Do Hedge Funds Exploit Rare Disaster Concerns?*

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Abstract

We investigate whether hedge fund managers with better skills of exploiting the market's *ex ante* rare disaster concerns, which may not realize as disaster shocks *ex post*, deliver superior future fund performance. We measure fund skills in exploiting rare disaster concerns (SED) using 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 disaster concerns. Our main result shows that high-SED funds on average outperform low-SED funds by 0.96% per month and even more during stressful market times, while high-SED funds have less exposure to disaster risk.

Keywords: Rare disaster concern; hedge fund; skill

JEL classifications: G11; G12; G23

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1 Introduction

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

We provide novel evidence that some hedge fund managers with skills in 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. The key to our study is to make a clear distinction between the *ex ante* disaster concerns and the *ex post* realized shocks. Figure 1 plots monthly time-series of a rare disaster concern index we construct using 30-day out-of-the-money put options on various economic sector indices. The index value essentially equals to the price of an insurance against extreme downside movements of the financial market in the future (see Section 2 for details). Two salient features emerge from this graph. First, the market's 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 2010, and the market rally in October 2011 that are not (immediately) 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 the increase on disaster concerns (or disaster insurance prices) seem to be enormous relative to the subsequent realized losses. Such a startling difference suggests that investors may be paying a "fear premium" beyond the compensation for disaster risk. In fact, Bollerslev and Todorov (2011) have shown that the fear premium is a critical component of market returns. Such a fear premium can be consistent with behaviors of agents with non-expected utility, or constrained agents facing market frictions, who are averse to the tail event (Barberis (2013); Bates (2008); Caballero and Krishnamurthy (2008); Quiggin (1993); Liu, Pan, and Wang (2005)), or consistent with market mispricing or sentiment (Bondarenko (2003); Han (2008)). Under such circumstances, hedge fund managers with better skills in exploiting such disaster concerns or "fear premium" could deliver superior future fund performance.

How can some hedge funds exploit such *ex ante* disaster concerns better than others while being less exposed to the *ex post* realization of disaster shocks? First, 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, some fund managers 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 realize 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)). Different investors can have different disaster concerns with different levels of "fear premium" when the market's 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 in identifying the investors who are willing to pay higher premium for disaster insurance. From an operational perspective, even some of the standard financial insurance contracts, including options on fixed-income securities, currencies, and a subset of equities, are traded on the over-the-counter (OTC) market. Thus, hedge funds with different networks may have different ability to locate investors who are willing to pay high premiums. In summary, skills in exploiting disaster concerns can contribute to higher returns of certain hedge funds, and at the same time not necessarily make them more exposed to disaster shocks.

While the 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 fund managers. In principal, funds with better skills should earn higher contemporaneous returns than those with no such skills when the market's disaster

[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.

concern is high. Empirically, we measure fund skills in exploiting rare disaster concerns (SED) by the covariation between fund returns and the disaster concern index we construct.[2] Consistent with our view that hedge funds exhibit different skills in exploiting disaster concerns, we document substantial heterogeneity of SED across hedge funds as well as significant persistence in SED.

Our main tests focus on the relation between the SED measure 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 (Newey-West t-statistic of 2.8).[3] Moreover, high-SED funds exhibit significant performance persistence. The return spread of the high-minus-low SED deciles ranges from 0.84% per month (t-statistic of 2.6) for a three-month holding horizon, to 0.44% per month (t-statistic of 1.9) 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 the disaster concern index, is interpreted as measuring disaster risk exposure, high-SED funds on average should earn lower returns (rather than higher returns we document) because they are good hedges against disaster risk under this interpretation.

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 period from 1996 through 2010. To address this concern, we carefully study the performance of all SED fund deciles in both stressful and normal times under various 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 being more exposed to disaster risk. Moreover, we study the disaster

[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 risk–β interpretation.

[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 the rare disaster concern index ($\mathbb{RIX}$), we find negative and statistically significant $\mathbb{RIX}$ loadings for the majority of HFRI investment strategies. These results confirm that the payoffs of hedge fund strategies resemble payoffs from writing put options, and hence these strategies are sensitive to extreme downside market movements (Lo (2001); Goetzmann et al. (2002); Agarwal and Naik (2004)).

risk exposure of SED fund deciles by estimating their loadings on macroeconomic and liquidity risk factors (Barro (2006); Brunnermeier, Nagel, and Pedersen (2008)). We find that hedge funds ranked in higher SED deciles have less disaster risk exposure, further collaborating our conclusion that hedge fund managers with better skills in exploiting the market's *ex ante* disaster concerns deliver superior future fund performance, yet being less exposed to disaster risk. Finally, we also confirm that high-SED funds exhibit significantly higher survival rates.

Throughout the paper, we also compute risk-adjusted abnormal returns using the Fung and Hsieh (2001, 2004) seven-factor model, and the return difference between the high and low SED funds remains highly significant. Specifically, funds in the highest SED decile on average outperform funds in the lowest SED decile by 1.11% per month (Newey-West t-statistic of 3.53) relative to the Fung-Hsieh model. In addition, we conduct portfolio analysis and Fama-MacBeth (1973) regressions to account for hedge fund characteristics and a number of risk factors developed 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 (2013); Mitchell and Pulvino (2012)), macroeconomic risk (Bali, Brown, and Caglayan (2011)), and hedge fund total variance risk (Bali, Brown, and Caglayan (2012)). Our results remain qualitatively similar in these extended analyses.

Our results are robust to alternative measures of *ex ante* disaster concerns such as the ones based on S&P 500 index and long-maturity (90-day) options. Our results also survive a battery of robustness checks including different choices of portfolio weight, fund size, fund backfill bias, fund delisting returns, fund December and non-December returns, different benchmark models, and different hedge fund databases.

Our paper mainly contributes to the literature studying hedge fund skills and cross-sectional fund performance.[4] The SED measure is distinct from other fund skill variables in predicting future fund performance, including the skill in hedging away of systematic risk (Titman and Tiu (2011)), the skill in adopting innovative strategies (Sun, Wang, and Zheng (2012)), the skill in timing market liquidity (Cao et al. (2013)), and the conditional performance measure of downside

[4] Recent studies include 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), among others.

returns (Sun, Wang, and Zheng (2013)). We also show that hedge fund skills in exploiting volatility concerns (captured through the return comovement with CBOE's Volatility Index) have no power in explaining cross-sectional fund performance.

The remainder of the paper is organized as follows. Section 2 describes the construction of our disaster concern index. Section 3 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. The Appendix provides technical details, and a separate Internet Appendix provides additional results of SED decile portfolios based on various fund performance measures and alternative hedge fund databases.

2 Quantify 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 market in the future, signaling variations of *ex ante* disaster concerns.

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]

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

[5] The variance here refers to stochastic changes of the asset price, and hence is different from (and more general than) the second-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.

become more out of the money, $1-\ln\left(K/S_t\right)$ 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.

$\mathbb{RIX}$ 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. In view 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); Wachter (2013)), 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 rare 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 $dS_t/S_t=\left(r-\lambda\mu_J\right)dt+\sigma dW_t+dJ_t$,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, $\mathbb{RIX}$ captures all the high-order (≥ 3) moments of the jump distribution with negative sizes given that $e^x-(1+x+x^2/2)=x^3/3+x^4/4+\cdots$. Technical details are provided in the appendix.

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 Option data and empirical estimation

We obtain daily data on options from OptionMetrics from 1996 through 2010. 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

[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).

equation (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 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 June 2010. 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 small.

2.3 Descriptive statistics

Table 2 presents descriptive statistics of disaster concern indices. Panel A shows the monthly aggregated $\mathbb{RIX}$ has a mean of 0.063, with standard deviation of 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, an artifact 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 rare disaster concerns may spike without being followed by subsequent realization of market losses, and often spike much more than the subsequent realized market losses.

Panel B of Table 2 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 and -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 importantly, $\mathbb{RIX}$ 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 in Exploiting Rare Disaster Concerns (SED)

In this section, we describe our sample of hedge funds, explain our measure of hedge fund skills in exploiting rare 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. "Live" funds are active ones that continue reporting monthly returns to the database as of the snapshot date (July 2010 in our case); and "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 (2013)), 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 at the time of portfolio formation (but not after) (Cao, et al. (2010); Hu, Pan, and Wang (2013)). Panel A reports summary statistics by year. 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 in exploiting rare disaster concerns (SED) through the covariation between fund returns and our measure of *ex ante* 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 have lower level of assets under management, larger fund flow, less liquidation and non-reporting rate. In addition, high-SED funds are better at hedging systematic risk with respect to the Fung and Hsieh (2001) seven factors (Titman and Tiu (2011)). They have more innovative strategies as measured by strategy distinctiveness index in Sun, Wang and Zheng (2012), and they tend to be low liquidity timers but high market and volatility timers (Cao et al. (2013)).

These results are consistent with our claim that high-SED funds have better skills in exploiting disaster concerns (and hence deliver superior return performance).

In Panel B, within each SED decile we report the likelihood distribution of different hedge fund investment styles. On average, among funds with the highest skills in exploiting disaster concerns, the managed futures type is most likely to show up, whereas the fund-of-funds type is least likely.

3.3 Properties of SED

If a hedge fund can exploit market rare disaster concerns, it should display relatively persistent SED over time. To examine whether there exists such a persistence, at the end of each month we sort our sample of hedge funds into SED decile portfolios, and 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 in that decile. 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, as well as the difference in SED measures between high and low-SED deciles, during the portfolio formation month and subsequent months. Although the differences in SED across decile portfolios slowly decrease over time, they are still meaningfully different even three-years after portfolio formation. For example, the differences in SED between the highest and lowest SED portfolios are 3.48, 2.18, and 1.11, at one-month, one-year, and three-year holding horizons, respectively. These results suggest a strong persistence in the SED measure.

In Table 6, we investigate the cross-sectional determinants of hedge fund skills in exploiting disaster concerns by performing a set of panel regressions. We apply the SED estimated each June from 1997 to 2010 as the dependent variable, and fund characteristics as of June each year as explanatory variables. Overall, funds with higher skills in exploiting disaster concerns have smaller assets under management and have positive return skewness in the past two years. We also find a strong negative relation between Fung-Hsieh 7-factor alpha and SED. This last piece of evidence 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 word, those funds with high Fung-Hsieh alpha behave more like demanding disaster insurance, and less likely to exploit disaster concerns, making them low-SED funds. Finally, the heterogeneity of hedge fund SED is attributed more to fund-specific characteristics than to year-to-year variations. For instance, the adjusted R-squared increases from 3.5% to 21.1% when fund fixed effects are included, and it only increases from 3.5% to 9.2% when year fixed effects are included.

4 SED and Hedge Fund Performance

In this section we test our main hypothesis that hedge fund skills in exploiting rare 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 affects hedge fund performance during normal and stressful market times. Finally, we probe funds' skills in exploiting disaster concerns by investigating their exposure to macro and liquidity risks.

4.1 SED sorted hedge fund portfolios

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 at the time of portfolio formation, 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 macro-based factors (the change in term spread and the change in credit spread) that are replaced by tradable bond

[8] During the sample period between January 1994 and June 2010, 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.

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 (Newey-West t-statistic of 2.8). In fact, 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 3.5), indicating that the outperformance of high-skill funds is not simply attributed to option-based strategies.[9]

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, with Newey-West t-statistics ranging from 1.9 to 2.6. The Fung-Hsieh alphas of high-minus-low SED portfolios are even larger and also statistically significant.

In the Internet Appendix, we examine the performance of hedge fund portfolios sorted on SED using manipulation-proof performance measure (MPPM) developed in Ingersoll et al. (2007), Sharpe ratio, and information ratio benchmarked on the Fung-Hsieh model. A number of studies find that hedge funds engage in return smoothing and generate artificially high Sharpe ratio and information ratio (see, Getmansky, Lo, and Makarov (2004); Bollen and Pool (2008), among others). Following Getmansky, Lo, and Makarov (2004), when we estimate Sharpe ratio and information ratio, we take into account potential hedge fund return smoothing. Similar to the evidence based on raw and factor-model adjusted returns, these alternative performance metrics show high-SED funds outperformance low-SED funds by a significant margin. For example, under the MPPM measure with the penalizing coefficient of three, we find that high-SED funds have an average MPPM of

[9] 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.

0.065 (Newey-West t-statistic of 6.0), low-SED funds have an average MPPM of -0.015 (t-statistic of -0.5), and the difference is 0.08 (t-statistic of 2.5). Using Sharpe ratio and information ratio as fund performance metrics, we find that high-SED funds outperform low-SED funds by more than 40% and 35% per month, with Newey-West t-statistics of 3.7 and 2.0, respectively.

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

4.2 Pervasiveness of SED in hedge fund performance

Are hedge fund skills in exploiting rare 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 those twelve TASS investment styles (we exclude "other" style). For the majority of investment styles, we observe a strong and positive relation between SED and portfolio returns. In nine investment styles high-SED funds outperform low-SED funds; for two investment styles (managed futures and global macro) we find positive but statistically insignificant 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.

Panel B shows the strong relation between SED and fund performance across different fund size groups at the time of portfolio formation (measured by net asset value, NAV). The high-minus-low SED portfolios earn 0.96% and 0.75% per month, respectively, for funds within the lowest and highest NAV groups, both at least three standard errors from zero.[10] The Fung-Hsieh alphas are large and highly significant. For funds within the lowest and highest NAV groups, the high-minus-low SED portfolios' alphas are 1.18% and 0.78% per month, respectively, both at least three standard errors from zero. Finally, across all NAV groups, 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 in 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 in 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 evident when the market is stressful. We classify the sample period (July 1997 through July 2010) as "normal" vs. "stressful" market times in three 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). Another test of our SED-based explanation of fund performance is that skills in exploiting disaster concerns do not lead to fund return differences when the market disaster concerns are fairly low. In the fourth specification of stressful times, we hence study (4) good times defined as those months in the highest decile when we rank all months into ten groups based on the market excess returns in these months, whereas stressful times as months in the lowest decile.

Table 9 presents results of SED decile returns in different subsamples. During normal market times defined in specifications (1)-(3), high-SED funds earn higher returns than low-SED funds. During stressful market times in specifications (1)-(4), all funds lose (except for certain funds in specification (3)), which is consistent with the view that hedge funds earn profits overall but incur

[10] 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.

losses during market downturns as they are suppliers of disaster insurance.[11] More importantly, funds with high skills in exploiting disaster concerns lose much less, and hence still outperform funds with low skills. 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), though they lost more than 1.6% themselves. Finally, we observe no significant return difference between high and low SED funds in the period of high market returns of specification (4), further collaborating our SED-based explanation of hedge fund performance.

4.4 Disaster risk exposure

To further verify that funds in higher SED deciles earn higher returns by better skills rather than simply being more exposed to disaster risk, we compute loadings of SED fund deciles on various realized disaster shocks, measured by a battery of macroeconomic risk factors. Following the literature (Barro, 2006; Wachter, 2013), macroeconomic risk factors we consider include GDP growth, inflation, corporate default, and term spread of bond yields. The GDP growth is the real per-capita growth rate of GDP, computed quarterly by the real GDP growth rate obtained from Federal Reserve Economic Data (FRED) of the Federal Reserve Bank of St. Louis and the annual population growth obtained from the World Economic Outlook (WEO) database of International Monetary Fund (IMF). The inflation rate is the monthly year-on-year percentage change of the core CPI. We proxy the corporate default risk using the difference between the Moody's AAA and BAA corporate bond yield obtained from the FRED for U.S. We also compute the term spread between the 10-year US Treasury yield and 3-month T-bill rate.

We also consider various market and funding liquidity variables (Brunnermeier, Nagel, and Pedersen, 2008). The funding liquidity variables include the Treasury-Eurodollar (TED) spread equal to 3-month LIBOR minus the 3-month T-bill rate, the LIBOR-Repo spread equal to the 3-month LIBOR minus the 3-month General Collateral Treasury repurchase rate, and the Swap-Treasury spread equal to the 10-year interest rate swap rate minus the 10-year Treasury yield. In

[11] The positive return of certain high-SED funds based on specification (3) (define NBER recessions as stressful times) is due to the fact that the NBER recessions include the period of March-May 2009, when the financial market was moving up in response to the Federal Reserve's further confirmation of its large-scale asset purchases. In those three months, monthly market excess returns were 8.95%, 10.19%, and 5.21%, respectively. Removing these periods from stressful times leads to high-SED fund deciles earning returns insignificantly different from zero. We thank Narayan Naik for suggesting alternative definitions of "stressful" periods.

order to measure liquidity shocks, we take the first-order difference in each of these monthly series.[12] For market liquidity, we use the on-the-run minus off-the-run 10-year Treasury yield spread obtained from the Federal Reserve Board, innovations of the liquidity factor in Pastor and Stambaugh (2003), and the "noise" measure in Hu, Pan, and Wang (2013) delineating relative availability of arbitrage capitals. We define the U.S. funding liquidity shocks, the U.S. market liquidity shocks, and the U.S. all liquidity shocks as the first principal components based on various correlation matrices of the corresponding sets of liquidity variables, respectively.

Table 10 reports loadings of SED-sorted hedge fund portfolios on macroeconomic and liquidity risk factors (Panel A), and the classic Fung-Hsieh seven factors (Panel B). Interestingly, high-SED funds are *less* exposed to macroeconomic and liquidity shocks than low-SED funds. The difference in factor loadings is statistically significant for all macro and liquidity factors, with the exception of inflation rate. For example, the loadings of high and low SED funds on default risk are -0.061 and -0.003, respectively, and the difference has a t-statistic of 3.43. In fact, high-SED funds are not significantly exposed to any macroeconomic and liquidity shocks. Results of loadings on Fung-Hsieh seven factors in Panel B are generally consistent with those in Panel A.[13] Overall, our empirical evidence on factor loadings of SED-based fund deciles shows that high-SED funds earn higher returns because of their better skills in exploiting disaster concerns rather than simply taking larger exposure to disaster risk.

5 Distinctiveness of SED

In this section, we explore the distinctiveness of SED from other fund skill measures in explaining cross-sectional hedge fund performance. We first apply a series of two-way sequentially-sorted portfolios, and then perform Fama-MacBeth (1973) cross-sectional regressions to take into account a number of fund skill measures developed in the recent literature.

[12] Defining shocks as the residuals from an AR(1) or AR(2) model (e.g., Korajczyk and Sadka, 2008; Moskowitz and Pedersen, 2012; Asness, Moskowitz, and Pedersen, 2013) does not change our results.

[13] In the Internet Appendix, we also conduct double-sorted portfolios using SED and a number of factors on downside risk, volatility risk, tail risk, macroeconomic risk, and liquidity risk. Our results show that SED-based hedge fund performance is not driven by exposures to any of these risk factors.

5.1 SED and other skill measures

We study whether our SED measure is distinct from four other fund skills documented in the literature that have explanatory power for hedge fund performance. Titman and Tiu (2011) show that skilled funds are less exposed to systematic risk, leading to a low R-squared (as the skill measure) when one regresses fund returns on the Fung-Hsieh seven factors. Sun, Wang, and Zheng (2012) argue that fund skills in pursuing unique investment strategies deliver superior performance, and propose a strategy distinctiveness index (SDI) based on the correlation of individual fund returns with the average returns of peer funds in the same style category. Cao et al. (2013) find that funds that can better time the market liquidity have better performance. Finally, Sun, Wang, and Zheng (2013) use fund returns during market downturns (*DownsideReturns*) as a measure of fund skills in managing downside risk, and show that DownsideReturns can explain cross-sectional hedge fund returns. We document the distinctiveness of SED measure from these four documented fund skills by sequentially sorted portfolios.

At the end of each month from June 1997 through June 2010, we rank funds sequentially into 25 portfolios first on one of these four fund skill variables and then on SED. We hold portfolios for one month and calculate equal-weighted portfolio returns. Table 11 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. The last two rows of each panel reports the average return performance of SED quintiles in control of the effect of the fund skill variable. Similar to our baseline estimation procedure, a hedge fund' SED is estimated based on a 24-month rolling-window regression of the fund's monthly excess returns on the market factor and the measure of rare disaster concerns ($\mathbb{RIX}$) (with at least 18-month return observations available).

Results in Table 11 show strong explanatory power of SED for hedge fund performance in the presence of other fund skill measures. Across quintiles of other skills, the return spreads of high-minus-low SED portfolios are both statistically and economically significant, averaging around 58, 64, 53, and 45 basis points per month, controlling for the skills in hedging systematic risk, strategy distinctiveness, liquidity timing, and downside risk management, respectively. The abnormal returns (the Fung-Hsieh seven-factor alphas) are even larger, ranging from 48 to 72 basis points per month, which are at least three standard errors from zero. Overall, these results show that the explanatory power of the SED on hedge fund performance is beyond those skill variables documented in the literature.

5.2 SED and skills in exploiting volatility concerns

In our construction of $\mathbb{RIX}$, the second component $\mathbb{IV}$ underlies construction of the CBOE Volatility Index (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. In fact, $\mathbb{RIX}$ and VIX have an in-sample correlation of 0.82 between 1996 and 2011. Therefore, it is imperative to ask whether our SED is driven by hedge fund skills in exploiting volatility concern (SEV) based on VIX analogously.

The answer is unequivocally no. First, in untabulated analysis, we rank hedge funds into deciles based on analogously defined fund skills in exploiting volatility concerns (SEV). This measure is defined as the covariation between fund excess returns and VIX, estimated in a similar way to the SED measure. 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 two sets of sequential sorts and rank hedge funds into 25 portfolios according to the SEV and SED measures. We report equal-weighted portfolio returns in Table 12.

In Panel A, we first sort all funds into quintiles based on each fund's SEV; and then we sort funds within each SEV quintile into another five portfolios based on each fund's SED. Panel A shows that SED, even in the presence of potential fund skills in exploiting volatility concerns (SEV), well explains cross-sectional hedge fund returns. On average, high-SED funds outperform low-SED funds by 0.64% per month (t-statistic of 4.4). In fact, we observe an almost monotonically increasing relation between SED and hedge fund returns within each 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 Panel B, we first sort all funds into quintiles based on each fund's SED; and then we sort funds within each SED quintile into another five portfolios based on each fund's SEV. In sharp contrast, Panel B shows 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). Collectively, these results suggest that fund skills in exploiting disaster concerns rather than volatility concerns explain cross-sectional hedge fund performance.

5.3 Fama-MacBeth cross-sectional regressions

The portfolio analysis so far suggests that the fund skills in exploiting disaster concerns is distinct from other documented fund skills in the literature in explaining cross-sectional hedge fund performance. In this section, we differentiate the SED from other fund skills using the Fama-MacBeth (1973) regression that allows us to control multiple skill measures simultaneously. Furthermore, our investigation of the characteristics of hedge funds in forming SED deciles indicates that certain characteristics of hedge funds 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 a set of hedge fund risk factors documented in the literature.

Table 13 presents the results of regression coefficients and Newey-West (1987) t-statistics when we regress funds' monthly excess returns in month (t+1) on SED and various subsets of the explanatory variables in month (t). In all seven specifications, the coefficients on SED decile rankings are positive and significant, showing that the explanatory power of the fund skills in exploiting disaster concerns on cross-sectional hedge fund performance is not subsumed by market beta, liquidity beta, default premium beta, inflation beta, total variance, other fund skill variables, 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

In this section, we perform additional robustness checks on SED hedge fund portfolios. Results are presented in Table 14 under seven different scenarios.

6.1 Fund size, backfilling 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 with significant t-statistics. 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 (2013)). 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 (with Newey-West t-statistic of 2.7), a return very close to the 0.96% reported in our baseline specification (see Table 7). Repeating the analysis with different AUM cutoffs such as $5 million and $50 million, we find similar results.

We mitigate the backfilling bias by excluding the first 25 months of returns of each hedge fund in the Lipper TASS database. The return spread of high-minus-low SED portfolio is 0.89% per month (with Newey-West t-statistic of 2.6).

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. We find 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 (with Newey-West t-statistic of 3.1). Results are similar for different negative numbers for hedge fund delisting returns.

Another issue related to hedge funds managing their reported returns is that returns during December are higher than returns during non-December months (see, Agarwal, Daniel, and Naik (2011). In our analysis return spreads of high-minus-low SED portfolios are 1.6% and 0.91% per month during December and non-December months, respectively, both are statistically significant.

We report details in the Internet Appendix.

6.2 Alternative construction of SED measures

We measure rare disaster concerns using 90-day OTM puts on sector indices.[14] The return spread of high-minus-low SED portfolio is 1.06% per month that is more than three standard errors from zero. We also measure rare disaster concerns using 30-day OTM puts on S&P 500 index. The return spread of high-minus-low SED portfolio is 0.64% per month (with Newey-West t-statistic of 1.8).[15]

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 in exploiting disaster concerns, we regress funds' monthly excess returns on a contemporaneous as well as lagged $\mathbb{RIX}$ factor. We find 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 three standard errors away from zero.

6.3 Different hedge fund databases

No single database completely covers the hedge fund universe. Our main results rely on hedge funds covered in Lipper TASS database, but we also examine hedge funds covered in HFR and CISDM databases. Our baseline results remain unchanged under these two different databases. For example, among funds from the HFR database, high-SED funds on average outperform low-SED funds by 0.84% per month (with Newey-West t-statistic of 2.6). Furthermore, subsample (normal vs. stressful times) results of fund performance of SED deciles are also similar to those in TASS database. We report details in the Internet Appendix Table 3 and Table 4.

[14] 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).

[15] We also construct a $\mathbb{RIX}$ by averaging disaster concern measures based on S&P 500 index options and sector index options. Results (available upon request) using this specification of rare disaster concern index are similar to those using only sector index options.

7 Conclusions

We provide novel evidence that hedge fund managers with better skills in exploiting rare disaster concerns (SED) 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 can deliver superior future fund performance if they are good at identifying the shoot-up of *ex ante* disaster concerns just as a fear with no subsequent disaster shocks, and/or identifying the investors who are willing to pay higher fear premiums.

We develop the rare disaster concern index that equals the price of a disaster insurance contract. We then measure fund SED based on the covariation between fund excess returns and this index. We document substantial heterogeneity as well as significant persistence in SED. We show that funds in the highest SED decile outperform funds in the lowest decile by 0.96% per month on average and even more during stressful market times. High-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 in exploiting disaster concerns deliver superior future fund performance, different from the popular view that hedge funds earn higher average returns 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 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).[16] 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

[16] 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 $\lambda\frac{1}{\sqrt{2\pi}\sigma_J}\exp\left(-\,(x-\mu_J)^2/2\right)$. 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 $\mathbb{V}$:

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

where only OTM put options that protect investors against negative price jumps are used. We then define our rare disaster concern 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 $\omega^- [dx, dt]$ the Poisson random measure associated with negative price jumps.

References

Acharya, Viral V., and Lasse Heje Pedersen, 2005, Asset pricing with liquidity risk, *Journal of Financial Economics* 77, 375-410.

Adrian, Tobia, Markus K. Brunnermeier, and Hoai-Luu Q. Nguyen, 2011, Hedge fund tail risk, Chapter in forthcoming NBER book Quantifying Systemic Risk, Joseph G. Haubrich and Andrew W. Lo editors.

Agarwal, Vikas, Naveen D. Daniel, and Narayan Y. Naik, Do Hedge Funds Manage Their Reported Returns?, *Review of Financial Studies* 24, 3281 - 3320.

Agarwal, Vikas, Gurdip Bakshi, and Joop Huij, 2010, Do higher-moment equity risks explain hedge fund returns?, Working paper, Georgia State University.

Agarwal, Vikas, and Narayan Y. Naik, 2004, Risks and portfolio decisions involving hedge funds, *Review of Financial Studies* 17, 63-98.

Agarwal, V., N. Daniel, and N. Naik, 2009, Role of Managerial Incentives and Discretion in Hedge Fund Performance. *Journal of Finance* 64, 2221–56.

Aggarwal, Rajesh, and Philippe Jorion, 2010, The Performance of Emerging Hedge Funds and Managers, *Journal of Financial Economics* 96, 238-256.

Ang, Andrew, Joseph Chen, and Yuhang Xing, 2006, Downside risk, *Review of Financial Studies* 19, 1191–1239.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259-299.

Aragon, George, 2007, Share Restriction and Asset Pricing: Evidence from the Hedge Fund Industry, *Journal of Financial Economics* 83, 33–58.

Asness, Clifford S., Tobias J. Moskowitz, and Lasse Heje Pedersen, 2013, Value and momentum everywhere, *Journal of Finance* 68, 929-985.

Bali, Turan G., Stephen J. Brown, and Mustafa Onur Caglayan, 2011, Do hedge funds' exposures to risk factors predict their future returns? *Journal of Financial Economics* 101, 36-68.

Bali, Turan G., Stephen J. Brown, and Mustafa Onur Caglayan, 2012, Systematic risk and the cross section of hedge fund returns, *Journal of Financial Economics* 106, 114-131.

Barro, Robert J., 2006, Rare disasters and asset markets in the twentieth century, *Quarterly Journal of Economics* 121, 823-866.

Black, Fischer, and Myron Scholes, 1973, The pricing of options and corporate liabilities, *Journal of Political Economy* 81, 637-654.

Bollen, Nicolas P. B., and Veronika K. Pool, 2008, Conditional Return Smoothing in the Hedge Fund Industry, *Journal of Financial and Quantitative Analysis* 43, 267-298.

Bollerslev, Tim, George Tauchen, and Hao Zhou, 2009, Expected stock returns and variance risk premia, *Review of Financial Studies* 22, 4463-4492.

Bollerslev, Tim, and Viktor Todorov, 2011, Tails, fears, and risk premia, *Journal of Finance* 66, 2165-2211.

Bondarenko, Oleg, 2004, Market price of variance risk and performance of hedge funds, Working paper, University of Illinois at Chicago.

Britten-Jones, Mark, and Anthony Neuberger, 2000, Option prices, implied price processes, and stochastic volatility, *Journal of Finance* 55, 839-866.

Brunnermeier, Markus K., and Lasse Heje Pedersen, 2009, Market liquidity and funding liquidity, *Review of Financial Studies* 22, 2201–2238.

Cao, Charles, Yong Chen, Bing Liang, and Andrew W. Lo, 2010, Can hedge funds time market liquidity? *Journal of Financial Economics*, forthcoming.

Carr, Peter, and Dilip Madan, 1998, Towards a theory of volatility trading, In R. Jarrow (ed.), *Volatility: New Estimation Techniques for Pricing Derivatives*, chap. 29, pp. 417–27. London: Risk Books.

Carr, Peter, and Liuren Wu, 2009, Variance risk premia, *Review of Financial Studies* 22, 1311-1341.

Carhart, Mark, 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

Demeterfi, Kresimir, Emanuel Derman, Michael Kamal, and Joseph Zou, 1999, A guide to volatility and variance swaps, *Journal of Derivatives* 6, 9-32.

Drechsler, Itamar, and Amir Yaron, 2011, What's vol got to do with it? *Review of Financial Studies* 24, 1-45.

Dybvig, Philip H., and Stephen A. Ross, 1985, Differential information and performance measurement using a security market line, *Journal of Finance* 40, 383–399.

Du, Jian, and Nikunj Kapadia, 2012, Tail and volatility indices from option prices, Working paper, University of Massachusetts.

Fama, Eugene, and Kenneth French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, Eugene, and James D. MacBeth, 1973, Risk, return and equilibrium: empirical tests, *Journal of Political Economy* 81, 607-636.

Fung, William, and David A. Hsieh, 1997, Empirical characteristics of dynamic trading strategies: the case of hedge funds, *Review of Financial Studies* 10, 275-302.

Fung, William, and David A. Hsieh, 2001, The risk in hedge fund strategies: theory and evidence from trend followers, *Review of Financial Studies* 14, 313–341.

Fung, William, and David A. Hsieh, 2004, Hedge fund benchmarks: a risk-based approach, *Financial Analysts Journal* 60, 65-80.

Fung, W., D. Hsieh, N. Naik, and T. Ramadorai, 2008, Hedge Funds: Performance, Risk, and Capital Formation, *Journal of Finance* 63, 1777–803.

Gabaix, Xavier, 2012, Variable rare disasters: an exactly solved framework for ten puzzles in macro-finance, *Quarterly Journal of Economics* 127, 645-700.

Garleanu, Nicolae, Lasse Heje Pedersen, and Allen M. Poteshman, 2009, Demand-based option pricing, *Review of Financial Studies* 22, 4259-4299.

Getmansky, Mila, Andrew W. Lo, and Igor Makarov, 2004, An econometric model of serial correlation and illiquidity in hedge fund returns, *Journal of Financial Economics* 74, 529-609.

Glosten, Lawrence R., and Ravi Jagannathan, 1994, A contingent claim approach to performance evaluation, *Journal of Empirical Finance* 1, 133-160.

Goetzmann, William, Jonathan Ingersoll, Matthew Spiegel, and Ivo Welch, 2002, Sharpening Sharpe ratios, No. w9116, National Bureau of Economic Research.

Goetzmann, William, Jonathan Ingersoll, Matthew Spiegel, and Ivo Welch, 2007, Portfolio performance manipulation and manipulation-proof performance measures, *Review of Financial Studies* 20, 1503-1546.

Hu Xing, Jun Pan, and Jiang Wang, 2013, Noise as Information for Illiquidity, *Journal of Finance* 68, 2223-2772.

Jagannathan, Ravi, and Robert A. Korajczyk, 1986, Assessing the market training performance of managed portfolios, *Journal of Business* 59, 217–235.

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

Jegadeesh, Narasimhan, and Sheridan Titman, 2001, Profitability of momentum strategies: An evaluation of alternative explanations, *Journal of Finance* 56, 699-718.

Kelly, Bryan, and Jiang Hao, 2012, Tail risk and hedge fund returns, Chicago Booth Fama–Miller Research Paper No. 12-44.

Korajczyk, Robert A., and Ronnie Sadka, 2008, Pricing the commonality across alternative measures of liquidity, *Journal of Financial Economics* 87, 45-72.

Liang, B., and H. Park. 2008, Share Restriction, Liquidity Premium, and Offshore Hedge Funds. Working Paper, University of Massachusetts.

Li, H., X. Zhang, and R. Zhao, 2011, Investing in Talents: Manager Characteristics and Hedge Fund Performances, *Journal of Financial and Quantitative Analysis* 46, 59–82.

Liu, Jun, Jun Pan, and Tan Wang, 2005, An equilibrium model of rare-event premia and its implication for option smirks, *Review of Financial Studies* 18, 131-164.

Lo, Andrew W., 2001, Risk management for hedge funds: introduction and overview, *Financial Analysts Journal* 57, 16–33.

Martin, Ian, 2012, Simple variance swaps, No. w16884, National Bureau of Economic Research.

Merton, Robert C., 1976, Option pricing when underlying stock returns are discontinuous, *Journal of Financial Economics* 3, 125-144.

Merton, Robert C., 1981, On market timing and investment performance. I. An Equilibrium Theory of Value for Market Forecasts, *Journal of Business* 54, 363–406.

Mitchell, Mark., and Todd Pulvino, 2001, Characteristics of risk in risk arbitrage, *Journal of Finance* 56, 2135–2175

Mitchell, Mark., and Todd Pulvino, 2012, Arbitrage crashes and the speed of capital, *Journal of Financial Economics* 104, 469-490.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703-708.

Pastor, Lubos, and Robert F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642–685.

Sadka, Ronnie, 2006, Momentum and post-earnings-announcement drift anomalies: the role of liquidity risk, *Journal of Financial Economics* 80, 309-349.

Sadka, Ronnie, 2010, Liquidity risk and the cross-section of hedge-fund returns, *Journal of Financial Economics* 98, 54-71.

Sialm, Clemens, Zheng Sun, and Lu Zheng, 2012, Home bias and local contagion: evidence from funds of hedge funds. Working paper, University of Texas at Austin.

Singleton, Kenneth J., 2006, Empirical dynamic asset pricing, Princeton University Press.

Stulz, Rene, 2007, Hedge funds: past, present and future, *Journal of Economic Perspectives* 21, 175–194.

Sun, Z., Wang, A., and Zheng, L. 2012. The Road Less Traveled: Strategy Distinctiveness and Hedge Fund Performance. *Review of Financial Studies* 25, 96-143.

Sun, Z., Wang, A., and Zheng, L. 2013. Only When the Tide Goes Out: Downside Returns and Hedge Fund Performance. working paper.

Titman, S., and C. Tiu. 2011, Do the Best Hedge Funds Hedge? *Review of Financial Studies* 24, 123–68.

Wachter, Jessica A, 2013, Can time-varying risk of rare disasters explain aggregate stock market volatility?, *Journal of Finance* 68, 987-1035.

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 concern indices

Rare disaster concern 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 concern index (RIX), is an equal-weighted average over all sector-level rare disaster concern indices. Panel A reports summary statistics of monthly rare disaster concern indices. Panel B presents time-series correlations between one rare disaster concern 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) liquidity risk factor; Sadka liquidity risk factor; Hu-Pan-Wang 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 concern 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 concern 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: SED 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' SEDs are estimated from 24-month rolling-window regressions of excess monthly returns on the market excess return and the measure of rare disaster concerns (RIX). We also require at least 18 months of return observations in estimating regressions. Panel A reports the following hedge fund characteristics: assets under management (AUM), number of months from a fund's inception to portfolio formation date (AGE), fund flow in the recent month, R-squared based on the Fung-Hsieh 7-factor regression in Titman and Tiu (2011), strategy distinctiveness index (SDI) in Sun, Wang, and Zheng (2012), timing ability in market liquidity, market return, and volatility in Cao et al. (2013), conditional performance measures of downside and upside returns in Sun, Wang, and Zheng (2013), and fund liquidation rate and non-reporting rate within one year of portfolio formation. Within each decile we first calculate cross-sectional average of funds' characteristics and then calculate time-series average over all portfolio formation months. We also report *t*-statistics and *p*-values of signed rank statistics for high-minus-low SED portfolios (in parentheses). Panel B reports likelihood of 12 hedge fund investment styles that are ranked within each SED decile. Given an investment style, we estimate its odds into a SED decile as follows: We count total number of funds at portfolio formation, divide by ten to get expected number of funds (assume funds are uniformly ranked into SED deciles), estimate the ratio between realized and expected number, and calculate time-series average of the ratios over all portfolio formation months. We normalize likelihoods of all investment styles within a SED decile so that the sum of probability equals one.

Panel A: Fund-level characteristics

Exploit Rare Disaster Concerns	AUM ($M)	AGE (Months)	Fund Flow	R-squared	SDI	Liquidity-Timing Ability	Market-Timing Ability	Volatility-Timing Ability	Downside Return	Upside Return	Liquidation Rate (%)	Non-Reporting Rate (%)
1 - Low Skill	172.8	68	0.010	0.533	0.305	0.059	-0.551	-0.007	-0.019	0.036	3.56	3.13
2	187.2	71	0.013	0.557	0.311	0.096	-0.269	-0.005	-0.011	0.024	2.77	2.54
3	186.7	72	0.016	0.559	0.331	0.100	-0.132	-0.008	-0.009	0.019	2.38	2.29
4	203.5	72	0.011	0.555	0.347	0.039	-0.126	-0.005	-0.007	0.016	2.69	1.91
5	193.4	71	0.015	0.546	0.362	0.014	-0.059	-0.005	-0.005	0.015	2.71	2.02
6	199.5	71	0.014	0.532	0.374	-0.012	-0.053	-0.004	-0.004	0.014	2.71	1.92
7	210.7	71	0.016	0.515	0.382	-0.018	0.059	-0.003	-0.004	0.014	2.89	2.39
8	192.3	70	0.044	0.505	0.382	-0.029	0.363	-0.002	-0.003	0.015	2.69	2.36
9	175.4	70	0.018	0.515	0.365	-0.099	0.574	-0.001	-0.004	0.019	2.46	2.33
10 - High Skill	151.2	69	0.051	0.524	0.348	-0.600	1.582	0.011	-0.005	0.028	2.13	2.25
High - Low	-21.6	1	0.041	-0.009	0.043	-0.659	2.133	0.018	0.014	-0.008	-1.40	-0.91
t-stat	(-2.25)	(0.64)	(2.13)	(-1.56)	(6.80)	(-3.43)	(3.55)	(3.68)	(10.99)	(-5.22)	(-7.50)	(-5.85)
Sgn. Rank (*p*-val)	(0.0068)	(0.9715)	(0.0000)	(0.5224)	(0.0000)	(0.0000)	(0.0028)	(0.0163)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Panel B: Likelihood distribution of hedge fund investment styles within a SED decile

Exploit Rare Disaster Concerns	Long/Short Equity Hedge	Equity Market Neutral	Dedicated Short Bias	Global Macro	Emerging Markets	Event Driven	Fund of Funds	Fixed Income Arbitrage	Convertible Arbitrage	Managed Futures	Multi Strategy	Options Strategy
1 - Low Skill	11.7%	3.5%	13.0%	11.0%	21.9%	6.3%	4.1%	9.0%	3.8%	8.4%	5.2%	2.1%
2	11.0%	7.4%	10.1%	7.9%	12.2%	8.8%	9.7%	6.6%	4.2%	8.2%	6.8%	7.1%
3	9.9%	9.5%	7.4%	7.7%	8.5%	10.7%	13.6%	9.2%	5.0%	8.2%	7.3%	3.1%
4	7.8%	8.8%	5.2%	7.1%	6.6%	10.8%	14.6%	10.6%	5.2%	6.3%	8.1%	8.7%
5	6.5%	8.0%	4.0%	6.2%	5.9%	10.6%	13.8%	10.5%	7.4%	5.3%	9.6%	12.2%
6	6.3%	10.0%	4.3%	6.8%	5.1%	11.1%	13.2%	10.7%	10.1%	5.6%	10.2%	6.7%
7	6.2%	9.5%	4.5%	7.8%	4.8%	10.0%	9.5%	9.2%	11.9%	5.7%	10.9%	10.0%
8	6.7%	9.5%	6.1%	8.7%	5.0%	8.5%	5.3%	8.5%	12.2%	6.6%	9.8%	13.1%
9	8.7%	9.8%	10.3%	9.7%	6.1%	6.4%	3.2%	6.2%	12.1%	9.8%	8.7%	8.9%
10 - High Skill	9.0%	7.1%	15.8%	9.4%	8.7%	2.7%	1.9%	4.7%	8.3%	16.7%	6.6%	9.0%

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

We report panel regressions of SED on lagged fund characteristics using the annual data that are collected in each June from 1997 through 2010. Model specifications depend on fixed fund and year effects. We use the following explanatory variables: (1) minimal investment, AUM, and AGE are in log; (2) high water mark, personal capital invested, and leverage are dummy variables; (3) redemption notice period and lockup period are in month; (4) average monthly fund flow within the past one year; (5) monthly excess return sample moment estimates within the past two years (standard deviation, skewness, and kurtosis); and (6) a set of fund skill variables that are the same ones used in Table 4, including Fung-Hsieh 7-factor alpha and R-squared, strategy distinctiveness index (SDI), downside return measure, and timing ability on market liquidity, market return, and market volatility. We report regression estimates in addition to robust *t*-statistics (in parenthese).

	(1)	(2)	(3)	(4)	(5)	(6)
Minimal Investment	0.029	0.0187				
	(2.25)	(1.49)				
Management Fee (%)	-5.7253	-5.1803				
	(-1.99)	(-1.82)				
Incentive Fee (%)	0.0077	-0.1361				
	(0.03)	(-0.56)				
Redemption Notice Period	0.0002	-0.0002				
	(0.40)	(-0.38)				
Lockup Period	-0.0022	-0.0011				
	(-1.29)	(-0.63)				
High Water Mark	0.0541	0.0571				
	(1.62)	(1.72)				
Personal Capital Invested	-0.0157	-0.0087				
	(-0.51)	(-0.28)				
Leverage	0.0509	0.0476				
	(1.85)	(1.75)				
AUM	-0.0291	-0.0225	-0.092	-0.0574	-0.0252	-0.0514
	(-2.49)	(-1.99)	(-3.13)	(-2.31)	(-0.57)	(-1.84)
AGE	0.0195	0.0066	0.0044	-0.0226	-0.0960	-0.0912
	(0.64)	(0.22)	(0.07)	(-0.25)	(-0.86)	(-0.81)
Fund Flow (past 1 year)	0.0164	0.0059	-0.0111	-0.0266	-0.0224	-0.0368
	(1.18)	(0.40)	(-0.23)	(-2.14)	(-1.62)	(-0.69)
Return Volatility (past 2 years)	1.7971	0.6537	6.5084	2.9082	-2.0171	2.9691
	(0.69)	(0.25)	(2.00)	(0.99)	(-0.58)	(0.81)
Return Skewness (past 2 years)	0.1032	0.0791	0.1703	0.127	0.165	0.1358
	(4.66)	(3.54)	(6.96)	(5.39)	(2.93)	(5.22)
Return Kurtosis (past 2 years)	0.0206	0.0069	0.0043	-0.0052	0.0108	-0.0010
	(2.47)	(0.81)	(0.44)	(-0.65)	(0.64)	(-0.11)
Alpha (F-H 7-factor)	-11.1859	-10.2262	-14.922	-17.3655	-21.0085	-13.8962
	(-3.95)	(-3.61)	(-4.20)	(-4.83)	(-3.76)	(-3.85)
R-squared (F-H 7-factor)	0.5228	0.4406	0.4021	0.2065	0.0554	0.3107
	(5.67)	(5.00)	(3.27)	(1.85)	(0.48)	(2.73)
SDI	0.458	0.3408	0.3079	0.2399		0.2646
	(4.96)	(3.70)	(2.28)	(1.80)		(1.99)

Downside Return	7.2535	9.451	4.7459	7.6435	-0.1577	6.7865
	(1.93)	(2.43)	(1.53)	(3.05)	(-0.02)	(2.13)
Liquidity Timing	-0.0073	-0.0178	-0.0122			-0.0186
	(-0.62)	(-1.44)	(-0.76)			(-1.15)
Market Timing	0.0118	0.0104	0.0116			0.0113
	(2.53)	(2.24)	(1.75)			(1.70)
Volatility Timing	-0.2435	0.0319	-0.4652			-0.3144
	(-0.82)	(0.10)	(-1.38)			(-0.88)
Constant	Included	Included	Included	Included	Included	Included
Year FEs	No	Yes	No	Yes	Yes	Yes
Fund FEs	No	No	Yes	Yes	Yes	Yes
Observations	10,330	10,330	10,330	13,445	18,115	10,330
Adjusted R-squared	0.0346	0.0921	0.2114	0.2353	0.1481	0.2550

Table 7: Return performance of SED hedge fund portfolios

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. On average, there are 147-149 hedge funds for each decile portfolio.

	1 month		3 months		6 months		12 months		18 months	
Exploit Rare Disaster Concerns	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
	(-0.14)	(-1.26)	(0.01)	(-0.95)	(0.10)	(-0.81)	(0.61)	(-0.07)	(0.92)	(0.55)
2	0.195	0.036	0.202	0.039	0.251	0.098	0.280	0.126	0.307	0.158
	(0.81)	(0.27)	(0.84)	(0.30)	(1.04)	(0.77)	(1.29)	(1.09)	(1.44)	(1.41)
3	0.294	0.148	0.288	0.139	0.296	0.153	0.323	0.186	0.327	0.188
	(1.45)	(1.31)	(1.44)	(1.25)	(1.46)	(1.40)	(1.81)	(1.88)	(1.85)	(1.94)
4	0.296	0.172	0.294	0.177	0.284	0.163	0.276	0.155	0.292	0.167
	(1.69)	(1.56)	(1.65)	(1.66)	(1.60)	(1.59)	(1.77)	(1.66)	(1.87)	(1.79)
5	0.264	0.121	0.273	0.145	0.275	0.154	0.270	0.151	0.277	0.157
	(1.47)	(0.91)	(1.60)	(1.32)	(1.62)	(1.43)	(1.80)	(1.62)	(1.85)	(1.72)
6	0.280	0.184	0.283	0.179	0.258	0.153	0.257	0.151	0.265	0.159
	(1.87)	(1.89)	(1.85)	(1.97)	(1.65)	(1.64)	(1.88)	(1.84)	(1.91)	(1.93)
7	0.337	0.232	0.281	0.172	0.261	0.155	0.271	0.164	0.271	0.160
	(2.40)	(2.88)	(1.94)	(2.11)	(1.80)	(1.99)	(2.04)	(2.21)	(2.01)	(2.12)
8	0.419	0.314	0.384	0.266	0.383	0.269	0.340	0.220	0.322	0.198
	(3.01)	(4.20)	(2.72)	(3.43)	(2.77)	(3.58)	(2.54)	(2.88)	(2.33)	(2.49)
9	0.568	0.445	0.502	0.365	0.478	0.342	0.423	0.277	0.394	0.247
	(3.15)	(3.67)	(2.86)	(3.45)	(2.82)	(3.48)	(2.71)	(2.93)	(2.49)	(2.62)
10 - High Skill	0.905	0.768	0.841	0.709	0.775	0.646	0.649	0.503	0.572	0.411
	(4.17)	(5.04)	(4.03)	(4.95)	(3.91)	(4.76)	(3.26)	(3.70)	(2.91)	(3.23)
High - Low	0.963	1.111	0.836	0.962	0.735	0.870	0.444	0.519	0.270	0.298
	(2.76)	(3.53)	(2.61)	(3.37)	(2.31)	(2.99)	(1.86)	(2.60)	(1.21)	(1.60)

Table 8: Pervasiveness of return performance of SED hedge fund portfolios

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 SED 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)
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: Subsample analysis of return performance of SED hedge fund portfolios

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. The full sample period of calculating equal-weighted portfolios returns is from July 1997 through July 2010. In our subsample analysis, we classify months in four different ways and report portfolio mean excess returns (in percent) over these months (*t*-statistics are in parentheses): (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) normal/stressful times based on NBER recession dates (stressful times are 28 months in total: March 2001 through November 2001, and December 2007 through June 2009); and (4) months in the lowest/highest decile when we rank all months into ten groups based on the market excess returns in these months. The market excess returns lose 10% or more in six months: 10/2008, 08/1998, 11/2000, 02/2001, 09/2002, and 02/2009. The decile breakpoints for ranking months by market excess returns are -6.5%, -3.5%, -2.0%, -0.8%, 1.1%, 1.8%, 3.2%, 4.3%, and 6.2%.

	(1) Rank months by market excess returns		(2) Rank months by market excess returns		(3) NBER Recession Dates		(4) Rank months by market excess returns	
Exploit Rare Disaster Concerns	Others	Lost 10% or More	Others	Lowest Quintile	Normal Times	Stressful Times	Highest Decile	Lowest Decile
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: Risk exposure of SED hedge fund portfolios

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 (2013) 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: Return performance of SED portfolios in presence of other fund skill variables

At the end of each month from June 1997 through June 2010, we rank funds sequentially into 25 portfolios first on a fund skill variable then on SED. 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. The last two rows of each panel reports the average return performance of SED quintiles in control of the effect of the fund skill variable. The set of fund skill variables contains R-squared from the Fung-Hsieh 7-factor regression in Titman and Tiu (2011), the strategy distinctiveness index (SDI) in Sun, Wang, and Zheng (2012), the ability of timing market liquidity in Cao et al. (2013), the conditional performance measure of downside returns in Sun, Wang, and Zheng (2013). Hedge funds' SEDs 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).

Panel A: 5×5 portfolios on R-squared and SED

R-Squared	SED 1 - Low	2	3	4	SED 5 - High	SED 5-1	F-H 7-Factor Alpha
1 - low	0.228	0.257	0.343	0.377	0.594	0.366	0.523
	(1.15)	(2.44)	(4.93)	(4.12)	(4.09)	(1.93)	(2.80)
2	0.287	0.335	0.321	0.426	0.704	0.417	0.532
	(1.14)	(2.36)	(3.04)	(4.49)	(4.40)	(2.06)	(2.78)
3	-0.019	0.265	0.259	0.285	0.625	0.644	0.903
	(-0.06)	(1.74)	(2.05)	(2.36)	(3.59)	(2.57)	(4.03)
4	0.138	0.317	0.357	0.278	0.796	0.658	0.681
	(0.49)	(1.79)	(2.47)	(1.94)	(3.30)	(2.82)	(2.99)
5 - High	-0.041	0.195	0.248	0.383	0.752	0.793	0.697
	(-0.13)	(0.82)	(1.23)	(1.78)	(2.73)	(3.27)	(2.80)
Average	0.118	0.274	0.306	0.350	0.694	0.576	0.667
	(0.49)	(1.83)	(2.56)	(2.90)	(3.98)	(3.41)	(4.23)

Panel B: 5×5 portfolios on SDI and SED

SDI	SED 1 - Low	2	3	4	SED 5 - High	SED 5-1	F-H 7-Factor Alpha
1 - low	-0.480	0.097	0.220	0.525	0.884	1.364	1.557
	(-1.10)	(0.36)	(0.88)	(2.29)	(3.06)	(3.68)	(4.60)
2	0.158	0.350	0.330	0.502	0.903	0.745	0.722
	(0.52)	(1.55)	(1.72)	(2.79)	(3.47)	(3.21)	(3.12)
3	0.399	0.342	0.391	0.435	0.752	0.353	0.427
	(1.57)	(2.02)	(2.49)	(3.12)	(3.36)	(1.73)	(2.08)
4	0.254	0.363	0.365	0.444	0.750	0.496	0.555
	(1.36)	(3.33)	(4.73)	(4.30)	(4.13)	(2.64)	(2.93)
5 - High	0.359	0.284	0.341	0.251	0.596	0.236	0.339
	(2.95)	(3.67)	(7.14)	(3.55)	(6.21)	(1.87)	(2.75)
Average	0.138	0.287	0.329	0.431	0.777	0.639	0.720
	(0.59)	(1.85)	(2.47)	(3.34)	(4.20)	(3.83)	(4.54)

Panel C: 5×5 portfolios on liquidity-timing ability and SED

Timing (Market Liquidity)	SED 1 - Low	2	3	4	SED 5 - High	SED 5-1	F-H 7-Factor Alpha
1 - low	0.099	0.095	0.401	0.472	0.818	0.719	0.929
	(0.23)	(0.35)	(1.67)	(2.04)	(2.78)	(2.51)	(3.33)
2	0.141	0.245	0.158	0.248	0.443	0.303	0.345
	(0.65)	(1.67)	(1.12)	(1.88)	(2.57)	(2.37)	(2.73)
3	0.229	0.249	0.220	0.255	0.493	0.263	0.355
	(1.05)	(1.61)	(1.83)	(2.42)	(3.19)	(1.84)	(2.60)
4	0.094	0.352	0.363	0.351	0.635	0.541	0.563
	(0.45)	(2.44)	(2.76)	(2.94)	(3.66)	(3.55)	(3.79)
5 - High	0.047	0.300	0.376	0.639	0.867	0.820	0.942
	(0.15)	(1.41)	(1.83)	(3.37)	(3.59)	(3.25)	(3.75)
Average	0.122	0.248	0.303	0.393	0.651	0.529	0.627
	(0.47)	(1.45)	(1.97)	(2.73)	(3.40)	(3.43)	(4.28)

Panel D: 5×5 portfolios on downside return and SED

Downside Return	SED 1 - Low	2	3	4	SED 5 - High	SED 5-1	F-H 7-Factor Alpha
1 - low	-0.279	0.035	0.328	0.482	0.784	1.063	1.286
	(-0.64)	(0.11)	(1.13)	(1.67)	(2.06)	(3.60)	(4.32)
2	0.132	0.260	0.174	0.333	0.597	0.465	0.403
	(0.61)	(1.47)	(0.98)	(1.99)	(2.68)	(2.87)	(2.44)
3	0.264	0.283	0.270	0.271	0.378	0.114	0.091
	(1.37)	(2.20)	(2.31)	(2.28)	(2.28)	(0.76)	(0.61)
4	0.360	0.276	0.276	0.367	0.561	0.201	0.212
	(2.35)	(2.30)	(3.36)	(4.21)	(4.51)	(1.89)	(1.97)
5 - High	0.371	0.332	0.411	0.449	0.777	0.406	0.406
	(2.06)	(2.87)	(4.94)	(4.28)	(4.45)	(2.01)	(1.95)
Average	0.170	0.237	0.292	0.381	0.620	0.450	0.480
	(0.83)	(1.57)	(2.19)	(2.85)	(3.53)	(3.41)	(3.58)

Table 12: Return performance of SEV and SED 25 portfolios

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 13: 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 SED decile rankings 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 liquidity beta, default premium beta, and inflation beta, we regress fund's excess returns on the Hu-Pan-Wang noise 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, skewness, and kurtosis (the sample variance, skewness, and kurtosis estimates of fund's excess returns within the past 24 months, respectively), 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. Funds' skill variables include R-squared based on the Fung-Hsieh 7-factor regression in Titman and Tiu (2011), strategy distinctiveness index (SDI) in Sun, Wang, Zheng (2012), timing ability in market liquidity, market return, and market volatility in Cao et al. (2013), and downside return measure in Sun, Wang, Zheng (2013). 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)	(7)
SED	0.0005	0.0004	0.0004	0.0004	0.0003	0.0004	0.0005
	(2.41)	(2.47)	(2.48)	(2.65)	(2.11)	(2.50)	(3.03)
Market Beta	0.0024	0.0036	0.0030	0.0033	0.0061	0.0056	0.0021
	(0.63)	(1.14)	(0.94)	(1.07)	(1.87)	(1.77)	(0.49)
Liquidity Beta			-0.1498				
			(-2.04)				
Default Premium Beta				0.0058			
				(0.72)			
Inflation Beta				-0.1052			
				(-2.12)			
Total Variance					0.0480		
					(0.37)		
Skewness					0.0005		
					(1.83)		
Kurtosis					-0.0001		
					(-1.51)		
Downside Return					0.0934	0.0958	
					(2.62)	(2.63)	
R-Squared						-0.0022	
						(-0.80)	
SDI						-0.0023	
						(-0.97)	
Liquidity Timing							0.0000
							(-0.16)
Market Timing							0.0002
							(1.25)

Volatility Timing							-0.0384
							(-1.94)
AUM		-0.0003	-0.0003	-0.0003	-0.0003	-0.0005	-0.0002
		(-1.75)	(-1.77)	(-1.70)	(-1.59)	(-2.05)	(-0.97)
AGE		-0.0002	-0.0002	-0.0003	-0.0001	-0.0002	-0.0004
		(-0.82)	(-0.79)	(-1.01)	(-0.29)	(-0.74)	(-1.34)
Lagged Return		0.1144	0.1022	0.1101	0.1076	0.1064	0.1116
		(7.36)	(6.25)	(7.12)	(7.01)	(7.08)	(5.14)
Management Fee		0.0849	0.0793	0.0847	0.0772	0.1241	0.0890
		(1.97)	(1.88)	(2.05)	(1.88)	(2.70)	(2.35)
Incentive Fee		0.0057	0.0059	0.0063	0.0051	0.0087	0.0031
		(2.72)	(2.90)	(2.80)	(2.41)	(2.31)	(1.34)
High Water Mark		0.0012	0.0011	0.0012	0.0010	0.0009	0.0013
		(3.50)	(3.25)	(3.49)	(2.98)	(2.32)	(3.27)
Personal Capital Invested		0.0003	0.0003	0.0003	0.0003	0.0002	0.0003
		(1.17)	(1.20)	(1.19)	(1.15)	(0.56)	(1.09)
Leverage Used		0.0006	0.0006	0.0005	0.0006	0.0006	0.0004
		(2.03)	(1.92)	(1.69)	(1.81)	(1.30)	(1.34)
Lockup Required		0.0012	0.0012	0.0012	0.0006	0.0007	0.0003
		(3.59)	(3.52)	(3.49)	(1.72)	(1.68)	(1.19)
Redemption Notice Period		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		(1.51)	(1.55)	(1.49)	(1.24)	(1.04)	(2.03)
Intercept	0.0001	-0.0015	-0.0016	-0.0017	-0.0013	-0.0001	-0.0021
	(0.06)	(-0.84)	(-0.86)	(-1.01)	(-0.81)	(-0.02)	(-1.21)
Avg # of funds per month	1485	1480	1480	1480	1335	995	1212
Avg adjusted R-sqr	0.157	0.210	0.228	0.235	0.249	0.233	0.240
Number of months	157	157	157	157	157	157	151

Table 14: Robustness checks on SED hedge fund portfolios

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 seven scenarios: (1) value-weighted portfolio returns (see Table 4 for details of portfolio formation); (2) 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 exclude the first 25 months of returns of each hedge fund in the Lipper TASS database to mitigate backfilling bias; (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; (5) we construct RIX based on 90-day OTM puts of sector indicies; (6) we construct RIX based on 30-day OTM puts of S&P 500 index; and (7) 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. For cases (2) - (7), we report equal-weighted portfolio returns below, and the results based on value-weighted portfolio returns are similar.

	(1) Portfolio Value Weight		(2) No Restriction on Funds' AUM		(3) Hedge Fund Backfilling Data Bias		(4) Hedge Fund Delisting Return		(5) RIX: 90-Day OTM Puts		(6) RIX: S&P 500 Index OTM Puts		(7) Lagged RIX Factor	
Exploit Rare Disaster Concerns	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	Excess Ret	F-H Alpha	Excess Ret	F-H Alpha
1 - Low Skill	-0.165	-0.445	0.073	-0.189	-0.020	-0.292	-0.970	-1.255	-0.128	-0.386	-0.093	-0.397	-0.185	-0.470
	(-0.43)	(-1.55)	(0.18)	(-0.76)	(-0.05)	(-1.15)	(-2.04)	(-3.88)	(-0.33)	(-1.48)	(-0.26)	(-1.37)	(-0.49)	(-1.79)
2	0.127	-0.096	0.229	0.092	0.169	0.010	-0.613	-0.788	0.186	0.028	0.353	0.134	0.184	0.013
	(0.44)	(-0.50)	(0.96)	(0.74)	(0.69)	(0.07)	(-2.00)	(-3.86)	(0.80)	(0.20)	(1.54)	(0.82)	(0.82)	(0.10)
3	0.276	0.114	0.292	0.168	0.294	0.157	-0.218	-0.372	0.287	0.136	0.087	-0.121	0.246	0.107
	(1.28)	(0.84)	(1.48)	(1.47)	(1.44)	(1.40)	(-0.91)	(-2.40)	(1.44)	(1.17)	(0.36)	(-0.64)	(1.29)	(0.89)
4	0.382	0.270	0.281	0.162	0.262	0.119	-0.279	-0.376	0.225	0.089	0.359	0.187	0.267	0.135
	(2.25)	(2.39)	(1.61)	(1.52)	(1.41)	(0.98)	(-1.22)	(-2.36)	(1.28)	(0.76)	(2.10)	(1.72)	(1.52)	(1.10)
5	0.267	0.094	0.277	0.161	0.259	0.120	-0.290	-0.441	0.248	0.145	0.217	0.098	0.270	0.157
	(1.38)	(0.62)	(1.73)	(1.58)	(1.45)	(0.92)	(-1.35)	(-2.70)	(1.57)	(1.54)	(1.37)	(0.89)	(1.60)	(1.44)
6	0.270	0.159	0.272	0.173	0.280	0.177	-0.300	-0.370	0.320	0.214	0.342	0.225	0.300	0.192
	(1.81)	(1.48)	(1.82)	(1.79)	(1.81)	(1.76)	(-1.62)	(-2.82)	(2.18)	(2.63)	(2.03)	(1.70)	(1.99)	(1.99)
7	0.404	0.295	0.330	0.232	0.343	0.237	-0.155	-0.251	0.324	0.221	0.275	0.191	0.328	0.228
	(2.72)	(2.87)	(2.40)	(3.00)	(2.39)	(2.84)	(-0.79)	(-2.04)	(2.23)	(2.62)	(1.27)	(1.41)	(2.28)	(2.87)
8	0.434	0.324	0.570	0.492	0.415	0.312	-0.243	-0.341	0.503	0.393	0.348	0.278	0.438	0.321
	(3.19)	(3.68)	(2.89)	(2.67)	(2.92)	(4.04)	(-1.23)	(-2.61)	(3.17)	(3.96)	(2.94)	(3.59)	(2.96)	(3.86)
9	0.362	0.254	0.585	0.464	0.549	0.417	-0.019	-0.140	0.605	0.471	0.365	0.235	0.686	0.559
	(1.44)	(1.71)	(3.47)	(4.62)	(3.02)	(3.52)	(-0.08)	(-0.95)	(3.34)	(4.13)	(2.25)	(1.85)	(3.81)	(5.43)
10 - High Skill	0.845	0.654	0.967	0.856	0.873	0.742	0.334	0.194	0.927	0.766	0.548	0.441	0.964	0.834
	(3.59)	(3.27)	(4.47)	(5.38)	(4.11)	(4.97)	(1.46)	(1.34)	(3.55)	(3.95)	(2.30)	(1.93)	(3.51)	(4.28)
High - Low	1.010	1.099	0.894	1.044	0.893	1.034	1.303	1.449	1.055	1.153	0.641	0.838	1.149	1.304
	(2.78)	(3.10)	(2.70)	(3.57)	(2.63)	(3.53)	(3.12)	(3.91)	(3.17)	(3.75)	(1.78)	(2.28)	(3.38)	(3.98)

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

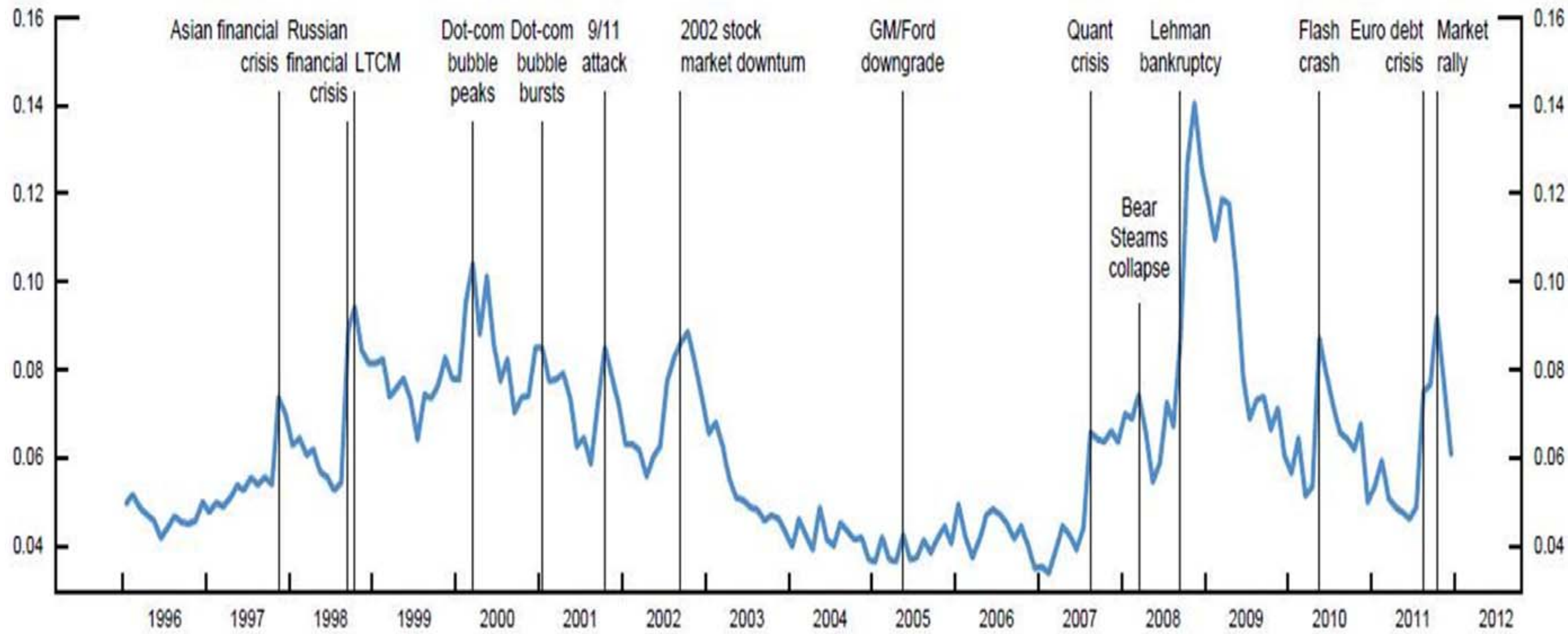
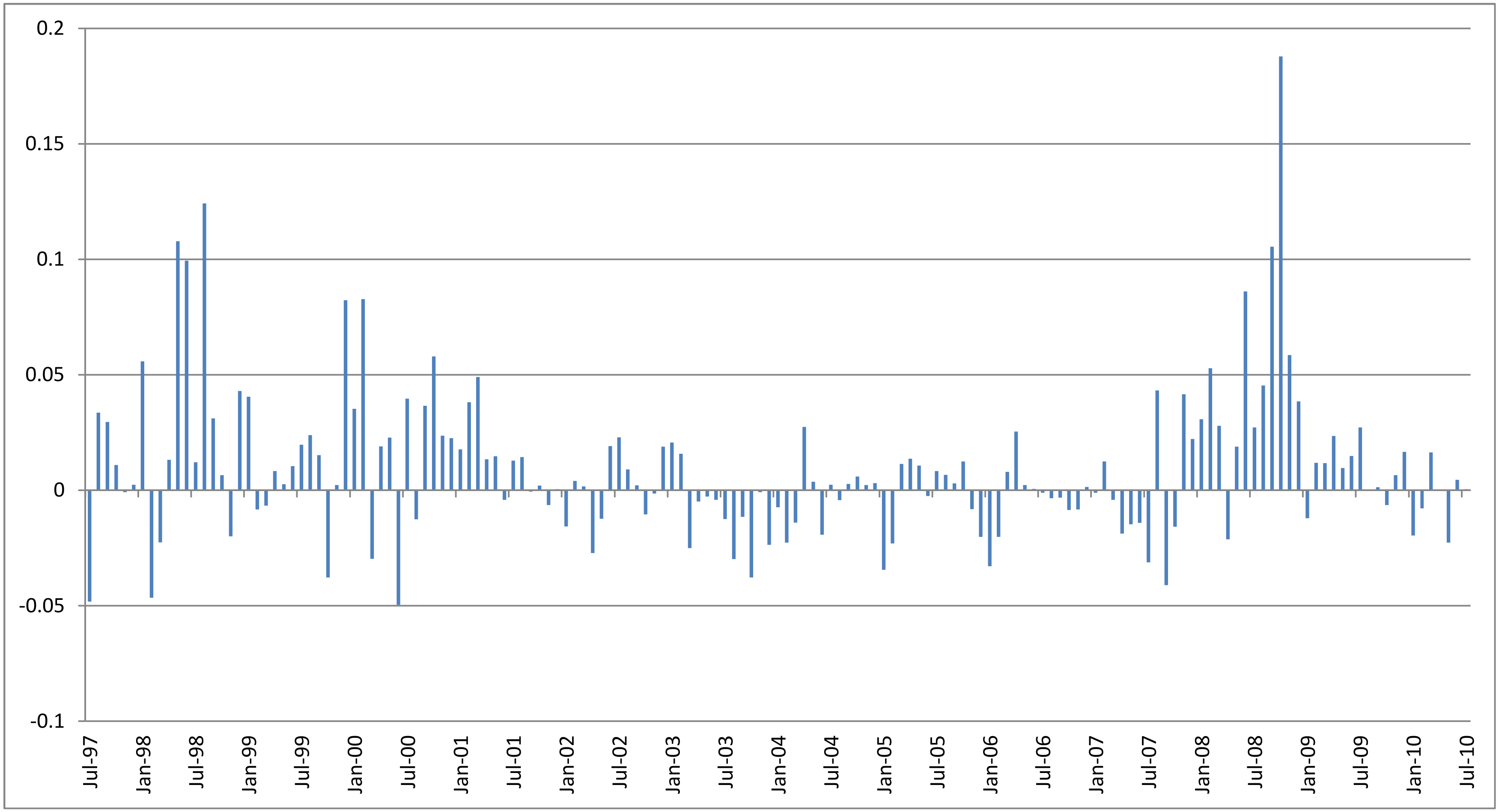


Figure 2: Time-series plot of high-minus-low SED portfolio returns



Do Hedge Funds Exploit Rare Disaster Concerns?

Internet Appendix: Additional Robustness Checks

Table IA-1: Additional results of SED decile portfolios

We present additional results for SED deciles. Decile 1 (10) contains Lipper TASS hedge funds with low (high) skills on exploiting rare disaster concerns. In specifications (1) - (3), we use different measures of hedge fund performance: (1) manipulation-proof performance measure (MPPM) with the rho coefficient to penalize hedge fund return equal to 3 (see details in Ingersoll et al., (2007)); (2) Sharpe ratio adjusted for hedge fund return smoothing (see details in Getmansky, Lo, and Makarov (2004); and (3) information ratio adjusted for hedge fund return smoothing. To calculate Sharpe ratio and information ratio, we estimate each fund's return volatility and Fung-Hsieh 7-factor abnormal return using its past 24 months of returns. In specifications (4) and (5), we separate hedge fund returns reported in December from those reported in non-December months (Agarwal, Daniel, and Naik (2011)). Our sample of Lipper TASS hedge funds consists of funds that report returns net of fees in US dollars and have at least $10 million in AUM. Funds' SEDs are estimated from rolling-window regressions of past 18-24 monthly excess returns on the market excess return and the measure of rare disaster concern (RIX). We monthly construct SED deciles and hold for one month. In all specifications, we report results for equal-weighted portfolios. Newey-West (1987) *t*-statistics are in parentheses.

Exploit Rare Disaster Concerns	(1) MPPM	(2) Sharpe Ratio	(3) Information Ratio	(4) Non-Dec Return	(5) Only Dec Return
1 - Low Skill	-0.015	0.148	0.173	-0.181	1.297
	(-0.46)	(1.04)	(1.00)	(-0.42)	(2.54)
2	0.026	0.221	0.189	0.096	1.290
	(1.55)	(1.56)	(1.41)	(0.38)	(3.28)
3	0.033	0.320	0.248	0.191	1.439
	(2.65)	(2.28)	(1.69)	(0.91)	(4.11)
4	0.036	0.320	0.355	0.226	1.064
	(3.28)	(2.24)	(2.69)	(1.25)	(3.90)
5	0.037	0.413	0.420	0.180	1.189
	(3.75)	(3.02)	(3.36)	(0.97)	(4.61)
6	0.039	0.454	0.525	0.201	1.160
	(4.26)	(3.18)	(4.50)	(1.31)	(3.62)
7	0.040	0.516	0.621	0.261	1.170
	(4.25)	(3.60)	(4.47)	(1.86)	(3.35)
8	0.044	0.576	0.653	0.340	1.299
	(3.70)	(3.45)	(5.25)	(2.40)	(4.57)
9	0.054	0.496	0.570	0.444	1.949
	(5.04)	(3.26)	(5.83)	(2.60)	(3.02)
10 - High Skill	0.065	0.580	0.535	0.725	2.897
	(5.95)	(4.61)	(5.10)	(3.55)	(3.60)
High - Low	0.080	0.433	0.362	0.906	1.600
	(2.49)	(3.69)	(2.04)	(2.51)	(2.14)

Table IA-2: Additional results of double-sorted portfolios

We present additional results of double-sorted hedge fund portfolios. In Panels A - C, we rank funds sequentially into 25 portfolios first on a fund skill variable then on SED. The set of fund skill variables contains the ability of timing market return and volatility in Cao et al. (2013), the conditional performance measure of upside returns in Sun, Wang, and Zheng (2013). In Panels D - G, we rank funds sequentially into 25 portfolios first on a fund risk/characteristic variable then on SED. The set of risk/characteristic variables is shown in prior studies to explain cross-sectional hedge fund returns, which contains total variance, noise beta, default premium beta, and inflation beta. In Panels H - J, we rank funds independently into 25 portfolios according to their risk exposure and SED. The set of risk exposure contains market beta, downside market beta, and volatility risk beta. In all panels, we form portfolios at the end of each month from June 1997 through June 2010, 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. In the context of sequentially sorted portfolios (Panels A - G), the last two rows of each panel reports the average return performance of SED quintiles. In the context of independently sorted portfolios (Panels H - J), the last two rows of each panel reports the high-minus-low return performance within each SED quintile. 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 sequential portfolios on market-timing ability and SED

Timing (Market Return)	SED 1 - Low	2	3	4	SED 5 - High	SED 5-1	F-H 7-Factor Alpha
1 - low	0.010	0.307	0.400	0.522	0.912	0.903	1.082
	(0.03)	(1.54)	(2.16)	(2.54)	(3.85)	(3.88)	(4.99)
2	0.228	0.333	0.314	0.317	0.578	0.349	0.417
	(1.07)	(2.31)	(2.59)	(2.44)	(3.90)	(2.37)	(3.15)
3	0.277	0.252	0.264	0.280	0.489	0.212	0.216
	(1.41)	(1.92)	(2.37)	(2.74)	(3.00)	(1.76)	(1.78)
4	0.126	0.150	0.151	0.373	0.528	0.402	0.491
	(0.50)	(0.83)	(0.92)	(2.84)	(3.19)	(2.58)	(3.48)
5 - High	0.009	0.115	0.404	0.437	0.829	0.821	0.948
	(0.02)	(0.39)	(1.88)	(1.89)	(2.82)	(2.64)	(3.15)
Average	0.130	0.231	0.306	0.386	0.667	0.537	0.631
	(0.50)	(1.30)	(2.07)	(2.59)	(3.64)	(3.37)	(4.31)

Panel B: 5×5 sequential portfolios on volatility-timing ability and SED

Timing (Market Volatility)	SED 1 - Low	2	3	4	SED 5 - High	SED 5-1	F-H 7-Factor Alpha

1 - low	0.092	0.262	0.400	0.448	0.922	0.830	0.972
	(0.29)	(1.17)	(1.93)	(2.18)	(3.38)	(3.45)	(4.04)
2	0.156	0.194	0.389	0.296	0.671	0.516	0.540
	(0.73)	(1.22)	(2.99)	(2.57)	(3.91)	(3.45)	(3.68)
3	0.180	0.235	0.239	0.276	0.494	0.314	0.352
	(0.93)	(1.81)	(2.05)	(2.51)	(3.08)	(2.37)	(2.68)
4	0.166	0.309	0.269	0.298	0.666	0.500	0.596
	(0.72)	(2.10)	(2.16)	(2.42)	(4.03)	(3.13)	(3.85)
5 - High	-0.046	0.145	0.326	0.495	0.721	0.768	0.954
	(-0.11)	(0.51)	(1.38)	(2.42)	(2.46)	(2.43)	(3.10)
Average	0.110	0.229	0.325	0.363	0.695	0.586	0.683
	(0.42)	(1.31)	(2.15)	(2.57)	(3.57)	(3.65)	(4.42)

Panel C: 5×5 sequential portfolios on upside return and SED

Upside Return	SED 1 - Low	2	3	4	SED 5 - High	SED 5-1	F-H 7-Factor Alpha
1 - low	-0.037	-0.106	0.078	0.113	0.457	0.494	0.472
	(-0.23)	(-0.93)	(1.10)	(1.65)	(3.45)	(2.73)	(2.73)
2	0.072	0.140	0.211	0.241	0.359	0.287	0.318
	(0.49)	(1.44)	(2.42)	(2.99)	(3.23)	(2.65)	(3.20)
3	0.258	0.288	0.322	0.363	0.512	0.254	0.249
	(1.58)	(2.26)	(2.41)	(2.81)	(3.89)	(2.02)	(1.98)
4	0.003	0.342	0.363	0.544	0.735	0.732	0.830
	(0.01)	(1.77)	(1.82)	(2.86)	(3.68)	(4.79)	(5.39)
5 - High	0.012	0.504	0.733	0.928	1.244	1.232	1.445
	(0.02)	(1.28)	(2.09)	(2.68)	(3.23)	(3.40)	(4.07)
Average	0.062	0.234	0.341	0.438	0.661	0.600	0.663
	(0.30)	(1.39)	(2.21)	(3.00)	(4.40)	(4.28)	(5.10)

Panel D: 5×5 sequential portfolios on total variance and SED

Total Variance	SED 1 - Low	2	3	4	SED 5 - High	SED 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 sequential portfolios on noise beta and SED

Noise Beta	SED 1 - Low	2	3	4	SED 5 - High	SED 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 sequentail portfolios on default premium beta and SED

Default Beta	SED 1 - Low	2	3	4	SED 5 - High	SED 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 sequential portfolios on inflation beta and SED

Inflation Beta	SED 1 - Low	2	3	4	SED 5 - High	SED 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)

Panel H: 5×5 independent portfolios on market beta and SED

Market Beta	SED 1 - Low	2	3	4	SED 5 - High	SED 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 I: 5×5 independent portfolios on downside market beta and SED

Downside Beta	SED 1 - Low	2	3	4	SED 5 - High	SED 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 J: 5×5 independent portfolios on volatility risk beta and SED

Volatility Risk Beta	SED 1 - Low	2	3	4	SED 5 - High	SED 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)

Table IA-3: SED portfolio results using HFR database

We report results using hedge funds from HFR database (1996:01 - 2010:07). In formulating portfolios, we require funds to report returns net of fees in US dollars and have at least $10 million in AUM.

Panel A: Hedge fund decile portfolio returns and Fung-Hsieh factor loadings for the portfolio holding horzion of 1 month

Exploit Rare Disaster Concerns	Excess Ret	Intercept	MKTRF	SMB	TERM	DEF	PTFSBD	PTFSFX	PTFSCOM	# of Funds
1 - Low Skill	0.080	-0.185	0.444	0.187	0.231	0.551	-0.011	0.008	0.009	242
	(0.20)	(-0.77)	(8.31)	(3.40)	(1.89)	(3.64)	(-0.79)	(0.71)	(0.54)	
2	0.263	0.106	0.284	0.095	0.166	0.425	-0.003	0.004	0.009	243
	(1.06)	(0.83)	(8.42)	(3.20)	(2.20)	(4.39)	(-0.54)	(0.67)	(1.06)	
3	0.325	0.180	0.226	0.084	0.121	0.326	-0.012	0.005	0.007	244
	(1.56)	(1.55)	(8.58)	(3.26)	(1.98)	(3.73)	(-1.68)	(0.97)	(0.90)	
4	0.295	0.165	0.204	0.071	0.115	0.288	-0.010	0.006	0.002	244
	(1.65)	(1.71)	(9.58)	(3.31)	(2.37)	(4.30)	(-1.43)	(1.37)	(0.29)	
5	0.264	0.128	0.177	0.078	0.112	0.288	-0.015	0.006	-0.002	244
	(1.52)	(1.16)	(7.40)	(3.66)	(2.12)	(3.88)	(-1.44)	(1.39)	(-0.33)	
6	0.283	0.172	0.162	0.059	0.094	0.279	-0.011	0.005	0.000	244
	(1.78)	(1.81)	(8.67)	(2.40)	(1.84)	(3.82)	(-1.54)	(1.44)	(0.03)	
7	0.373	0.257	0.169	0.087	0.105	0.227	-0.005	0.006	-0.002	244
	(2.53)	(3.16)	(9.16)	(3.21)	(2.21)	(3.39)	(-0.91)	(1.73)	(-0.28)	
8	0.418	0.320	0.176	0.091	0.077	0.222	0.001	0.006	0.002	244
	(2.82)	(3.99)	(8.54)	(2.89)	(1.78)	(4.59)	(0.11)	(1.32)	(0.27)	
9	0.568	0.448	0.225	0.146	0.023	0.092	-0.002	0.012	0.003	244
	(3.58)	(4.85)	(7.57)	(4.29)	(0.47)	(1.05)	(-0.29)	(2.42)	(0.63)	
10 - High Skill	0.918	0.752	0.295	0.254	0.016	0.062	0.004	0.025	0.010	245
	(4.03)	(4.78)	(7.36)	(4.23)	(0.16)	(0.37)	(0.35)	(2.80)	(0.90)	
High - Low	0.838	0.936	-0.149	0.067	-0.215	-0.489	0.015	0.017	0.001	
	(2.58)	(3.36)	(-3.02)	(0.76)	(-1.31)	(-1.76)	(1.12)	(1.47)	(0.06)	

Panel B: Subsample analysis of return performance of SED deciles

Exploit Rare Disaster Concerns	(1) Rank months by market excess returns		(2) Rank months by market excess returns		(3) NBER Recession Dates		(4) Rank months by market excess returns	
	Others	Lost 10% or More	Others	Lowest Quintile	Normal Times	Stressful Times	Highest Decile	Lowest Decile
1 - Low Skill	0.390	-7.715	1.111	-3.947	0.514	-1.918	3.277	-5.567
	(1.40)	(-3.14)	(4.12)	(-5.38)	(1.72)	(-1.99)	(4.78)	(-4.60)
2	0.440	-4.202	0.988	-2.569	0.537	-1.000	2.306	-3.273
	(2.47)	(-2.77)	(6.22)	(-5.70)	(2.92)	(-1.58)	(4.54)	(-4.24)
3	0.482	-3.637	0.889	-1.880	0.552	-0.724	1.752	-2.545
	(3.32)	(-2.73)	(6.66)	(-4.74)	(3.54)	(-1.45)	(3.68)	(-3.65)
4	0.432	-3.137	0.801	-1.678	0.507	-0.678	1.443	-2.384
	(3.49)	(-2.42)	(7.27)	(-4.71)	(3.82)	(-1.53)	(5.32)	(-3.78)
5	0.399	-3.143	0.713	-1.491	0.456	-0.619	1.299	-2.296
	(3.54)	(-1.95)	(7.18)	(-3.69)	(3.61)	(-1.39)	(4.87)	(-3.14)
6	0.397	-2.570	0.692	-1.311	0.447	-0.470	1.465	-2.005
	(3.64)	(-2.06)	(7.09)	(-3.82)	(3.98)	(-1.09)	(4.61)	(-3.23)
7	0.485	-2.440	0.784	-1.234	0.533	-0.363	1.505	-1.829
	(4.51)	(-2.51)	(7.91)	(-4.27)	(4.67)	(-0.97)	(4.42)	(-3.63)
8	0.511	-1.938	0.837	-1.221	0.536	-0.130	1.837	-1.615
	(4.35)	(-2.53)	(7.28)	(-5.34)	(4.29)	(-0.36)	(4.31)	(-4.07)
9	0.665	-1.856	1.035	-1.253	0.647	0.208	2.584	-1.468
	(4.74)	(-2.46)	(7.23)	(-5.63)	(4.05)	(0.67)	(5.17)	(-4.08)
10 - High Skill	1.040	-2.166	1.498	-1.348	0.975	0.652	3.384	-1.583
	(4.81)	(-2.03)	(6.49)	(-3.86)	(4.08)	(1.25)	(4.03)	(-2.79)
High - Low	0.650	5.549	0.387	2.599	0.462	2.570	0.107	3.984
	(3.05)	(2.07)	(1.79)	(3.52)	(2.11)	(3.17)	(0.14)	(3.10)

Table IA-4: SED portfolio results using CISDM database

We report results using hedge funds from CISDM database (1996:01 - 2009:03). In formulating portfolios, we require funds to report returns net of fees in US dollars and have at least $10 million in AUM.

Panel A: Hedge fund decile portfolio returns and Fung-Hsieh factor loadings for the portfolio holding horzion of 1 month

Exploit Rare Disaster Concerns	Excess Ret	Intercept	MKTRF	SMB	TERM	DEF	PTFSBD	PTFSFX	PTFSCOM	# of funds
1 - Low Skill	-0.005	-0.056	0.424	0.067	0.334	0.789	-0.001	0.017	0.013	143
	(-0.01)	(-0.24)	(9.58)	(1.03)	(2.44)	(4.08)	(-0.10)	(1.29)	(0.70)	
2	0.284	0.262	0.207	0.027	0.320	0.662	0.004	0.005	0.015	144
	(1.09)	(1.77)	(5.43)	(0.75)	(3.10)	(4.90)	(0.28)	(0.59)	(1.40)	
3	0.388	0.367	0.172	0.036	0.226	0.474	0.007	0.008	0.010	144
	(1.79)	(2.68)	(5.28)	(0.97)	(2.76)	(4.34)	(0.58)	(1.22)	(1.04)	
4	0.272	0.245	0.133	0.061	0.172	0.429	0.001	0.010	0.004	145
	(1.54)	(2.38)	(6.21)	(2.35)	(2.82)	(4.51)	(0.10)	(1.92)	(0.48)	
5	0.232	0.183	0.149	0.055	0.161	0.356	-0.014	0.007	0.004	145
	(1.27)	(1.56)	(5.92)	(2.27)	(2.55)	(3.73)	(-1.49)	(1.53)	(0.52)	
6	0.327	0.300	0.124	0.055	0.125	0.326	-0.006	0.004	0.001	144
	(2.11)	(3.02)	(5.98)	(2.46)	(2.40)	(3.84)	(-0.86)	(1.04)	(0.10)	
7	0.326	0.289	0.130	0.062	0.119	0.285	-0.004	0.010	0.000	144
	(2.26)	(3.48)	(6.74)	(2.51)	(2.30)	(3.76)	(-0.74)	(2.50)	(0.02)	
8	0.410	0.375	0.118	0.095	0.071	0.217	0.004	0.012	0.002	144
	(3.16)	(4.81)	(5.11)	(3.24)	(1.53)	(4.08)	(0.79)	(2.31)	(0.25)	
9	0.583	0.473	0.120	0.150	0.115	0.081	0.000	0.027	-0.000	144
	(3.89)	(3.91)	(3.42)	(4.44)	(1.69)	(0.88)	(0.05)	(3.50)	(-0.04)	
10 - High Skill	0.935	0.787	0.172	0.270	0.082	-0.025	0.016	0.038	0.006	145
	(4.43)	(4.45)	(3.77)	(6.06)	(0.77)	(-0.18)	(1.05)	(4.11)	(0.45)	
High - Low	0.940	0.843	-0.252	0.203	-0.252	-0.814	0.018	0.021	-0.006	
	(2.32)	(3.14)	(-4.49)	(2.83)	(-1.59)	(-2.92)	(0.91)	(1.70)	(-0.37)	

Panel B: Subsample analysis of return performance of SED deciles

Exploit Rare Disaster Concerns	(1) Rank months by market excess returns		(2) Rank months by market excess returns		(3) NBER Recession Dates		(4) Rank months by market excess returns	
	Others	Lost 10% or More	Others	Lowest Quintile	Normal Times	Stressful Times	Highest Decile	Lowest Decile
1 - Low Skill	0.298	-6.857	0.967	-3.632	0.514	-2.317	3.593	-5.344
	(1.01)	(-2.82)	(3.35)	(-4.62)	(1.73)	(-2.20)	(3.79)	(-4.14)
2	0.414	-2.662	0.861	-1.871	0.640	-1.307	1.796	-2.366
	(2.20)	(-1.42)	(4.88)	(-3.51)	(3.56)	(-1.93)	(2.20)	(-2.43)
3	0.476	-1.606	0.865	-1.394	0.683	-0.929	1.507	-1.526
	(2.94)	(-1.17)	(5.64)	(-3.36)	(4.26)	(-1.84)	(2.46)	(-2.07)
4	0.367	-1.886	0.658	-1.171	0.511	-0.796	0.941	-1.614
	(2.82)	(-1.70)	(5.37)	(-3.28)	(4.04)	(-1.80)	(1.80)	(-2.58)
5	0.355	-2.566	0.615	-1.198	0.465	-0.812	0.964	-1.860
	(2.99)	(-1.72)	(5.46)	(-2.98)	(3.68)	(-1.84)	(2.36)	(-2.52)
6	0.427	-1.958	0.671	-0.958	0.527	-0.566	0.984	-1.525
	(3.96)	(-1.64)	(6.75)	(-2.77)	(4.78)	(-1.43)	(2.42)	(-2.44)
7	0.417	-1.722	0.665	-0.939	0.517	-0.526	1.302	-1.333
	(3.78)	(-2.13)	(6.26)	(-3.37)	(4.63)	(-1.51)	(3.14)	(-2.73)
8	0.477	-1.115	0.697	-0.662	0.535	-0.146	1.523	-0.784
	(4.09)	(-2.33)	(5.59)	(-3.32)	(4.29)	(-0.50)	(3.17)	(-2.43)
9	0.643	-0.784	0.792	-0.198	0.655	0.262	1.211	-0.015
	(4.35)	(-1.11)	(5.01)	(-0.61)	(3.92)	(0.94)	(1.57)	(-0.03)
10 - High Skill	0.989	-0.279	1.185	0.004	0.977	0.751	1.969	0.283
	(4.20)	(-0.24)	(4.46)	(0.01)	(3.82)	(1.38)	(2.01)	(0.40)
High - Low	0.691	6.578	0.218	3.636	0.463	3.069	-1.624	5.627
	(2.50)	(2.25)	(0.81)	(4.12)	(1.67)	(2.98)	(-1.44)	(3.93)