHLX Gold Silver Sector (XAU)	702	1042	900	621	406	221
PHLX Housing Sector (HGX)	272	479	581	444	465	306
PHLX Oil Service Sector (OSX)	636	1209	1562	1326	1005	536
PHLX Utility Sector (UTY)	50	71	116	58	53	85

Table 2: Descriptive statistics of rare disaster indices

Rare disaster indices are constructed using prices of 30-day out-of-the-money put options on different sector indices from 1996 through 2011 (see Section 2 in detail). The aggregated factor, called the rare disaster index (RIX), is an equal-weighted average over all sector-level rare disaster indices. Panel A reports summary statistics of monthly rare disaster indices. Panel B presents time-series correlations between one rare disaster index and a number of factors: Fama-French-Carhart four factors (MKTRF, SMB, HML, and UMD); Fung-Hsieh five trend-following factors (PTFSBD, PTFSFX, PTFSCOM, PTFSIR, and PTFSSTK); Pastor-Stambaugh (PS) market liquidity risk factor; Sadka market liquidity risk factor; Hu-Pan-Wang funding liquidity risk factor (noise); term risk factor (change in term spread); default risk factor (change in default spread); and volatility risk factor (change in VIX).

Panel A: Summary statistics of aggregated and sector-level rare disaster indices

	Mean	Min	P25	Median	P75	Max	Std	N
KBW Banking Sector (BKX)	0.057	0.017	0.037	0.054	0.068	0.165	0.029	192
PHLX Semiconductor Sector (SOX)	0.076	0.037	0.055	0.070	0.095	0.143	0.025	192
PHLX Gold Silver Sector (XAU)	0.065	0.036	0.051	0.063	0.073	0.140	0.018	192
PHLX Housing Sector (HGX)	0.063	0.030	0.046	0.054	0.073	0.139	0.023	114
PHLX Oil Service Sector (OSX)	0.072	0.039	0.053	0.066	0.087	0.165	0.025	179
PHLX Utility Sector (UTY)	0.029	0.012	0.023	0.027	0.033	0.071	0.010	165
Aggregated Factor (RIX)	0.063	0.034	0.046	0.061	0.074	0.141	0.020	192

Panel B: Correlations between rare disaster indices and other common factors

	RIX factor	BKX	SOX	XAU	HGX	OSX	UTY
MKTRF	-0.102	-0.110	-0.013	-0.150	-0.172	-0.067	-0.177
SMB	0.002	-0.019	0.087	-0.019	-0.030	-0.032	-0.051
HML	-0.165	-0.109	-0.112	-0.211	-0.209	-0.171	-0.032
UMD	-0.121	-0.202	-0.055	0.017	-0.225	-0.020	-0.080
PTFSBD	0.248	0.194	0.259	0.226	0.277	0.239	0.172
PTFSFX	0.051	0.073	-0.024	0.130	0.102	0.009	-0.005
PTFSCOM	-0.055	-0.031	-0.112	0.056	0.048	-0.083	-0.154
PTFSIR	0.177	0.242	-0.029	0.163	0.348	0.091	0.069
PTRSSTK	-0.026	0.032	-0.114	0.017	0.139	-0.079	-0.015
Liquidity risk: PS	-0.193	-0.214	-0.087	-0.226	-0.325	-0.096	-0.242
Liquidity risk: Sadka	-0.310	-0.401	-0.130	-0.283	-0.408	-0.195	-0.220
Liquidity risk: Noise	-0.009	-0.046	-0.055	0.092	-0.009	0.005	0.010
Change of term spread	0.222	0.251	0.169	0.167	0.280	0.141	0.259
Change of default spread	0.221	0.146	0.123	0.256	0.208	0.241	0.002
Change of VIX	-0.094	-0.065	-0.112	-0.025	-0.048	-0.096	-0.057

Table 3: Hedge fund sample descriptive statistics

The sample consists of hedge funds that report returns net of fees in US dollars and have at least 18 months of return history in the Lipper TASS database (the snapshot of the database is in July 2010). We also require funds to have at least $10 million in assets under management every month. Panel A reports summary statistics by year. That is, within a year, we calculate the total number of funds reporting returns, the total number of funds that are "delisted" in the database (i.e., "graveyard" funds no longer reporting returns), the cross-sectional fund averages of initial net asset value (NAV), minimal investment, management fee, and incentive fee, the pooled average of monthly assets under management (AUM), and the mean, standard deviation, min, and max of monthly equal-weighted hedge fund portfolio returns. Panel B reports similar summary statistics by investment style over the full sample period from January 1996 through July 2010.

	No. Funds (report return)	No. Funds (graveyard)	Initial NAV	Minimal Investment (thousand)	Mgt. Fee (%)	Incentive Fee (%)	AUM (million)	EW Fund Return (mean)	EW Fund Return (std.)	EW Fund Return (min)	EW Fund Return (max)
Panel A: Summary statistics by year (1996-2010)											
1996	720	25	1912.5	891.6	1.5	16.6	110.1	0.015	0.015	-0.018	0.039
1997	926	21	1747.4	888.0	1.4	16.8	122.8	0.016	0.021	-0.012	0.048
1998	1093	43	1252.5	886.3	1.4	16.9	135.2	0.003	0.025	-0.059	0.033
1999	1285	56	1043.5	929.6	1.3	17.0	114.3	0.022	0.023	-0.007	0.070
2000	1521	93	965.0	953.8	1.3	17.0	114.0	0.009	0.025	-0.021	0.064
2001	1708	96	971.6	998.9	1.3	17.0	121.1	0.005	0.012	-0.016	0.026
2002	1886	101	1256.1	1022.1	1.4	17.0	130.8	0.002	0.009	-0.015	0.016
2003	2221	125	1202.1	993.0	1.4	16.8	141.9	0.013	0.009	-0.002	0.032
2004	2562	140	1148.1	1028.6	1.4	16.6	181.2	0.007	0.012	-0.013	0.029
2005	2847	227	1130.8	1061.3	1.4	16.5	201.1	0.007	0.013	-0.015	0.020
2006	2946	276	1461.3	1432.7	1.5	16.2	219.0	0.010	0.014	-0.015	0.035
2007	3144	375	1324.6	1449.8	1.5	15.9	251.1	0.010	0.015	-0.017	0.031
2008	3080	696	1481.7	1109.4	1.5	15.2	249.5	-0.014	0.025	-0.057	0.019
2009	2398	294	4137.2	1061.0	1.5	14.8	189.3	0.015	0.015	-0.006	0.048
2010	1967	144	4904.8	1038.6	1.5	15.0	212.3	0.002	0.018	-0.030	0.025
All	5864	3674	2702.0	1136.1	1.5	15.8	183.3	0.008	0.019	-0.059	0.070
Panel B: Full sample by investment style											
Long/Short Equity Hedge	1575	1040	5569.8	1498.5	1.3	18.9	141.5	0.010	0.029	-0.098	0.125
Equity Market Neutral	268	201	6782.6	905.9	1.3	19.4	133.5	0.007	0.008	-0.027	0.033

Dedicated Short Bias	32	26	600.8	539.8	1.4	18.5	46.3	0.001	0.054	-0.117	0.242
Global Macro	244	157	970.2	1322.3	1.5	17.5	328.7	0.009	0.018	-0.046	0.079
Emerging Markets	457	219	960.6	608.2	1.6	17.7	148.3	0.012	0.043	-0.220	0.165
Event Driven	488	345	3131.7	1519.7	1.4	18.4	277.4	0.008	0.016	-0.075	0.046
Fund of Funds	1603	940	662.5	748.5	1.4	8.6	164.2	0.006	0.017	-0.062	0.063
Fixed Income Arbitrage	180	151	4033.2	1106.0	1.4	19.6	255.7	0.006	0.013	-0.077	0.030
Convertible Arbitrage	162	126	757.9	1120.6	1.4	18.3	183.6	0.007	0.023	-0.157	0.086
Managed Futures	345	185	866.7	1092.6	2.0	19.6	201.6	0.008	0.032	-0.063	0.103
Multi Strategy	324	190	1050.4	1377.0	1.6	16.3	265.4	0.008	0.015	-0.064	0.055
Options Strategy	12	2	775.0	1195.8	1.5	19.6	108.6	0.006	0.011	-0.035	0.044
Other	168	86	2664.2	1622.5	1.4	18.6	180.6	0.009	0.016	-0.115	0.044

Table 4: Hedge fund portfolio characteristics

At the end of each month from June 1997 through June 2010, we rank hedge funds into ten decile portfolios according to their skills on exploiting rare disaster concerns (SED). Decile 1 (10) consists of funds with the lowest (highest) skills. In formulating portfolios, we require funds to report returns net of fees in US dollars and have at least $10 million in AUM. Funds' SERs are estimated from 24-month rolling-window regressions of excess monthly returns on the market excess return and the measure of rare disaster concern (RIX). We also require at least 18 months of return observations in estimating regressions. Panel A reports the following hedge fund characteristics: the fraction of funds that employ leverage/personal capital/lock up/high water mark, minimal investment, management fee, incentive fee, redemption notice period, the total number of months of reporting returns in the TASS database, assets under management (AUM), number of months from a fund's inception to portfolio formation date (AGE), fund flow in the recent month, fund liquidation rate and non-reporting rate within one year of portfolio formation, and R-square based on the Fung-Hsieh 7-factor regression. Within each decile we first calculate cross-sectional average of funds' characteristics and then calculate time-series average over all portfolio formation months. Panel B reports distribution of hedge funds across ten skill portfolios within each investment style.

	1 - Low Skill	2	3	4	5	6	7	8	9	10 - High Skill
Panel A: hedge fund characteristics										
Leveraged	0.660	0.595	0.574	0.557	0.550	0.549	0.581	0.632	0.658	0.703
Personal Capital Invest.	0.439	0.419	0.400	0.386	0.375	0.394	0.402	0.409	0.408	0.414
Lock Up	0.307	0.303	0.293	0.290	0.282	0.276	0.284	0.295	0.294	0.298
High Water Mark	0.618	0.629	0.608	0.589	0.591	0.591	0.604	0.639	0.647	0.666
Min. Invest. (thousand)	830	964	1026	1179	1147	1157	1093	1058	945	1030
Management Fee (%)	1.47	1.41	1.39	1.38	1.35	1.34	1.37	1.39	1.41	1.49
Incentive Fee (%)	17.72	16.34	15.29	14.56	14.45	14.93	15.74	17.18	18.07	19.06
Notice Period (month)	36.2	39.7	41.6	42.6	43.7	43.6	42.3	39.6	36.5	32.9
Ret. Reporting (month)	115.7	121.9	123.9	124.5	123.6	123.5	124.7	123.6	122.3	120.7
AUM (million)	173	187	187	203	193	200	211	192	175	151
AGE (month)	68	71	72	72	71	71	71	70	70	69
Fund Flow (%)	0.048	0.050	0.035	0.083	0.099	0.100	0.187	0.163	0.132	0.173
Liquidation Rate (%)	3.563	2.771	2.382	2.693	2.714	2.705	2.892	2.687	2.455	2.133
Non-Reporting Rate (%)	3.135	2.540	2.288	1.905	2.020	1.915	2.385	2.364	2.328	2.247
R-square	0.533	0.557	0.559	0.555	0.546	0.532	0.515	0.505	0.515	0.524

Panel B: Distribution of hedge funds within investment style (%)										
Long/Short Equity Hedge	14.3	11.8	9.6	8.0	7.1	6.9	7.7	9.5	12.0	13.0
Equity Market Neutral	4.2	7.2	8.5	8.5	8.6	10.7	12.0	14.6	15.5	10.3
Dedicated Short Bias	14.8	11.0	7.3	5.4	4.7	4.7	5.4	9.0	14.9	22.9
Global Macro	11.2	8.0	6.8	6.9	6.6	7.5	10.0	12.8	14.8	15.5
Emerging Markets	23.7	12.1	7.9	6.6	6.3	6.1	6.5	7.7	9.2	13.7
Event Driven	7.8	10.1	10.8	11.0	11.5	11.9	12.4	12.0	8.7	3.8
Fund of Funds	4.5	10.3	13.7	15.6	16.0	14.6	11.6	7.0	4.0	2.7
Fixed Income Arbitrage	8.1	6.6	8.6	9.8	10.7	11.6	12.8	14.1	10.4	7.4
Convertible Arbitrage	3.6	3.8	4.1	4.7	7.1	9.9	14.0	18.5	19.6	14.7
Managed Futures	9.7	8.3	7.2	6.0	5.5	6.0	7.1	9.5	13.9	26.7
Multi Strategy	7.8	7.8	7.6	8.3	9.7	10.6	12.2	13.2	12.2	10.6
Options Strategy	3.0	8.7	3.6	6.2	8.1	8.3	11.4	18.5	16.4	15.9
Other	10.6	9.9	9.8	10.0	9.0	10.7	10.5	10.2	11.0	8.2

Table 5: Persistence of the hedge fund skill on exploiting rare disaster concerns (SED)

For each decile portfolio sorted on the funds' SEDs estimated from the 24-month rolling-window regressions, we report the time-series mean of the average SED for the month of portfolio formation and the subsequent portfolio holding period (1 month, 3 months, and up to 36 months). We also report the difference between the high and low skill deciles, and the corresponding *t* -statistics (in parentheses).

	Portfolio Formation	Holding 1M	3M	6M	9M	12M	18M	24M	36M
1 - Low Skill	-2.255	-2.068	-1.922	-1.715	-1.543	-1.388	-1.121	-0.946	-0.787
2	-0.974	-0.906	-0.855	-0.781	-0.721	-0.669	-0.576	-0.508	-0.439
3	-0.599	-0.568	-0.544	-0.513	-0.485	-0.457	-0.411	-0.373	-0.335
4	-0.389	-0.371	-0.360	-0.346	-0.334	-0.323	-0.304	-0.291	-0.269
5	-0.238	-0.231	-0.231	-0.233	-0.233	-0.232	-0.229	-0.224	-0.210
6	-0.109	-0.114	-0.118	-0.130	-0.137	-0.144	-0.157	-0.162	-0.154
7	0.027	0.013	-0.008	-0.034	-0.052	-0.067	-0.090	-0.102	-0.104
8	0.208	0.175	0.144	0.100	0.064	0.034	-0.013	-0.040	-0.057
9	0.508	0.452	0.392	0.313	0.252	0.198	0.117	0.070	0.024
10 - High Skill	1.573	1.407	1.257	1.066	0.916	0.789	0.578	0.447	0.318
High - Low	3.827	3.475	3.179	2.781	2.460	2.177	1.699	1.392	1.106
	(23.85)	(25.40)	(27.01)	(29.48)	(28.58)	(27.01)	(24.25)	(23.88)	(26.50)

Table 6: Determinants of the hedge fund skill on exploiting rare disaster concerns (SED)

We report the panel of regression of SED on lagged fund characteristics using the annual data that are collected in each June from 1997 through 2010. Minimal investment, AUM, and AGE are in log; high water marke, personal capital invested, leverage, and fund-of-funds type are dummy variables. The standard errors in parentheses are cluster adjusted.

	(1)	(2)	(3)	(4)
Minimal Investment	0.0168***	0.0135***		
	(0.00484)	(0.00460)		
Management Fee (%)	-3.034	-2.455		
	(2.124)	(2.051)		
Incentive Fee (%)	0.326**	0.339**		
	(0.152)	(0.150)		
Redemption Notice Period	0.000707***	0.000978***		
	(0.000271)	(0.000270)		
Lockup Period	-0.00138	-0.00102		
	(0.00108)	(0.00105)		
High Water Mark	0.0427**	0.0374*		
	(0.0196)	(0.0192)		
Personal Capital Invested	-0.0250	-0.0188		
	(0.0178)	(0.0178)		
Leverage	0.0165	0.0151		
	(0.0164)	(0.0160)		
Fund-of-Funds Type	-0.0830***	-0.0777***		
	(0.0247)	(0.0252)		
AUM	-0.0291***	-0.0212***	-0.0730***	-0.0324**
	(0.00680)	(0.00664)	(0.0164)	(0.0159)
AGE	0.0474***	0.0287**	0.00542	-0.0190
	(0.0135)	(0.0132)	(0.0279)	(0.0496)
Fund Flow (past 1 year)	0.000523***	0.000811***	-0.0135	-0.0165*
	(0.000129)	(0.000111)	(0.0113)	(0.0100)
Return Volatility (past 2 years)	-1.671**	-2.810***	1.321	-1.763
	(0.699)	(0.884)	(1.031)	(1.101)
Return Skewness (past 2 years)	0.132***	0.111***	0.140***	0.118***
	(0.0101)	(0.0102)	(0.0137)	(0.0139)
Return Kurtosis (past 2 years)	0.0198***	0.0140***	0.00219	0.00169
	(0.00383)	(0.00393)	(0.00484)	(0.00465)
Alpha (F-H 7-factor)	-5.634***	-2.790**	-9.984***	-6.971***
	(1.180)	(1.137)	(1.631)	(1.593)
R-square (F-H 7 -factor)	0.0641	0.0117	0.0717	0.0421
	(0.0490)	(0.0518)	(0.0669)	(0.0647)
Constant	Included	Included	Included	Included
Year FEs	No	Yes	No	Yes
Fund FEs	No	No	Yes	Yes
Observations	19,939	19,939	19,939	19,939
Adjusted R-squared	0.028	0.096	0.174	0.228

Table 7: Returns of hedge fund portfolio formed on SED

At the end of each month from June 1997 through June 2010, we rank hedge funds into ten decile portfolios according to their skills on exploiting rare disaster concerns (SED). Decile 1 (10) consists of funds with the lowest (highest) skills (see Table 4 for details). Portfolio returns are equally weighted. We report results for the portfolio holding period of one month, three months, and up to 18 months. For overlapped holding months, we follow the independently managed portfolio approach (Jegadeesh and Titman (1993)) and calculate average monthly returns. Monthly mean returns (in percent) and Newey-West (1987) t-statistics (in parentheses) are reported for each decile and high-minus-low SED portfolio. We also report regression intercepts (monthly alphas) from the Fung-Hsieh 7-factor model.

Exploit Rare Disaster Concerns	1 month		3 months		6 months		12 months		18 months	
	Excess Ret	F-H Alpha	Excess Ret	F-H Alpha	Excess Ret	F-H Alpha	Excess Ret	F-H Alpha	Excess Ret	F-H Alpha
1 - Low Skill	-0.058	-0.343	0.005	-0.253	0.040	-0.224	0.205	-0.016	0.302	0.113
	(-0.19)	(-1.61)	(0.02)	(-1.22)	(0.13)	(-1.09)	(0.70)	(-0.08)	(1.06)	(0.60)
2	0.195	0.036	0.202	0.039	0.251	0.098	0.280	0.126	0.307	0.158
	(1.02)	(0.30)	(1.06)	(0.34)	(1.32)	(0.86)	(1.45)	(1.13)	(1.62)	(1.45)
3	0.294	0.148	0.288	0.139	0.296	0.153	0.323	0.186	0.327	0.188
	(1.80)	(1.45)	(1.78)	(1.43)	(1.83)	(1.58)	(2.02)	(1.95)	(2.07)	(1.99)
4	0.296	0.172	0.294	0.177	0.284	0.163	0.276	0.155	0.292	0.167
	(2.15)	(1.94)	(2.15)	(2.06)	(2.08)	(1.93)	(2.02)	(1.85)	(2.13)	(2.00)
5	0.264	0.121	0.273	0.145	0.275	0.154	0.270	0.151	0.277	0.157
	(1.84)	(1.27)	(2.03)	(1.73)	(2.08)	(1.87)	(2.07)	(1.89)	(2.13)	(2.00)
6	0.280	0.184	0.283	0.179	0.258	0.153	0.257	0.151	0.265	0.159
	(2.37)	(2.39)	(2.39)	(2.46)	(2.15)	(2.10)	(2.17)	(2.14)	(2.21)	(2.26)
7	0.337	0.232	0.281	0.172	0.261	0.155	0.271	0.164	0.271	0.160
	(2.96)	(3.15)	(2.43)	(2.43)	(2.28)	(2.31)	(2.33)	(2.47)	(2.30)	(2.39)
8	0.419	0.314	0.384	0.266	0.383	0.269	0.340	0.220	0.322	0.198
	(3.55)	(4.30)	(3.21)	(3.73)	(3.25)	(3.90)	(2.79)	(3.11)	(2.58)	(2.76)
9	0.568	0.445	0.502	0.365	0.478	0.342	0.423	0.277	0.394	0.247
	(3.71)	(4.20)	(3.30)	(3.60)	(3.23)	(3.60)	(2.88)	(3.10)	(2.65)	(2.81)
10 - High Skill	0.905	0.768	0.841	0.709	0.775	0.646	0.649	0.503	0.572	0.411
	(4.38)	(4.89)	(4.28)	(4.89)	(4.04)	(4.63)	(3.41)	(3.82)	(3.03)	(3.32)
High - Low	0.963	1.111	0.836	0.962	0.735	0.870	0.444	0.519	0.270	0.298
	(3.71)	(4.72)	(3.56)	(4.54)	(3.21)	(4.31)	(2.20)	(3.02)	(1.44)	(1.85)

Table 8: Pervasiveness of SED hedge fund portfolio returns

At the end of each month from June 1997 through June 2010, we rank funds into five quintiles according to their skills on exploiting rare disaster concerns (SED). In Panel A, we form quintiles within each Lipper TASS hedge fund investment style, and in Panel B we form quintiles within each size group based on fund net asset value (NAV). Quintile 1 (5) consists of funds with the lowest (highest) skills. We hold portfolios for one month and calculate equal-weighted portfolio returns. Each panel reports portfolios' monthly mean excess returns (in percent) and Newey-West (1987) *t*-statistics (in parentheses). The last column reports the Fung-Hsieh 7-factor monthly alphas (in percent) of high-minus-low RIX-beta portfolio.

	1 - Low Skill	2	3	4	5 - High Skill	5-1	F-H Alpha
Panel A: Lipper TASS hedge fund investment style							
Long/Short Equity Hedge	0.266	0.452	0.548	0.911	0.904	0.638	0.695
	(0.88)	(2.18)	(2.84)	(2.49)	(3.25)	(3.12)	(3.35)
Equity Market Neutral	0.188	0.069	0.212	0.347	0.614	0.427	0.557
	(1.16)	(0.76)	(3.08)	(5.23)	(4.35)	(2.28)	(2.95)
Dedicated Short Bias	0.060	-0.483	-0.079	-0.003	-0.291	-0.351	-0.278
	(0.10)	(-0.99)	(-0.17)	(-0.01)	(-0.54)	(-0.71)	(-0.53)
Global Macro	0.144	0.379	0.227	0.331	0.383	0.240	0.289
	(0.58)	(2.16)	(1.82)	(3.01)	(1.99)	(0.92)	(1.15)
Emerging Markets	0.236	0.361	0.439	0.586	1.186	0.951	1.297
	(0.42)	(0.91)	(1.29)	(1.91)	(2.84)	(2.25)	(3.06)
Event Driven	0.236	0.446	0.328	0.398	0.731	0.494	0.547
	(1.12)	(2.85)	(2.69)	(3.30)	(4.98)	(3.29)	(3.76)
Fund of Funds	-0.004	0.226	0.227	0.234	0.387	0.391	0.473
	(-0.02)	(1.60)	(1.84)	(2.06)	(3.10)	(2.86)	(4.02)
Fixed Income Arbitrage	0.064	0.071	0.112	0.244	0.546	0.481	0.474
	(0.32)	(0.45)	(1.12)	(3.01)	(4.10)	(2.40)	(2.35)
Convertible Arbitrage	-0.110	0.101	0.359	0.452	0.656	0.766	0.857
	(-0.33)	(0.50)	(2.32)	(2.77)	(3.26)	(2.69)	(3.41)
Managed Futures	0.364	0.394	0.374	0.415	0.714	0.350	0.345
	(1.18)	(1.63)	(1.59)	(1.71)	(2.20)	(1.14)	(1.12)
Multi Strategy	0.191	0.318	0.307	0.400	0.807	0.616	0.708
	(0.90)	(2.58)	(3.02)	(4.00)	(5.29)	(3.83)	(4.40)
Options Strategy	-0.081	0.542	0.534	0.126	0.675	0.804	1.295
	(-0.27)	(2.34)	(3.94)	(0.77)	(2.68)	(1.69)	(2.56)
Other	0.698	0.120	0.384	0.429	0.434	-0.264	-0.151
	(2.19)	(0.58)	(2.21)	(4.27)	(2.04)	(-0.78)	(-0.45)
Panel B: Fund size based on net asset value							
NAV - Low	-0.164	0.073	0.239	0.261	0.794	0.959	1.179
	(-0.49)	(0.41)	(1.86)	(1.96)	(3.95)	(3.49)	(4.64)
2	0.103	0.280	0.250	0.424	0.743	0.640	0.754
	(0.41)	(1.71)	(1.62)	(2.88)	(3.79)	(3.06)	(3.70)
3	0.096	0.274	0.220	0.323	0.520	0.424	0.434
	(0.46)	(2.24)	(1.96)	(3.43)	(3.68)	(2.28)	(2.57)
4	0.299	0.447	0.294	0.368	0.694	0.395	0.461
	(1.29)	(3.13)	(2.59)	(3.61)	(4.21)	(2.34)	(2.90)
NAV - High	0.119	0.283	0.458	0.471	0.865	0.746	0.779
	(0.42)	(1.33)	(2.60)	(3.23)	(3.74)	(3.27)	(3.69)

Table 9: SED hedge fund portfolio returns during normal and stressful market times

We monthly form hedge fund decile portfolios based on their skills on exploiting rare disaster concerns (SED). Decile 1 (10) consists of funds with the lowest (highest) skills. We report equal-weighted portfolio returns during normal and stressful market times (t-statistics are in parentheses). During the sample period of calculating returns (July 1997 through July 2010), we classify stressful market times in four different ways: (1) months during which the CRSP value-weighted market excess returns lose 10% or more; (2) months in the lowest quintile when we rank all months into five groups based on the market excess returns in these months; (3) NBER recessions (28 months in total: March 2001 through November 2001, and December 2007 through June 2009); and (4) months in the lowest decile when we rank all months into ten groups based on the market excess returns in these months. In specifications (1)-(3) above, we define normal market times as non-stressful months; and in specification (4), we define normal market times as months in the highest decile when we rank all months into ten groups based on the market excess returns in these months.

	(1)		(2)		(3)		(4)	
Exploit Rare Disaster Concerns	Normal Times	Stressful Times	Normal Times	Stressful Times	Normal Times	Stressful Times	Normal Times	Stressful Times
1 - Low Skill	0.260	-8.078	0.935	-3.940	0.379	-2.075	2.958	-5.670
	(0.94)	(-2.84)	(3.35)	(-5.19)	(1.20)	(-2.34)	(4.38)	(-4.41)
2	0.365	-4.083	0.903	-2.570	0.487	-1.150	2.009	-3.332
	(2.03)	(-3.00)	(5.56)	(-5.89)	(2.59)	(-1.97)	(4.13)	(-4.70)
3	0.452	-3.694	0.890	-2.034	0.522	-0.756	1.669	-2.573
	(3.03)	(-2.95)	(6.56)	(-5.27)	(3.21)	(-1.56)	(3.41)	(-3.87)
4	0.428	-3.038	0.748	-1.471	0.506	-0.674	1.316	-2.176
	(3.47)	(-2.33)	(6.48)	(-4.03)	(3.73)	(-1.64)	(4.17)	(-3.35)
5	0.416	-3.563	0.717	-1.505	0.446	-0.576	1.109	-2.291
	(3.63)	(-1.80)	(6.69)	(-3.33)	(3.06)	(-1.38)	(3.43)	(-2.73)
6	0.381	-2.262	0.690	-1.319	0.437	-0.440	1.302	-1.865
	(3.55)	(-1.94)	(7.16)	(-4.25)	(3.84)	(-1.15)	(4.02)	(-3.31)
7	0.429	-1.980	0.710	-1.121	0.493	-0.385	1.450	-1.597
	(4.02)	(-2.09)	(6.97)	(-4.17)	(4.47)	(-1.07)	(3.95)	(-3.27)
8	0.517	-2.040	0.806	-1.094	0.529	-0.090	1.695	-1.581
	(4.60)	(-2.66)	(7.38)	(-4.30)	(4.35)	(-0.26)	(4.82)	(-3.62)
9	0.679	-2.203	1.045	-1.293	0.665	0.123	2.455	-1.665
	(4.56)	(-2.39)	(6.68)	(-5.44)	(3.86)	(0.39)	(3.68)	(-4.24)
10 - High Skill	1.005	-1.615	1.409	-1.066	0.904	0.910	3.335	-1.245
	(4.86)	(-1.50)	(6.33)	(-3.08)	(3.99)	(1.79)	(3.83)	(-2.13)
High - Low	0.745	6.462	0.474	2.874	0.525	2.984	0.377	4.425
	(3.26)	(2.12)	(1.99)	(3.62)	(2.09)	(3.79)	(0.44)	(3.14)

Table 10: SED hedge fund portfolio risk exposure

We monthly form hedge fund decile portfolios based on their skills on exploiting rare disaster concerns (SED). Decile 1 (10) consists of funds with the lowest (highest) skills. We report portfolio loadings on macroeconomic and liquidity risk factors (Panel A) and Fung-Hsieh seven factors (Panel B). In Panel A, we regress monthly equal-weighted hedge fund portfolio returns on the market excess return and one of the following factor: (1) default risk, the change in default yield that is the difference between the Moody's AAA and BAA corporate bond yield; (2) term risk, the change in term spread that is the difference between the 10-year T-bond yield and the 3-month T-bill rate; (3) real GDP growth that is based on the quarterly growth rate of real per-capita GDP; (4) inflation rate that is the monthly year-on-year percentage change of the consumer price index (CPI); (5) market liquidity risk that is the extracted first principal component based on the correlation matrix of the U.S. market liquidity shocks, including the on-the-run-minus-off-the-run 10-year Treasury yield spread, the Pastor and Stambaugh (2003) liquidity level, and the Hu, Pan, and Wang (2012) noise; (6) funding liquidity risk that is the extracted first principal component based on the correlation matrix of the U.S. funding liquidity shocks, including the TED spread, the LIBOR-Repo spread, and the Swap-Treasury spread; and (7) all liquidity risk that is the extracted first principal component based on the correlation matrix of all market liquidity and funding liquidity shocks in (5) and (6). We measure liquidity shocks by taking the first-order difference in each of liquidity measures above and we also define a liquidity measure such that an increased value means less liquidity. In Panel B, we regress hedge fund portfolio returns on the Fung and Hsieh (2001) seven factors, including the market factor (MKTRF), the size factor (SMB), the term factor (TERM), the default factor (DEF), and three trend-following factors (PTFSBD, PTFSFX, and PTFSCOM). Following Sadka (2010), TERM and DEF factors are tradable bond portfolio returns based on the 7-10-year Treasury Index and the Corporate Bond Baa Index from Barclays Capital. Note these return-based factors are negatively correlated with term risk and default risk factors in Panel A because of the negative relation between yield and price.

Panel A: Macroeconomic and liquidity factor loadings

Exploit Rare Disaster Concerns	Default Risk	Term Risk	Real GDP Growth	Inflation Rate	Market Liquidity Risk	Funding Liquidity Risk	All Liquidity Risk
1 - Low Skill	-0.061	-0.008	0.008	-0.013	-0.006	-0.004	-0.005
	(-3.88)	(-0.95)	(3.20)	(-2.42)	(-3.61)	(-3.19)	(-4.15)
2	-0.044	-0.004	0.003	-0.005	-0.004	-0.003	-0.004
	(-4.90)	(-0.85)	(2.36)	(-1.40)	(-4.55)	(-3.65)	(-4.98)
3	-0.037	-0.006	0.002	-0.003	-0.003	-0.003	-0.003
	(-4.84)	(-1.43)	(1.96)	(-1.19)	(-4.08)	(-4.58)	(-5.47)
4	-0.030	-0.005	0.002	-0.002	-0.003	-0.003	-0.003
	(-4.40)	(-1.41)	(2.25)	(-0.80)	(-4.13)	(-4.33)	(-5.32)
5	-0.029	-0.003	0.002	-0.001	-0.003	-0.003	-0.003
	(-3.91)	(-0.74)	(1.30)	(-0.26)	(-3.85)	(-4.44)	(-5.20)
6	-0.025	-0.003	0.001	-0.001	-0.003	-0.002	-0.002
	(-4.29)	(-1.05)	(1.25)	(-0.36)	(-4.19)	(-3.81)	(-4.91)
7	-0.026	-0.004	0.001	-0.000	-0.003	-0.002	-0.003
	(-4.55)	(-1.43)	(1.06)	(-0.18)	(-4.84)	(-4.81)	(-6.06)
8	-0.020	0.001	0.000	-0.001	-0.002	-0.002	-0.002
	(-3.46)	(0.45)	(0.43)	(-0.60)	(-3.28)	(-4.22)	(-4.74)
9	-0.015	-0.002	-0.001	-0.001	-0.001	-0.001	-0.001
	(-1.75)	(-0.36)	(-0.80)	(-0.35)	(-1.62)	(-1.27)	(-1.69)
10 - High Skill	-0.003	0.010	-0.003	-0.004	-0.000	-0.001	-0.001
	(-0.23)	(1.52)	(-1.31)	(-0.84)	(-0.27)	(-0.77)	(-0.70)
High - Low	0.058	0.018	-0.010	0.010	0.006	0.004	0.005
	(3.43)	(2.03)	(-4.07)	(1.62)	(3.15)	(2.37)	(3.28)

Panel B: Fung-Hsieh seven-factor loadings

Exploit Rare Disaster Concerns	MKTRF	SMB	TERM	DEF	PTFSBD	PTFSFX	PTFSCOM
1 - Low Skill	0.454	0.125	0.219	0.479	-0.031	0.014	0.007
	(9.09)	(2.29)	(1.71)	(3.18)	(-2.01)	(1.06)	(0.43)
2	0.281	0.105	0.145	0.373	-0.007	0.002	0.013
	(10.27)	(3.49)	(2.06)	(4.51)	(-0.87)	(0.34)	(1.49)
3	0.236	0.082	0.142	0.325	-0.008	0.007	0.007
	(9.88)	(3.15)	(2.31)	(4.50)	(-1.11)	(1.06)	(0.94)
4	0.189	0.071	0.088	0.257	-0.013	0.005	0.002
	(9.12)	(3.14)	(1.66)	(4.10)	(-2.07)	(0.92)	(0.37)
5	0.178	0.092	0.094	0.263	-0.020	0.004	0.000
	(7.99)	(3.78)	(1.66)	(3.92)	(-2.89)	(0.64)	(0.05)
6	0.158	0.062	0.054	0.222	-0.011	0.004	0.003
	(8.78)	(3.16)	(1.16)	(4.08)	(-1.91)	(0.81)	(0.56)
7	0.148	0.083	0.090	0.227	-0.005	0.005	-0.000
	(8.56)	(4.38)	(2.03)	(4.37)	(-1.00)	(1.15)	(-0.00)
8	0.163	0.088	0.082	0.226	-0.004	0.006	0.001
	(9.52)	(4.72)	(1.88)	(4.38)	(-0.80)	(1.45)	(0.16)
9	0.232	0.145	0.003	0.052	-0.007	0.011	0.006
	(9.38)	(5.34)	(0.05)	(0.70)	(-0.88)	(1.62)	(0.82)
10 - High Skill	0.253	0.247	-0.030	0.047	0.004	0.022	0.011
	(6.89)	(6.13)	(-0.31)	(0.43)	(0.35)	(2.32)	(0.98)
High - Low	-0.201	0.122	-0.248	-0.432	0.035	0.009	0.005
	(-3.65)	(2.02)	(-1.76)	(-2.60)	(2.06)	(0.59)	(0.26)

Table 11: SEV and SED 25 portfolio returns

At the end of each month from June 1997 through June 2010, we employ sequential sorts and rank hedge funds into 25 portfolios according to their skills on exploiting volatility concerns (SEV) and skills on exploiting disaster concerns (SED). We hold portfolios for one month and calculate equal-weighted portfolio returns. Hedge fund skills are estimated on 24-month rolling-window regression of funds' excess monthly returns on the market factor, the CBOE Volatility Index (VIX) factor, and the RIX factor (with at least 18-month return observations available). This table presents portfolios' monthly mean excess returns (in percent) and Newey-West (1987) *t*-statistics (in parentheses). In Panel A, we report average returns of SED quintiles after controlling for SEV effect; in Panel B, we report average returns of SEV quintiles after controlling for SED effect.

Panel A: 5×5 portfolios based on sequential sorts first on SEV and then on SED

Exploiting Volatility Concerns	1 - Low Skill	2	3	4	5 - High Skill	5-1
1 - low	0.111	0.330	0.505	0.941	1.183	1.073
	(0.36)	(1.47)	(2.32)	(3.58)	(3.36)	(4.30)
2	0.067	0.277	0.259	0.479	0.639	0.572
	(0.29)	(2.06)	(1.77)	(3.59)	(3.19)	(3.40)
3	0.103	0.194	0.297	0.359	0.629	0.526
	(0.58)	(1.54)	(2.79)	(3.69)	(4.35)	(3.71)
4	0.137	0.279	0.242	0.260	0.566	0.429
	(0.72)	(2.23)	(2.19)	(2.45)	(4.82)	(3.19)
5 - High	-0.092	0.032	0.107	0.286	0.524	0.616
	(-0.30)	(0.17)	(0.61)	(2.02)	(3.29)	(2.47)
Average	0.065	0.223	0.282	0.465	0.708	0.643
	(0.30)	(1.56)	(2.06)	(3.50)	(4.14)	(4.44)

Panel B: 5×5 portfolios based on sequential sorts first on SED and then on SEV

Exploiting Disaster Concerns	1 - Low Skill	2	3	4	5 - High Skill	5-1
1 - Low Skill	-0.260	0.137	0.125	0.003	0.017	0.277
	(-0.83)	(0.65)	(0.69)	(0.01)	(0.06)	(0.97)
2	0.116	0.287	0.213	0.308	0.334	0.218
	(0.57)	(2.09)	(1.74)	(2.65)	(2.65)	(1.36)
3	0.201	0.245	0.264	0.320	0.419	0.218
	(1.04)	(1.94)	(2.45)	(3.34)	(3.92)	(1.65)
4	0.389	0.371	0.388	0.429	0.513	0.124
	(1.92)	(2.56)	(3.09)	(3.72)	(4.22)	(0.85)
5 - High Skill	1.035	0.799	0.660	0.680	0.752	-0.283
	(2.90)	(3.08)	(3.09)	(3.68)	(3.61)	(-1.10)
Average	0.296	0.368	0.330	0.348	0.407	0.111
	(1.27)	(2.29)	(2.43)	(2.78)	(2.91)	(0.73)

Table 12: Fama-MacBeth regressions of hedge fund returns

This table reports results from Fama-MacBeth (1973) cross-sectional regressions of hedge funds' excess returns in month $t+1$ on their SEDs and other explanatory variables as of month t. The sample consists of funds that report returns net of fees in US dollars and have at least $10 million AUM. Funds' market beta and SED are estimated from 24-month rolling-window regressions of funds' excess monthly returns on market excess return and the measure of rare disaster concerns (RIX). Other betas are estimated in a similar way. That is, to estimate noise beta, liquidity beta, default premium beta, and inflation beta, we regress fund's excess returns on the Hu-Pan-Wang noise factor, Sadka's liquidity factor, default spreads, and inflation, respectively, in presence of the controls of market excess return and the RIX. We also require at least 18 months of return observations in estimating regressions. Funds' characteristic variables include total variance (the sample variance of fund's excess returns within the past 36 months), AUM (the log of assets under management), AGE (the log of fund's age that equals number of months from inception to month t), lagged return (the fund's excess return in month t), management fee, incentive fee, four dummy variables (high water mark requirement, personal capital invested, leverage used, and lockup requirement), and redemption notice period. We report the time-series average of Fama-MacBeth regression coefficients and Newey-West (1987) t-statistics (in parentheses).

	(1)	(2)	(3)	(4)	(5)	(6)
Market Beta	0.0028	0.0040	0.0035	0.0010	0.0036	0.0038
	(0.84)	(1.31)	(1.13)	(0.32)	(1.19)	(1.24)
SED	0.0012	0.0011	0.0013	0.0016	0.0013	0.0011
	(1.85)	(1.82)	(2.19)	(2.60)	(2.24)	(2.04)
Noise Beta			-0.1232			
			(-2.22)			
Liquidity Beta				0.0172		
				(0.58)		
Default Premium Beta					0.0076	
					(0.79)	
Inflation Beta					-0.0823	
					(-1.82)	
Total Variance						0.1220
						(1.07)
AUM		-0.0003	-0.0003	-0.0004	-0.0003	-0.0002
		(-1.97)	(-2.01)	(-2.34)	(-1.92)	(-1.66)
AGE		-0.0004	-0.0004	-0.0003	-0.0004	-0.0004
		(-1.26)	(-1.22)	(-0.84)	(-1.36)	(-1.46)
Lagged Return		0.1112	0.0994	0.1194	0.1043	0.1169
		(6.09)	(5.26)	(5.74)	(5.77)	(6.63)
Management Fee		0.0919	0.0850	0.0903	0.0873	0.0713
		(2.16)	(2.05)	(2.03)	(2.15)	(1.76)
Incentive Fee		0.0064	0.0063	0.0050	0.0066	0.0058
		(2.87)	(2.99)	(2.13)	(2.96)	(2.63)
High Water Mark		0.0011	0.0011	0.0012	0.0011	0.0011
		(3.95)	(3.75)	(4.02)	(3.98)	(3.78)
Personal Capital Invested		0.0003	0.0003	0.0001	0.0003	0.0003
		(1.13)	(1.15)	(0.47)	(1.24)	(0.97)
Leverage Used		0.0006	0.0005	0.0005	0.0005	0.0006
		(1.73)	(1.63)	(1.55)	(1.46)	(1.74)

Lockup Required		0.0012	0.0012	0.0011	0.0012	0.0011
		(3.26)	(3.23)	(2.80)	(3.32)	(2.97)
Redemption Notice Period		0.0000	0.0000	0.0000	0.0000	0.0000
		(1.27)	(1.36)	(1.27)	(1.21)	(1.65)
Intercept	0.0035	0.0016	0.0018	0.0016	0.0015	0.0018
	(4.90)	(1.32)	(1.44)	(1.27)	(1.26)	(1.52)
Avg # of funds per month	1485	1480	1480	1447	1480	1475
Avg adjusted R-sqr	0.168	0.219	0.236	0.233	0.242	0.235
Number of months	157	157	157	139	157	157

Table 13: Double-sorted hedge fund portfolio returns

At the end of each month from June 1997 through June 2010, we rank funds into 25 portfolios according to their skills on exploiting disaster concerns (SED) and other variables. We hold portfolios for one month and calculate equal-weighted portfolio returns. This table presents portfolios' monthly mean excess returns (in percent) and Newey-West (1987) *t*-statistics (in parentheses). The last column of each panel reports the Fung-Hsieh 7-factor alphas (in percent) of high-minus-low SED portfolios. We use independent sorts in the first three panels and sequential sorts in the last four panels. In addition to SED, we use the following variables to form portfolios: market beta (Panel A), downside market beta (Panel B), volatility risk beta (Panel C), total variance (Panel D), noise beta (Panel E), default premium beta (Panel F), and inflation beta (Panel G). Hedge funds' market beta and SED are estimated on 24-month rolling-window regression of funds' excess monthly returns on the market factor and the measure of rare disaster concerns (RIX) (with at least 18-month return observations available). Other types of betas are estimated similarly. We follow Ang et al. (2006) in estimating downside market beta. That is, when running 24-month rolling-window regressions, we only use fund returns in the months where the market excess return is below its sample mean. We measure volatility risk by the month-to-month change of VIX. We follow Bali et al. (2012) in estimating total variance from the sample variance of fund's excess returns within the past 36 months. The noise factor is the liquidity risk factor in Hu et al. (2012). We follow Bali et al. (2011) to construct the macroeconomic risk factors of default premium and inflation.

Panel A: 5×5 portfolios based on independent sorts on market beta and SED

Market Beta	1 - Low Skill	2	3	4	5 - High Skill	5-1	F-H 7-Factor Alpha
1 - low	0.395	0.176	0.094	0.240	0.420	0.025	0.043
	(1.61)	(1.26)	(1.01)	(2.89)	(2.81)	(0.10)	(0.17)
2	0.174	0.290	0.210	0.297	0.523	0.350	0.393
	(0.93)	(3.18)	(2.52)	(4.03)	(4.57)	(1.91)	(2.14)
3	0.242	0.238	0.202	0.303	0.510	0.268	0.239
	(1.48)	(1.73)	(1.50)	(2.35)	(3.31)	(1.59)	(1.49)
4	0.255	0.341	0.443	0.479	0.790	0.536	0.511
	(1.17)	(1.78)	(2.31)	(2.69)	(3.27)	(2.86)	(2.88)
5 - High	0.143	0.547	0.570	0.681	0.946	0.803	0.988
	(0.33)	(1.47)	(1.54)	(1.81)	(2.38)	(3.15)	(3.84)
5-1	-0.252	0.372	0.476	0.442	0.527	0.778	0.945
	(-0.47)	(0.92)	(1.27)	(1.14)	(1.16)	(2.17)	(2.51)

Panel B: 5×5 portfolios based on independent sorts on downside market beta and SED

Downside Beta	1 - Low Skill	2	3	4	5 - High Skill	5-1	F-H 7-Factor Alpha
1 - low	0.140	0.205	0.143	0.275	0.353	0.213	0.287
	(0.69)	(1.60)	(1.26)	(2.82)	(2.54)	(1.10)	(1.47)
2	-0.099	0.235	0.245	0.288	0.417	0.515	0.649
	(-0.46)	(2.20)	(2.63)	(4.01)	(3.35)	(2.83)	(3.49)
3	0.291	0.232	0.248	0.304	0.780	0.490	0.599
	(1.49)	(1.70)	(2.19)	(2.75)	(4.54)	(2.57)	(3.01)
4	0.235	0.363	0.347	0.471	0.681	0.447	0.443
	(1.04)	(2.13)	(1.85)	(2.48)	(2.75)	(2.80)	(2.73)
5 - High	0.059	0.419	0.591	0.715	0.916	0.857	0.952

	(0.15)	(1.28)	(1.76)	(2.09)	(2.37)	(3.51)	(3.77)
5-1	-0.081	0.213	0.448	0.440	0.563	0.644	0.665
	(-0.21)	(0.66)	(1.34)	(1.28)	(1.38)	(2.44)	(2.45)

Panel C: 5×5 portfolios based on independent sorts on volatility risk beta and SED

Volatility Risk Beta	1 - Low Skill	2	3	4	5 - High Skill	5-1	F-H 7-Factor Alpha
1 - low	-0.008	0.359	0.325	0.523	0.909	0.916	0.978
	(-0.03)	(1.93)	(1.76)	(2.87)	(3.67)	(3.42)	(3.83)
2	0.056	0.216	0.238	0.369	0.652	0.596	0.625
	(0.27)	(1.72)	(2.21)	(3.33)	(3.61)	(3.31)	(3.50)
3	0.116	0.210	0.213	0.372	0.666	0.550	0.661
	(0.52)	(1.63)	(1.95)	(3.41)	(3.95)	(2.92)	(3.57)
4	0.145	0.377	0.353	0.363	0.711	0.566	0.622
	(0.66)	(2.71)	(2.32)	(2.88)	(3.90)	(2.94)	(3.33)
5 - High	0.116	0.386	0.328	0.523	0.728	0.612	0.792
	(0.36)	(1.64)	(1.41)	(2.43)	(3.53)	(2.58)	(3.73)
5-1	0.123	0.027	0.003	0.000	-0.181	-0.304	-0.186
	(0.54)	(0.15)	(0.01)	(0.00)	(-0.90)	(-1.21)	(-0.72)

Panel D: 5×5 portfolios based on sequential sorts first on total variance and then on SED

Total Variance	1 - Low Skill	2	3	4	5 - High Skill	5-1	F-H 7-Factor Alpha
1 - low	0.113	0.198	0.226	0.271	0.281	0.168	0.215
	(1.21)	(2.69)	(3.49)	(5.71)	(4.93)	(2.33)	(3.09)
2	0.206	0.212	0.227	0.207	0.405	0.199	0.198
	(1.76)	(1.78)	(2.02)	(2.03)	(4.74)	(2.14)	(2.14)
3	0.323	0.317	0.313	0.364	0.490	0.167	0.180
	(2.20)	(1.97)	(2.06)	(2.65)	(4.32)	(1.55)	(1.63)
4	0.161	0.229	0.394	0.565	0.737	0.576	0.562
	(0.80)	(1.16)	(2.01)	(2.83)	(4.25)	(3.29)	(3.36)
5 - High	-0.113	0.162	0.527	0.760	1.144	1.257	1.531
	(-0.26)	(0.44)	(1.49)	(2.29)	(3.81)	(3.39)	(4.57)
Average	0.138	0.224	0.338	0.433	0.612	0.474	0.537
	(0.75)	(1.31)	(2.04)	(2.83)	(4.82)	(3.64)	(4.45)

Panel E: 5×5 portfolios based on sequential sorts first on noise beta and then on SED

Noise Beta	1 - Low Skill	2	3	4	5 - High Skill	5-1	F-H 7-Factor Alpha
1 - low	0.497	0.500	0.633	0.946	1.111	0.614	0.630
	(1.50)	(2.08)	(2.65)	(3.74)	(3.85)	(2.36)	(2.43)
2	0.172	0.341	0.311	0.428	0.611	0.439	0.442
	(0.90)	(2.34)	(2.25)	(3.22)	(3.50)	(2.78)	(2.85)
3	0.174	0.292	0.248	0.298	0.574	0.400	0.445
	(0.96)	(2.30)	(2.31)	(3.06)	(4.27)	(3.05)	(3.45)
4	-0.041	0.157	0.218	0.326	0.445	0.486	0.563
	(-0.20)	(1.25)	(2.18)	(3.54)	(3.36)	(3.09)	(3.83)

5 - High	-0.437	-0.086	0.111	0.372	0.520	0.957	1.210
	(-1.28)	(-0.49)	(0.69)	(2.47)	(2.86)	(3.19)	(4.42)
Average	0.073	0.241	0.304	0.474	0.652	0.579	0.658
	(0.32)	(1.61)	(2.25)	(3.70)	(3.99)	(3.60)	(4.36)

Panel F: 5×5 portfolios based on sequential sorts first on default premium beta and then on SED

Default Beta	1 - Low Skill	2	3	4	5 - High Skill	5-1	F-H 7-Factor Alpha
1 - low	-0.307	0.022	0.255	0.290	0.490	0.797	0.923
	(-0.97)	(0.10)	(1.36)	(1.63)	(2.12)	(2.84)	(3.63)
2	0.003	0.132	0.189	0.302	0.455	0.452	0.506
	(0.01)	(0.88)	(1.59)	(3.05)	(3.19)	(2.95)	(3.45)
3	0.148	0.212	0.255	0.296	0.498	0.349	0.373
	(0.87)	(1.68)	(2.51)	(3.19)	(3.95)	(2.83)	(3.05)
4	0.256	0.355	0.274	0.455	0.674	0.418	0.489
	(1.26)	(2.59)	(2.09)	(3.76)	(4.65)	(2.76)	(3.39)
5 - High	0.521	0.701	0.610	0.667	0.982	0.461	0.637
	(1.50)	(3.04)	(3.08)	(3.14)	(3.82)	(1.87)	(2.88)
Average	0.124	0.284	0.316	0.402	0.620	0.496	0.586
	(0.54)	(1.80)	(2.37)	(3.19)	(4.02)	(3.24)	(4.42)

Panel G: 5×5 portfolios based on sequential sorts first on inflation beta and then on SED

Inflation Beta	1 - Low Skill	2	3	4	5 - High Skill	5-1	F-H 7-Factor Alpha
1 - low	0.195	0.596	0.385	0.544	0.978	0.783	0.943
	(0.61)	(2.85)	(2.03)	(2.96)	(4.33)	(2.86)	(3.87)
2	0.188	0.281	0.305	0.378	0.565	0.376	0.458
	(0.93)	(2.22)	(2.92)	(4.17)	(4.32)	(2.27)	(3.04)
3	0.183	0.212	0.235	0.271	0.458	0.276	0.355
	(1.05)	(1.85)	(2.31)	(2.83)	(3.80)	(2.26)	(3.11)
4	0.070	0.194	0.222	0.393	0.638	0.568	0.645
	(0.33)	(1.26)	(1.65)	(2.82)	(3.94)	(3.73)	(4.24)
5 - High	-0.232	0.240	0.482	0.315	0.619	0.850	1.068
	(-0.63)	(0.92)	(2.43)	(1.31)	(2.11)	(2.98)	(4.00)
Average	0.081	0.305	0.325	0.380	0.652	0.571	0.694
	(0.35)	(1.96)	(2.53)	(2.90)	(4.15)	(3.42)	(4.69)

Table 14: Robustness checks on SED hedge fund portfolio returns

For SED sorted deciles and high-minus-low SED portfolio, we present monthly mean returns and the Fung-Hsieh 7-factor alphas (in percent) and Newey-West (1987) *t*-statistics (in parentheses) under four scenarios: (1) portfolio returns are value weighted (see Table 4 for details of portfolio formation); (2) we impose no restriction on AUM in selecting hedge funds to construct deciles (we still require funds to report returns net of fees in US dollars); (3) we estimate each fund's SED by first regressing its returns on the contemporaneous as well as the lagged RIX factor and then summing two RIX betas; and (4) we assume large negative returns (i.e., -100%) for all exiting funds after they are delisted in Lipper TASS database and enter into "graveyard" fund sample. For cases (2) - (4), we report equal-weighted portfolio returns below (see Table 4 in detail), and the results based on value-weighted portfolio returns are similar.

	(1) Value-Weight Portfolio		(2) No Restriction on Funds' AUM		(3) Lagged RIX Factor		(4) Hedge Fund Delisting Return	
Exploit Rare Disaster Concerns	Excess Ret	F-H Alpha	Excess Ret	F-H Alpha	Excess Ret	F-H Alpha	Excess Ret	F-H Alpha
1 - Low Skill	-0.165	-0.445	0.073	-0.189	-0.185	-0.470	-0.970	-1.255
	(-0.53)	(-1.82)	(0.24)	(-0.94)	(-0.62)	(-2.24)	(-2.80)	(-5.12)
2	0.127	-0.096	0.229	0.092	0.184	0.013	-0.613	-0.788
	(0.54)	(-0.56)	(1.23)	(0.79)	(0.98)	(0.11)	(-2.71)	(-4.84)
3	0.276	0.114	0.292	0.168	0.246	0.107	-0.218	-0.372
	(1.59)	(0.93)	(1.89)	(1.67)	(1.63)	(1.09)	(-1.18)	(-2.96)
4	0.382	0.270	0.281	0.162	0.267	0.135	-0.279	-0.376
	(2.87)	(2.63)	(2.08)	(1.84)	(1.93)	(1.50)	(-1.74)	(-3.15)
5	0.267	0.094	0.277	0.161	0.270	0.157	-0.290	-0.441
	(1.76)	(0.85)	(2.21)	(1.97)	(2.12)	(1.93)	(-1.76)	(-3.76)
6	0.270	0.159	0.272	0.173	0.300	0.192	-0.300	-0.370
	(2.27)	(1.84)	(2.32)	(2.25)	(2.58)	(2.54)	(-2.17)	(-3.52)
7	0.404	0.295	0.330	0.232	0.328	0.228	-0.155	-0.251
	(3.10)	(2.90)	(2.97)	(3.31)	(2.82)	(3.06)	(-1.08)	(-2.46)
8	0.434	0.324	0.570	0.492	0.438	0.321	-0.243	-0.341
	(3.60)	(3.62)	(3.02)	(2.91)	(3.44)	(3.86)	(-1.66)	(-3.15)
9	0.362	0.254	0.585	0.464	0.686	0.559	-0.019	-0.140
	(1.69)	(1.51)	(4.00)	(4.77)	(4.41)	(5.62)	(-0.11)	(-1.06)
10 - High Skill	0.845	0.654	0.967	0.856	0.964	0.834	0.334	0.194
	(3.36)	(2.96)	(4.72)	(5.39)	(3.93)	(4.56)	(1.56)	(1.20)
High - Low	1.010	1.099	0.894	1.044	1.149	1.304	1.303	1.449
	(3.37)	(3.97)	(3.58)	(4.66)	(4.45)	(5.13)	(4.45)	(5.32)

Figure 1: Time-series plot of rare disaster index (RIX) from January 1996 through December 2011

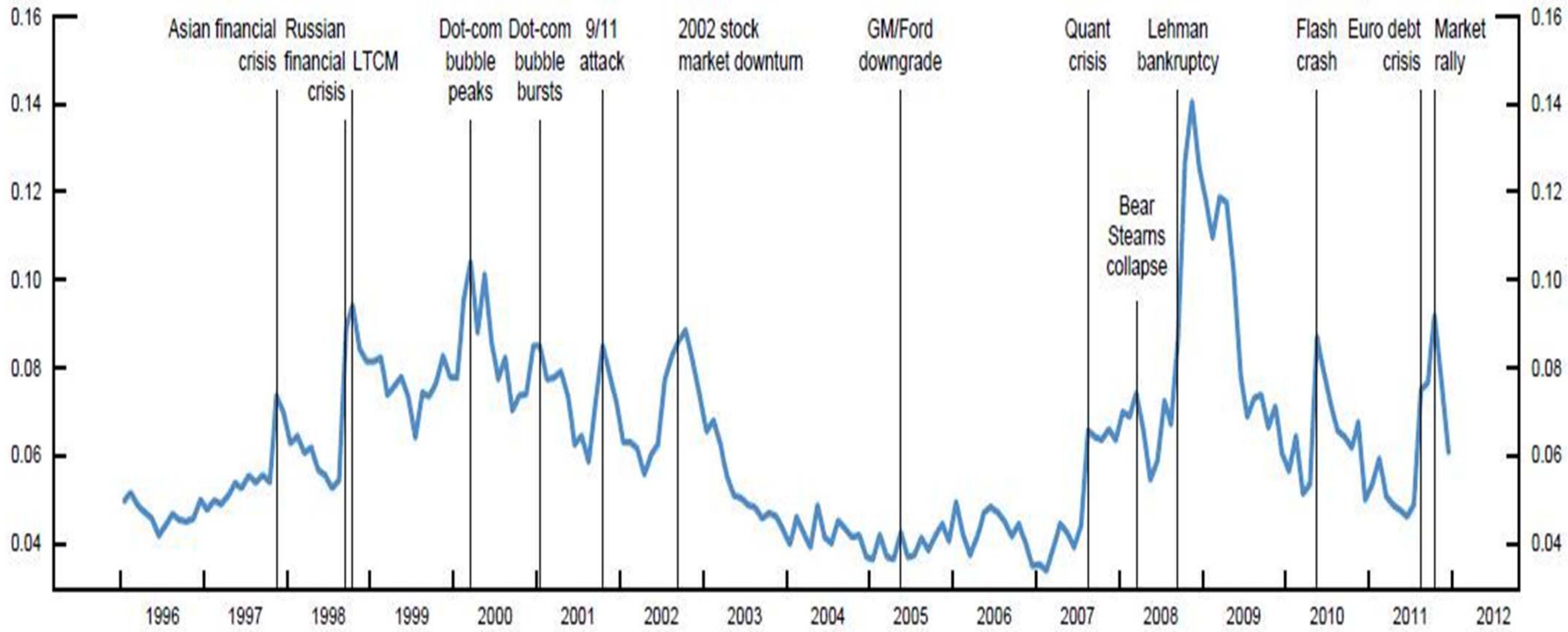

Figure 2: Time-series plot of high-minus-low SED portfolio returns