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 the 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 be realized as *ex post* disaster shocks, deliver superior future fund performance while being less exposed to disaster risk. Our basic idea is illustrated in Figure 1, which plots the monthly time-series of a rare disaster concern index ($\mathbb{RIX}$) we construct using out-of-the-money put options on various economic sector indices. The index value at time t is essentially equal to the price of insurance against extreme downside movements of the financial market from time t to $(t+\tau)$ *in the future* (see Section 2 for details). The graph shows the following salient feature of the market's disaster concerns.

When market shocks occur at time t, concerns for future disasters between t and $(t+\tau)$ increases substantially. Most importantly, the magnitude of such increased concerns at time t seems to be enormous relative to *subsequently* realized losses, if any, between t and $(t+\tau)$.[1] This startling difference between the *ex ante* disaster concerns and the *ex post* realized shocks suggests that investors may be paying a "fear premium" beyond the compensation for the disaster risk. In fact, Bollerslev and Todorov (2011) suggest that the fear premium is a critical component of market returns. Such a fear premium can be consistent with the behavior of agents with non-expected utility or constrained agents who face market frictions and are averse to tail events (Liu, Pan, and Wang (2005); Bates (2008); Caballero and Krishnamurthy (2008); Barberis (2013)), or consistent

[1] Another feature of disaster concerns is that the index spikes not only when disaster shocks hit the market such as the LTCM collapse, the crash of Nasdaq, and the recent financial crisis, but also during bull markets such as the peak of Nasdaq and the market rally in October 2011.

with market mispricing or sentiment (Bondarenko (2004); Han (2008)). Under these 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 at identifying market concerns that are fears with no subsequent disaster shocks. By supplying disaster insurance to investors with high disaster concerns, some fund managers profit more than others who do not possess such skills and are thus unable to take advantage of these opportunities.[2] Second, even when disaster concerns are subsequently realized as disaster shocks, some fund managers may be better than others at identifying whether there is a "fear premium" beyond the compensation for realized shocks. By extracting such a "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 at identifying the investors who are willing to pay higher premiums 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 over-the-counter (OTC) markets. Thus, hedge funds with different networks may have differing ability to locate investors who are willing to pay high premiums. In summary, skills in exploiting disaster concerns can contribute to higher returns for 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 us to identify skillful fund managers. In principal, when the market's disaster concern is high, funds with more skilled managers should earn higher contemporaneous returns

[2] "Supplying 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.

than those with less skilled managers in supplying disaster insurance. Empirically, we measure fund skills in exploiting rare disaster concerns (SED) using the covariation between fund returns and the disaster concern index we construct.[3] Consistent with our view that hedge funds exhibit different levels of 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. In our baseline results, 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).[4] 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 the higher returns we document) because they are good hedges against disaster risk under this interpretation.

We further elaborate on the relationship between the SED and hedge fund performance from several important perspectives. First, we provide additional evidence that high-SED funds earn higher returns but are less exposed to disaster risk. Examining the covariances of SED portfolios with various disaster risk factors, we provide evidence that high-SED funds are not particularly risky. Furthermore, when we directly purge the disaster risk premium from the $\mathbb{RIX}$ factor based on the stochastic disaster risk model of Seo and Wachter (2014) and re-estimate funds' SED, we continue to observe high-SED funds outperform low-SED funds. Overall, our empirical evidence on factor loadings of SED fund portfolios and fund performance with the purged $\mathbb{RIX}$ measure show

[3] 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.

[4] 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 the payoffs of writing put options, and hence these strategies are sensitive to extreme downside market movements (Lo (2001); Goetzmann et al. (2002, 2007); Agarwal and Naik (2004)).

that high-SED funds earn higher returns because of their superior skill at exploiting rare disaster concerns rather than simply taking larger exposure to disaster risk.

Second, it is possible that high-SED funds may have more disaster risk exposure when 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 perform a conditional test of SED-sorted fund portfolios during both normal and stressful market times. A risk-based explanation would suggest that high-SED portfolio significantly underperform during stressful market times. In contrast, we find that high-SED funds (based on either the original version of $\mathbb{RIX}$, or the version of $\mathbb{RIX}$ purged of the disaster risk premium) outperform low-SED funds even more during stressful market times, though most fund deciles incur losses during market downturns. Moreover, we observe no significant return difference between high- and low-SED funds when the market shows fairly low disaster concerns (e.g., bull markets) and there is simply not much space for high-SED funds to exploit, corroborating our SED-based explanation of hedge fund performance.

Third, as the spikes in the $\mathbb{RIX}$ factor often occur when disaster shocks hit the market, it is possible that some of our high-SED funds earn profits by purchasing – rather than selling – disaster insurance before the disaster shock: these funds realize large positive payoffs when such disastrous outcomes hit the market. Among the credit-style hedge fund sample, we identify a potential set of such funds and find even stronger SED effects on future fund performance after excluding them from our portfolio analysis. Moreover, we explore a general identification condition for the funds purchasing disaster insurance: time $t-1$ returns of these funds, who pay a cost to buy disaster insurance before disastrous events at time t, should have significant negative loadings on the $\mathbb{RIX}$ at time t. Accordingly, we identify funds with skills of purchasing disaster insurance by regressing the fund's monthly excess return at $t-1$ on the next-period $\mathbb{RIX}$ at t. We find that there is no significant return difference between low- and high-exposure funds, contradicting the interpretation of high-SED funds as purchasing disaster insurance. These results provide further support that the skills of high-SED fund managers are to identify the existence and magnitude of the "fear premium" and sell insurance contracts against future disaster events, rather than forecasting the disaster event and buying disaster insurance beforehand.

Fourth, we conduct analysis to shed some light on the possible channels of hedge funds exploiting disaster concerns. In particular, we analyze how high-SED funds manage leverage and time extreme market conditions. We calculate the leverage implied by $\mathbb{RIX}$ and estimate each fund's ability in managing leverage. We find that high-SED funds do have leverage-managing ability: they reduce exposure to market-wide leverage shocks when the market leverage condition worsens and the market is on de-leverage. Moreover, we estimate each fund's extreme-market-timing ability and find that high-SED funds on average have strong bear-market-timing ability. In sum, our analysis indicates the positive relation between fund in exploiting disaster concerns and leverage-managing and extreme-market-timing abilities. However, we note that such evidence is only suggestive because of the lack of fund-level data on portfolio holdings, investment positions, and balance sheets.

Throughout the paper, we also compute risk-adjusted abnormal returns using the Fung and Hsieh (2001) eight-factor model and the ten-factor model recently developed by Namvar, Phillips, Pukthuanthong, and Rau (2014; NPPR (2014) hereafter). 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 1.27% and 0.80% per month with Newey-West t-statistics of 3.8 and 2.8 relative to the Fung-Hsieh and NPPR models, respectively. 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 (Ang, Chen, and Xing (2006)), volatility risk (Ang et al. (2006)), market liquidity risk (Pastor and Stambaugh (2003); Acharya and Pedersen (2005); Sadka (2006); Hu, Pan, and Wang (2013)), funding liquidity risk (Brunnermeier and Pedersen (2009); 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 similar in these extended analyses.

Our results are robust to alternative measures of *ex ante* disaster concerns such as the ones based on the 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 backfilling 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.[5] The SED measure is distinct from other fund skill variables in predicting future fund performance, including the skill in hedging 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 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 rare disaster concern index. Section 3 presents the SED measure and its properties across the pool of hedge funds. Section 4 reports our baseline results of cross-sectional fund performance based on SED. We dissect the fund performance based on SED in detail in Section 5 and show the distinctiveness of SED in Section 6. Section 7 provides additional results and robustness checks and Section 8 concludes. The Appendix provides technical details, and a separate Internet Appendix provides open interest statistics of index options and additional analyses of SED portfolios.

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, building on the model-free implied volatility measures of Carr and Madan (1998), Britten-Jones and Neuberger (2000), Carr and Wu (2009), and especially Du and Kapadia (2012). 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 $\mathbb{RIX}$ is equal to the insurance price against extreme downside market movements in the future. Over time, the $\mathbb{RIX}$ signals variations of *ex ante* disaster concerns.

[5]Recent studies include Aragon (2007), Fung, Hsieh, Naik, and Ramadorai (2008), Liang and Park (2008), Agarwal, Daniel, and Naik (2009), Aggarwal and Jorion (2010), Li, Zhang, and Zhao (2011), Titman and Tiu (2011), Cao, Chen, Liang, and Lo (2013), and Sun, Wang and Zheng (2012, 2013), among others.

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.[6] 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)).

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 approx-

[6] 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.

imation, and determines $\mathbb{VP}$ as

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

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

Our measure of disaster concerns is essentially equal to the difference between $\mathbb{V}$ and $\mathbb{IV}$, 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 (Liu, Pan, and Wang (2005); Ang, Chen and Xing (2006); Barro (2006); Gabaix (2012); 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 $\mathbb{V}$:

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

where only OTM put options that protect investors against negative price jumps are used. We then define our rare disaster concern index ($\mathbb{RIX}$) as

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

Assume the price process follows the Merton (1976) jump-diffusion model with $dS_t/S_t = (r-\lambda\mu_J)\,dt+\sigma dW_t + dJ_t$,where r is the constant risk-free rate, σ is the volatility, W_t is a standard Brownian motion, J_t is a compound Poisson process with jump intensity λ, and the compensator for the

Poisson random measure $\omega[dx, dt]$ is equal to $\lambda \frac{1}{\sqrt{2\pi}\sigma_J} \exp\left(-(x-\mu_J)^2/2\right)$. We can show that

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

where $\omega^-[dx, dt]$ 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 equation (4), the computation of $\mathbb{RIX}$ relies on a continuum of moneyness levels. Similar to Carr and Wu (2009), 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 based on 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. We further divide $\mathbb{RIX}$ by $\mathbb{V}^-$ as a normalization to mitigate the effect of different volatility levels across different economy sectors. 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.[8]

2.3 Descriptive Statistics

Table 1 presents descriptive statistics of disaster concern indices. Panel A shows the monthly aggregated $\mathbb{RIX}$ has a mean of 0.063, with a standard deviation of 0.02. Among sector-level

[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).

[8] Table IA-1 of the Internet Appendix 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 $K/S \leq 0.90$).

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 1 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 indicate 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 2 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, Chen, Liang, and Lo (2013); 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 a standard deviation of 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 those reporting returns and those 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 3 presents the characteristics of SED-sorted hedge fund portfolios. Panel A presents evidence that high-SED funds have a lower level of assets under management, a larger fund flow, less liquidation, and a lower non-reporting rate. In addition, high-SED funds are better at hedging systematic risk with respect to the Fung and Hsieh (2001) benchmark factors (the R-squared measure used in Titman and Tiu (2011)). They have more innovative strategies, as measured by the 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, we report the likelihood distribution of different hedge fund investment styles within each SED decile. 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 the market's rare disaster concerns, it should display a 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 4 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 5, we investigate the cross-sectional determinants of hedge fund managers' 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 a higher SED have a smaller level of AUM and have positive return skewness over the past two years. We also find a strong negative relation between Fung-Hsieh alpha and SED. This last piece of evidence is not surprising. On average, a hedge fund with a 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.[9] In other words, those funds with a high Fung-Hsieh alpha behave more like they are demanding disaster insurance, and are 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.[10]

4 SED and Hedge Fund Performance

In this section, we present our baseline results on the hedge fund skills in exploiting rare disaster concerns (SED) and future fund performance. From an institutional investment and market impact perspective, funds with small AUM (e.g., less than \$10 million) are of less economic importance and we exclude them in our main analysis (Cao, Chen, Liang, and Lo (2013); Hu, Pan, and Wang (2013)). Following their approach, we restrict the sample to include only those funds that have at least \$10 million AUM *at the time of portfolio formation* in our baseline specification. After selecting the sample of funds that reports monthly returns net of fees in US dollars, 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 short on funds in decile 1. We hold portfolios for one month and calculate equal-weighted returns.[11]

[9] 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.

[10] We defer the discussion related to extreme market timing to Section 6.2.

[11] We also look at value-weighted portfolio returns and returns at longer holding horizons (see details in Section 7). There is significant persistence in fund performance for at least 12 months after portfolio formation. In addition, value-weighted and equal-weighted returns are of similar magnitude.

To measure portfolio-level risk-adjusted abnormal returns (alphas), we consider two benchmark models. The first one is the Fung-Hsieh (2001) eight-factor model, including two equity factors, a 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 portfolio returns based on the 7-10-year Treasury Index and the Corporate Bond Baa Index from Barclays Capital (Sadka (2010)). The second benchmark model is a ten-factor model recently developed by Namvar, Phillips, Pukthuanthong, and Rau (2014; NPPR (2014) hereafter). Applying the method in Pukthuanthong and Roll (2009), NPPR (2014) extract the first 10 return-based principal components (PCs) from 251 global assets across different countries and asset classes, and show these 10 PCs explain approximately 99% of the variability in the returns of the considered assets. Prior studies document significant serial auto-correlation of hedge fund returns because of illiquidity and return smoothing (e.g., Getmansky, Lo, and Makarov (2004)). Following Titman and Tiu (2011), our estimates of alphas are adjusted for hedge fund return smoothing.

Specification (1) in Table 6 presents our baseline results of SED-sorted hedge fund portfolio returns. Each decile has 148 hedge funds on average and is well diversified. We report mean excess returns, the Fung-Hsieh 8-factor model alphas, and NPPR 10-factor model alphas (all in percent). At a one-month holding horizon, we observe a near monotonically increasing relation between SED and average excess return. High-skill funds (SED decile 10) outperform low-skill funds (SED decile 1) by more than 0.96% per month (with a Newey-West t-statistic of 2.8). In fact, the return performances 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 Fung-Hsieh 8-factor alpha of the high-minus-low SED portfolio is around 1.27% (with a t-statistic of 3.8), indicating that the high-skill funds' outperformance cannot simply be attributed to option-based strategies.[12] The NPPR 10-factor alpha of the high-minus-low SED portfolio is around 0.80% (with a t-statistic of 2.8), indicating that the high-skill funds' outperformance cannot be explained by the combination of passive index investments on global equities, currencies, bonds, commodities, and real estates.[13] Figure 2 graphs monthly high-

[12] We report estimates and Newey-West t-statistics of all factor loadings in Table IA-2 of the Internet Appendix.

[13] The monthly alpha difference (47 basis points) between the 8-factor model and the 10-factor model mainly comes from low-SED funds: -0.63% (t-statistic $= -2.8$) under the 8-factor model vs. -0.09% (t-statistic $= -0.3$). In other words, the 10-factor model has the most significant impact on adjusting the returns of low-SED funds, but not high-SED funds.

minus-low SED portfolio returns over the 157-month period. High-SED funds seem to outperform low-SED funds even more during times of financial crisis (we present detailed subsample analysis in Section 5.2).[14]

Specification (2) in Table 6 reports returns for a broader sample of TASS hedge funds without restrictions on AUM. Results are similar. High-skill funds (SED decile 10) outperform low-skill funds (SED decile 1) by 0.89% per month (with a t-statistic of 2.7). Alphas based on the Fung-Hsieh 8-factor model and the NPPR 10-factor models are 1.18% and 0.76% per month, respectively, and both are significant.

Bhardwaj, Gorton, and Rouwenhorst (2013) show that database backfilling introduces a significant upward bias in assessing fund performance. Following their recommendation, we rely on the date that a fund was *first* added into the TASS database to correct for the backfilling bias in hedge fund returns (i.e., we use monthly fund returns only after this date). Specification (3) shows excess returns and alphas of SED portfolios after removing the backfilled data. Consistent with Bhardwaj, Gorton, and Rouwenhorst (2013), we also find an upward backfilling bias in fund returns. For example, among high-skill funds (SED decile 10), such bias inflates returns by 0.18% ($\simeq 0.905\% - 0.724\%$) per month, and interestingly, among low-skill funds (SED decile 1), returns are also inflated about 0.18% ($\simeq (-0.058\%) - (-0.233\%)$) per month. Putting these numbers into the perspective of average-skill funds (SED decile 5), we see the effect of the backfilling bias on fund returns is around 0.092% ($= 0.264\% - 0.172\%$). Nevertheless, removing the backfilling hardly changes our conclusion. High-skill funds continue to outperform low-skill funds by 0.96% per month (with a t-statistic of 2.7), and monthly alphas are 1.37% (with a t-statistic of 3.9) and 0.80% (with a t-statistic of 2.6) for the Fung-Hsieh 8-factor model and the NPPR 10-factor model, respectively.[15]

The TASS database doesn't report "delisted" hedge fund returns. We address this issue by

[14] In an unreported analysis, we also estimate alphas using the set of global asset pricing factors recently developed in the literature, including value, momentum, betting-against-beta, and futures-based trend-following (Asness, Moskowitz, and Pedersen (2013); Frazzini and Pedersen (2014); Moskowtiz, Ooi, and Pedersen (2012); Baltas and Kosowski (2012)). Our results are unchanged. The alphas of high-minus-low SED portfolios remain highly significant, and they range from 0.83% to 1.20% per month depending on the model specification.

[15] Our results are not sensitive to how we handle backfilling bias. Following the procedure in Jagannathan, Malakhov, and Novikov (2010), we mitigate the backfilling bias by excluding the first 25 months from the history of each fund. The return spread of the high-minus-low SED portfolio is 0.89% per month (with a Newey-West t-statistic of 2.6), the Fung-Hsieh 8-factor alpha is 1.15%, and the NPPR 10-factor alpha is 0.81% (both are at least three standard errors from zero).

assuming a large negative return (such as -100%) in the month immediately after a hedge fund exits the database for reasons such as liquidation, no longer reporting, or unable to contact fund. The last three columns in Table 6 report portfolio results after accounting for hedge fund "delisting" events. We find return patterns of SED deciles similar to those of our main result. In fact, the return spread of the high-minus-low SED portfolio is 1.3% per month (with a t-statistic of 3.1). Results are similar when we use different assigned values for hedge fund "delisting" returns (such as -90%, -50%, etc.). The evidence is consistent with the earlier observation in Table 3 that high-SED funds have *lower* liquidation rates.

Overall, our results strongly suggest that hedge fund managers' skills in exploiting rare disaster concerns play an important role in explaining their future return performance.

5 Dissecting SED and Hedge Fund Performance

In this section, we elaborate on the relationship between the SED and hedge fund performance from three important perspectives. First, we provide collaborative evidence that high-SED funds earn higher returns while being less exposed to disaster risk. Examining the covariances of SED portfolios with various disaster risk factors, we do not find high-SED funds are particularly risky. Moreover, when we directly purge the (rational) disaster risk premium from the $\mathbb{RIX}$ factor and re-estimate funds' SED, we continue to observe that high-SED funds outperform low-SED funds.

Second, we perform a conditional test of SED-sorted fund portfolios during both normal and stressful market times. A risk-based explanation would suggest that high-SED funds significantly underperform during stressful market times. In contrast, we find high-SED funds outperform low-SED funds even more during stressful market times. Moreover, we observe no significant return difference between high and low SED funds when the market shows fairly low disaster concerns (e.g., bull markets) and there is simply not much space for high-SED funds to exploit, corroborating our SED-based explanation of hedge fund performance.

Third, as the spikes of the $\mathbb{RIX}$ factor often coincide times of realized disaster shocks on the market, it is possible that some of our high-SED funds earn profits by purchasing – rather than selling – disaster insurance before the disaster shock: these funds realize large positive payoffs when disastrous outcomes hit the market. Among the credit-style hedge fund sample, we identify a potential set of such funds and find even stronger SED effects on future fund performance after excluding them from our portfolio analysis. Furthermore, we investigate the general relation between fund skills of purchasing disaster insurance before $\mathbb{RIX}$ run-up and fund future performance, and our empirical evidence doesn't support this alternative story to explain cross-sectional hedge fund performance.

5.1 Can Disaster Risk Explain the SED-Sorted Portfolio Returns?

It is important to emphasize that our baseline results in the previous section are inconsistent with the view that high-SED 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 the higher returns we document) because they are good hedges against disaster risk under this interpretation.[16] Nevertheless, we provide two additional pieces of evidence against a risk-based explanation of our SED-based fund performance.

5.1.1 Disaster Risk Exposure

To verify that funds in higher SED deciles earn higher returns by having superior 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, liquidity, and disaster risk factors. Guided by the macro-finance literature (e.g., Barro (2006); Wachter (2013)), we include the following set of macroeconomic risk factors: GDP growth, inflation, corporate default, and term spread of bond yields. GDP growth is the real per-capita growth rate of GDP, computed quarterly by the real GDP growth rate obtained from the 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 the International Monetary Fund (IMF). The inflation rate

[16] It is also important to recognize that hedge funds are *actively managed assets*, and the relationship between rare disaster concerns and returns is different from that for *passively managed assets*. For example, in the context of passively managed assets including MSCI international equity indices, foreign currencies, global government bonds, and commodity futures, Gao and Song (2015) find high RIX-beta assets are favorable securities because they deliver contemporaneously higher returns when the market is fearful about rare disasters. High RIX-beta assets receive higher demand today and their prices are being pushed up; and they subsequently earn lower returns in the future. In other words, high-RIX beta assets provide protection against market disaster concerns and the high demand from investors for such assets lead to lower expected returns.

is the monthly year-on-year percentage change of the core consumer price index (CPI). We proxy the corporate default risk using the difference between the Moody's Aaa and Baa corporate bond yields obtained from the FRED. We also compute the term spread between the 10-year US Treasury yield and the 3-month T-bill rate.

We additionally consider various market and funding liquidity risk measures because liquidity crunches often happen at the same time as macroeconomic downturns and market shocks (Brunnermeier, Nagel, and Pedersen (2008)). The funding liquidity variables include the Treasury-Eurodollar (TED) spread, which is equal to the 3-month LIBOR minus the 3-month T-bill rate, the LIBOR-Repo spread, which is equal to the 3-month LIBOR minus the 3-month General Collateral Treasury repurchase rate, and the Swap-Treasury spread, which is equal to the 10-year interest rate swap rate minus the 10-year Treasury yield. In order to measure liquidity shocks, we take the first-order difference in each of these monthly series.[17] For market liquidity, we use the on-the-run minus the off-the-run 10-year Treasury yield spread obtained from the Federal Reserve Board, the level of liquidity measure from Pastor and Stambaugh (2003), and the "noise" measure from Hu, Pan, and Wang (2013) delineating the relative availability of arbitrage capitals. We define U.S. funding liquidity shocks, U.S. market liquidity shocks, and U.S. all liquidity shocks as the first principal components based on various correlation matrices of the corresponding sets of liquidity variables.

Panel A from Table 7 reports the loadings of SED-sorted hedge fund portfolios on macroeconomic and liquidity risk factors. 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 3.4. In fact, high-SED funds are not significantly exposed to any macroeconomic and liquidity shocks.

Some readers may be concerned that general macroeconomic and liquidity risk factors are not sufficient to capture disaster risk, and prefer to measure disaster risk directly using option-based factors. In Panel B of Table 7, we consider an alternative set of risk factors based on option prices. We regress hedge fund portfolio returns on the market excess return itself (the first column), and

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

the market excess return plus one of the following factors (the other columns): (1) volatility skew, which is the implied volatility difference between the S&P 500 index OTM put and ATM call (Xing, Zhang, and Zhao (2010)); (2) high-order moment risk of volatility, skewness, and kurtosis based on the S&P 500 index options (Bakshi, Kapadia, and Madan (2003)); and (3) the option return spread between the S&P 500 index OTM and ATM puts.

The patterns of loadings on these option-based factors in Panel B are very similar to those in Panel A.[18] Again, high-SED funds have economically small and statistically insignificant exposure to any of these factors with the exception of market return, and this market factor exposure is significantly smaller for high-SED funds than for low-SED funds.

5.1.2 Rare Disaster Concerns Purged of Rational Disaster Risk Premiums

Our $\mathbb{RIX}$ measure of rare disaster concerns is the price of a disaster insurance contract and it contains compensations for both objective disaster shocks (rational disaster risk premiums) and purely "concerns" (or "fears") about disaster risk. To identify funds with skills in exploiting the "irrational" overpriced disaster insurance, we consider an alternative measure by purging the rational disaster risk premium from the $\mathbb{RIX}$.

To construct a measure of the rational disaster risk premium, we deploy the time-varying disaster risk model of Seo and Wachter (2014). Option prices calculated from this model, being calibrated to consumption and aggregate market data, only reflect the compensation that investors seek for bearing their losses when disaster shocks are realized. In particular, we use the OTM put prices from the Seo-Wachter stochastic disaster risk model to back out a model-implied $\mathbb{RIX}^M$ (via equation (4)), and then subtract it from our original $\mathbb{RIX}$. This difference, dubbed $\mathbb{RIX}^C$, measures the premium of disaster insurance that investors are willing to pay beyond rational disaster risk premiums implied from the disaster risk model of Seo and Wachter (2014). In other words, $\mathbb{RIX}^C$ exclusively measures investors' overpricing of the disaster insurance.[19]

Theoretically, such overpricing or concerns can arise from different mechanisms, including the

[18] In Table IA-8 of the Internet Appendix, we also conduct double-sorted portfolios using SED and a number of factors on market risk, downside market risk, volatility 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.

[19] The $\mathbb{RIX}^C$ can be regarded as a version of the "unexpected" $\mathbb{RIX}$, where $\mathbb{RIX}^M$ proxies for the rationally expected diaster risk that invesotrs learn from the historical realizations of disaster shocks. Besides taking the difference, we also regress the $\mathbb{RIX}$ on $\mathbb{RIX}^M$ and use the residual as the unexpected $\mathbb{RIX}$. Conclusions are similar.

crash aversion from Bates (2008), the aversion to uncertainty with respect to disaster risk from Liu, Pan, and Wang (2005), the probability weighting of tail events from Barberis and Huang (2008) and Barberis (2013), the sentiment from Han (2008), and other channels beyond standard (and rational) disaster risk models with tail risk probability fitted to the historical observations. For the sentiment channel, the argument on limits of arbitrage is required for the fear premium to exist in equilibrium, which is unlikely in our case because hedge funds are typically large and institutional investors devoted to arbitrage activities. For other channels, the fear premium exists in equilibrium as compensation for crash aversion, uncertainty aversion, and probability weighting of tail events. Prices of disaster insurance contracts in such models are higher than those in a standard (and rational) disaster risk model because of the compensation for economic mechanisms that are beyond rational disaster risk. Skilled funds are not constrained by these mechanisms in their investment decisions, probably because they have advantage from research, information, and experiences in understanding the economy and financial market better. Hence, extracting such compensation by providing disaster insurance, funds with skills of identifying fear premium can earn profits.

We re-estimate each fund's SED from 24-month rolling-window regressions of excess monthly returns (with at least 18 months of fund returns available) on the market factor and the $\mathbb{RIX}^C$. Then we form SED decile portfolios each month, hold them for one month, and calculate equal-weighted returns. The first column of Table 8 presents the monthly returns of these decile portfolios as well as the high-minus-low SED portfolio. Results are stronger than those of our baseline analysis (shown in Table 6). Under the $\mathbb{RIX}^C$ measure, high-SED funds outperform low-SED funds by 1.21% per month (with a Newey-West t-statistic of 3.5). Benchmarked against the Fung-Hsieh 8-factor model and the NPPR 10-factor model, respectively, alphas of the high-minus-low SED portfolio are 1.47% and 1.11% per month; both are at least four standard errors from zero.[20] Because the $\mathbb{RIX}^C$ measure is free of the disaster risk premium to the degree that the Seo-Wachter disaster risk model implies, these results provide reaffirming evidence that fund managers' skills in exploiting disaster concerns drive cross-sectional differences in fund performance.[21]

Overall, our empirical evidence on the factor loadings of SED fund portfolios and the perfor-

[20] For brevity these results are not tabulated but are available upon request.

[21] Table IA-3 of the Internet Appendix presents results using different specifications of the jump size and intensity under the disaster risk framework of Seo and Wachter (2014). Conclusions are similar.

mance of $\mathbb{RIX}^C$-based fund portfolios show that high-SED funds earn higher returns because of their superior skills in exploiting rare disaster concerns, as opposed to simply taking greater exposure to disaster risk. Finally, there is one caveat with $\mathbb{RIX}^C$. While we believe the theoretical underpinning behind the construction of $\mathbb{RIX}^C$ is valid and general, its empirical implementation depends on the specifications of the disaster risk model. Thus we opt for $\mathbb{RIX}$ as our main measure throughout the paper.

5.2 Fund Performance: Normal vs. Stressful Times

In the previous analysis, we argue that high-SED funds earn higher average returns because their managers have better skills in exploiting disaster concerns. However, the higher returns of high-SED funds we document are the average returns for the full sample period (1996 – 2010). Hypothetically, this may be attributable to better performance during normal times, and worse performance during stressful times that are too short in our sample period to provide the expected balance. As a result, it remains possible that high-SED funds have more disaster risk exposure.

To address this concern, we study the conditional performance of SED fund portfolios during stressful and normal times under various definitions of market states. To sharpen our analysis, we estimate each fund's SED based on $\mathbb{RIX}^C$ (i.e., disaster-risk-premium purged $\mathbb{RIX}$).[22] We first divide the sample period (July 1997 through July 2010) into "normal" vs. "stressful" times using 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 market excess returns; (3) NBER recessions (28 months in total: March 2001 through November 2001, and December 2007 through June 2009).

These results are presented in specifications (1) - (3) of Table 8. During normal times defined in specifications (1) - (3), high-SED funds earn higher returns than low-SED funds, ranging between 66 – 97 basis points per month, all statistically significant at the 1% level. During stressful times, all funds lose (except for certain funds in specification (3)), which is consistent with the view that hedge funds earn profits overall but incur losses during market downturns as they are suppliers of disaster insurance.[23] More importantly, high-SED funds lose much less, and hence still outperform

[22] Results are very similar when we use funds' SEDs based on the original $\mathbb{RIX}$ factor (see Table IA-4 of the Internet Appendix).

[23] The positive returns of certain high-SED funds based on specification (3) (which defines NBER recessions as

low-SED funds. For example, in months when the market lost 10% or more, high-SED funds outperform low-SED funds by 7.32% per month (with a t-statistic of 2.6), though they lost more than 1.5% themselves.

Comparing SED-sorted hedge fund portfolios during "good" vs. "bad" times is also informative. If high-SED funds outperform low-SED funds because of disaster-concern-related skills, those skills should not be useful in explaining fund performance when the market shows fairly low disaster concerns (e.g., bull markets) and there is simply not much space for high-SED funds to exploit. In contrast, a risk-based story would predict otherwise. In specification (4), we define good times as those months in the highest decile when we rank all months into ten groups based on market excess returns, while bad times are those months in the lowest decile. Consistent with the skill-based explanation, we observe no significant return difference between high- and low-SED funds in periods of high market returns, further corroborating our SED-based explanation of hedge fund performance.

In summary, high-SED funds outperform low-SED funds in both normal and stressful times; the outperformance is particularly pronounced during stressful times, and indistinguishable from zero during good times. Overall, our empirical evidence favors a skill-based explanation of hedge fund performance.

5.3 Fund Exploiting Disaster Concerns: Purchasing vs. Selling Insurance

In the previous section, we show that high-SED funds that act as disaster insurance suppliers incur losses during market downturns, but they still substantially outperform low-SED funds. These high-SED funds, however, may include ones that purchase (rather than sell) disaster insurance before disaster events happen, and receive positive payoffs after disaster shocks are realized. To shed light on how high-SED funds outperform by selling disaster insurance, it is important to identify funds that purchase disaster insurance, and eliminate them from our baseline analysis.

A particular type of such funds, which has experienced an increase in popularity, is called the

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 the stressful times catgory leads to high-SED fund deciles earning returns insignificantly different from zero. We thank Narayan Naik for suggesting alternative definitions of stressful periods.

short credit fund; this type essentially buys credit risk insurance.[24] For example, a short credit fund can purchase credit default swaps (CDS) before stressful times and benefits from widening credit spreads afterwards. Therefore, we perform the analysis in this section on a "clean" set of credit-style hedge funds from the TASS database (funds with investment styles of event driven, fixed income arbitrage, and convertible arbitrage). The selection of these funds seems sensible because their styles all have significant exposure to the credit market.

To the best of our knowledge, no hedge fund database directly identifies short credit funds. Based on the style analysis from Sharpe (1992), we identify short credit funds in a simple and transparent way. First, we estimate each fund's credit exposure by regressing its past 24-month (with a minimum of 18 months) returns on the U.S. credit spread (an empirical proxy for credit event shocks that is equal to the yield difference between Moody's Aaa and Baa corporate bonds). Then, we define a short credit fund as a fund with positive and significant (at 10% level or better) exposure to this credit factor.

Table 9 presents the returns of SED-sorted credit-style hedge fund decile portfolios. As a benchmark case, among credit-style hedge funds, high-SED funds outperform low-SED funds by about 0.77% per month (with a Newey-West t-statistic of 2.6). The Fung-Hsieh and NPPR alphas are of similar magnitudes, and both are three standard errors from zero. After excluding the short credit funds, we find even stronger evidence that high-SED funds outperform low-SED funds: the return spread of the high-minus-low SED portfolio is about 0.95% per month (with a t-statistic of 3.0). Similarly, alphas from the Fung-Hsieh 8-factor model and the NPPR 10-factor model are 1.04% and 0.92% per month, and both are significant at the 1% level. The return difference between the SED portfolios including short credit funds and those excluding short credit funds are also significant. For example, the return difference between two high-minus-low SED portfolios is about 18 basis points per month (with a t-statistic of 2.6).[25]

More generally, we directly test the alternative story of hedge funds' skills in purchasing disaster

[24] According to the credit derivatives glossary of Markit, the definition of short credit is the following: "This (Short credit) is the credit risk position of the Protection Buyer, who sold the credit risk of a bond to the Protection Seller." (p. 35, Markit Credit Indices A Primer (2013)).

[25] For robustness, we also use a CDS factor in addition to the U.S. credit spread to identify short credit funds. Our CDS factor is the average of five CDS indices across different regions and is related to both corporate and sovereign credit risks. The CDS indices are from Markit. Results are similar (see Table IA-6 of the Internet Appendix for details): the high-minus-low SED portfolio earns above 1% per month (with a t-statistic of 3.1) after we exclude the short credit funds from the credit-style fund sample.

insurance prior to escalated $\mathbb{RIX}$: (1) (skilled) funds purchase insurance at $t-1$ and outperform from market distress at t; that is, they pay an insurance premium at $t-1$ to purchase the insurance (e.g., deep-out-of-the-money put) that becomes valuable at t when the market is distressed (and the $\mathbb{RIX}$ at t is high); and (2) (non-skilled) funds sell insurance at $t-1$ and underperform from market distress at t; that is, they receive an insurance premium at $t-1$ to sell the insurance that becomes toxic at t when the market is hit by a diaster shock. The returns at $t-1$ of hedge funds in the first (second) category should have negative (positive) loadings on $\mathbb{RIX}$ at t, and should earn high (low) future returns. Empirically, we estimate each hedge fund's exposure to rare disaster concerns by regressing the fund's monthly excess return at $t-1$ on the next-period $\mathbb{RIX}$ at t, and then examine future fund performance according to this exposure. We adopt the same rolling-window specification, portfolio formation, and return calculation as in our baseline analysis. The following set of results, presented in the Internet Appendix (Tables IA-5 and IA-7), do not support the aforementioned alternative story: (1) low-exposure (high-exposure) funds do not earn positive (negative) returns. They earn zero returns, both economically and statistically, during each month over the three-month holding period after portfolio formation; (2) there is no significant return difference between low- and high-exposure funds during portfolio holding periods; and (3) after we exclude the funds that are likely to purchase disaster insurance from our sample, the SED decile results are similar to, if not stronger than, our baseline analysis.

In summary, the analysis on disaster-insurance-purchase funds in this section corroborates our theory that high-SED hedge funds supply disaster insurance and outperform, and these funds are not simply repackaging portfolio insurance in one way or another.

6 Distinctiveness of SED

In this section, we first establish the distinctiveness of SED from skills in other dimensions by both applying a series of two-way sequentially-sorted portfolios and performing Fama-MacBeth (1973) cross-sectional regressions. We then conduct exploratory analysis to shed light on how high-SED funds may exploit the market's rare disaster concerns.

6.1 SED and Skills in Other Dimensions

6.1.1 SED and Existing Skill Measures

We study whether our SED measure is distinct from four other fund skills recently 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 benchmark 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 as a measure of fund skills in managing downside risk, and show that such downside returns can explain cross-sectional hedge fund returns. We document the distinctiveness of the SED measure from these four documented fund skills by using 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 10 shows that SED has significant explanatory power 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. Alphas from the 8-factor model and 10-factor model are similar in magnitude, ranging from 41 to 79 basis points per month; they are at least three standard errors from zero. Overall, these results show that the explanatory power of SED on hedge fund performance is beyond those skill variables documented in the literature.

6.1.2 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 are 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 SED is driven by hedge fund skills in exploiting volatility concerns 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 11.

In Panel A, we first sort all funds into quintiles based on each fund's SEV. 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 quintile of SEV: The return spreads of the high-minus-low SED portfolios range from 0.43% to 1.1% per month (all are statistically significant at the 1% level). Alphas from the 8-factor model and 10-factor model are similar in magnitude and statistical significance.

In Panel B, we first sort all funds into quintiles based on each fund's SED. 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 with high and low SEV is 0.11% and it is less than one standard error from zero. Moreover, SEV has no power to explain hedge fund returns within each SED quintile (all return spreads are economically small and statistically insignificant). Alphas from the 8-factor model and 10-factor model are 0.17% and 0.11% per month, and none of them is statistically significant.[26] Collectively, these results suggest that fund skills in exploiting disaster concerns rather than volatility concerns explain cross-sectional hedge fund performance.

6.1.3 Cross-Sectional Regressions

The portfolio analysis so far suggests that the fund skills in exploiting disaster concerns measure is distinct from other fund skills in explaining cross-sectional hedge fund performance. In this section, we differentiate the SED from other fund skills using the Fama-MacBeth (1973) regression approach, which allows us to control for 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 12 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 SED 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.

Because SED measure is empirically estimated and subject to the error-in-variable (EIV) problem, we comment on potential bias driven by EIV. First, when we regress funds' monthly excess returns only on their SED measures, we find the coefficient is 0.0022 (with a Newey-West t-statistic of 2.2). It is known that the EIV problem in the context of univariate regression introduces a downward bias in the estimate of coefficient, and it works against us on finding any significant effect of SED. Second, to mitigate the EIV problem, we use each fund's SED decile ranking as the regressor

[26] In our baseline analysis, factor loadings on Fung-Hsieh's option-based lookback straddle factors are also revealing. First, as shown in the internet appendix (Table IA-2), high-SED funds have small and statistically insignificant exposure to these three option straddle factors. Second, the return difference between high-SED and low-SED funds have small and statistically insignificant exposure to these three option straddle factors.

in the Fama-MacBeth regression. Incidentally, this shrinkage-type modification also makes the coefficient estimates comparable across different regression specifications. Third, we perform a full set of double-sorted portfolios on SED and other variables (including other well-known skill variables, fund characteristics, macroeconomic and liquidity risk betas). In *each* of the 14 cases, we find both economically and statistically significant SED effect. We provide detailed results in Table IA-8 of the Internet Appendix. Overall, our evidence collectively suggests that the SED effect we present in the paper is unlikely to be driven by the EIV problem.

6.2 Leverage Managing and Extreme Market Timing

In this section, we analyze how high-SED funds manage leverage and time extreme market condition to shed some light on the possible channels of hedge funds exploiting disaster concerns. First, we calculate the $\mathbb{RIX}$-implied leverage as $\Omega_{\mathbb{RIX}} = (\partial \mathbb{RIX}/\mathbb{RIX})/(\partial S/S) = \Delta_{\mathbb{RIX}} \cdot S/(\mathbb{RIX})$, where S is the underlying index level for the corresponding OTM put options and $\Delta_{\mathbb{RIX}}$ is the delta of $\mathbb{RIX}$. The leverage is essentially an elasticity measure that captures the percentage change in $\mathbb{RIX}$ (the price of a disaster insurance contract) for one percentage change in the underlying index. Figure 3 presents the monthly time series of $\mathbb{RIX}$ leverage.[27] The clear countercyclical pattern is consistent with recent studies on hedge fund leverage (Ang, Gorovyy, and van Inwegen (2011); Jiang (2014)).

We investigate whether the outperformance of high-SED funds arises from their ability to manage leverage; that is, they reduce exposure to market-wide leverage shocks when the market leverage condition worsens and the market de-leverages. Specifically, we estimate each fund's leverage-managing ability by the following 24-month rolling-window regression: $RET_{i,t} = a_i + b_i MKT_t + c_i \cdot \Omega_{\mathbb{RIX},t} + d_i^1 \cdot (\Omega_{\mathbb{RIX},t} - \Omega_{\mathbb{RIX},t-1}) + d_i^2 \cdot \max\{0, -(\Omega_{\mathbb{RIX},t} - \Omega_{\mathbb{RIX},t-1})\} + \epsilon_{i,t}$, where $RET_{i,t}$ is the fund's monthly excess return and MKT_t is the CRSP value-weighted market excess return. When the aggregate leverage condition worsens (improves), a fund i's exposure to leverage shock is $d_i^1 - d_i^2$ (d_i^1), and hence we expect $d_i^2 > 0$ for funds with leverage-managing ability. Figure 3 and Table IA-9 of the Internet Appendix show that high-SED funds have superior ability to managing leverage

[27] We follow our $\mathbb{RIX}$ estimation procedures to compute $\Omega_{\mathbb{RIX}}$. For a sector, we first obtain daily estimates of its leverage and then take the daily average over the month to get monthly leverage. Because our $\mathbb{RIX}$ factor is aggregated over six sector-level rare disaster concern indices, and because the leverage (elasticity) measure is not additive, we standardize the leverage of each sector's $\mathbb{RIX}$ over its full sample, and then average them across sectors to get the aggregated market-level leverage $\Omega_{\mathbb{RIX}}$. Note the BKW banking index had 10:1 split on March 22, 2004, and we make adjustment accordingly in the leverage calculation.

than low-SED funds. Interestingly, in the panel regression the significant positive relation between leverage-managing ability and the fund's $\mathbb{RIX}$ exposure exists only among funds reporting leverage use in the TASS database.

We also examine whether the fund's SED is systematically related to its extreme-market-timing ability (during both bull and bear market states). Specifically, we estimate each fund's extreme-market-timing ability by the following regression: $RET_{i,t} = a_i + b_i MKT_t + c_i \cdot MKT_i^2 \times Bull_t + d_i \cdot MKT_i^2 \times Bear_t + \epsilon_{i,t}$, where $Bull_t$ and $Bear_t$ are dummy variables equal to one for months in which the market returns are ranked into top and bottom quintiles of the monthly returns over the hedge fund sample period. The regression coefficients c_i and d_i capture the fund's market-timing ability during the "bull market" and the "bear market", respectively. Table 5 shows that high-SED funds on average have strong bear-market-timing ability across different model specifications but much weaker bull-market-timing ability especially in presence of fund fixed effects.

In sum, our analysis indicates the positive relation between fund's disaster-concern-exploiting skills and leverage- and extreme-market-timing abilities. Note that such evidence is only suggestive because of the lack of fund-level data on portfolio holdings, investment positions, and balance sheets. We leave a formal exploration on how hedge funds exploit rare disaster concerns for future research.

7 Additional Analyses and Robustness Checks

In this section, we perform additional analyses and present further robustness checks on SED-sorted hedge fund portfolios.

7.1 Performance Persistence

In Section 3.3, we find a strong persistence in the SED measure. A natural question is whether funds skilled in exploiting rare disaster concerns also show persistence in their return performance. We extend our baseline analysis of monthly SED deciles by holding them for horizons ranging from 3 months to 18 months. To deal with returns from overlapped holding months, we follow the independently managed portfolio approach introduced by Jegadeesh and Titman (1993) and calculate average monthly returns. Table 13 presents the results in detail. We observe significant performance persistence up to 12 months. 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 8-factor and 10-factor alphas of the high-minus-low SED portfolios are of similar magnitudes and statistically significance.

7.2 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 14 presents the results in detail. In Panel A, we sort all hedge funds into five SED quintiles within each of the twelve TASS investment styles (we exclude the "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 earn significantly positive returns for all investment styles except dedicated short bias, and low-SED quintiles earn 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.[28] 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. Our conclusion remains the same if we focus on the alphas from the Fung-Hsieh 8-factor model and the NPPR 10-factor model.

[28] 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.

In sum, the return results shown in Table 14 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 superior ability to exploit disaster concerns and provide disaster insurance.

7.3 Value-weighted Returns, and December vs. Non-December Returns

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). Specification (1) of Table 15 shows that the mean excess return and the Fung-Hsieh alpha of the high-minus-low SED portfolio are above 1% per month with significant t-statistics.[29]

Another issue related to hedge funds managing their reported returns is that returns during December are higher than returns during non-December months (Agarwal, Daniel, and Naik (2011)). Specification (2) of Table 15 shows that the return spreads of the high-minus-low SED portfolios are 1.6% and 0.91% per month during December and non-December months, respectively, and both are statistically significant.

7.4 Alternative Construction of SED Measures

In our baseline analysis, we measure the fund's SED using the $\mathbb{RIX}$ from 30-day options. As an alternative, we measure rare disaster concerns using 90-day OTM puts on sector indices.[30] Specification (4) from Table 15 shows that the return spread of high-minus-low SED portfolio is 1.06% per month, which is more than three standard errors from zero. The Fung-Hsieh alpha is larger, 1.25% per month (with a t-statistic of 4.4). We also measure rare disaster concerns using 30-day OTM puts on the S&P 500 index. Specification (5) from Table 15 illustrates that the return spread of the high-minus-low SED portfolio is 0.64% per month (with a t-statistic of 1.8) and the

[29] To preserve space, we do not tabulate results based on the 10-factor model. Our inference remains the same if we focus on the alphas from the 10-factor model. They are available from authors upon request.

[30] 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 to capture market expectations of future disaster and hence drive cross-sectional fund performance. The answer is no. Using this sector-index-return-based factor to estimate hedge funds' betas and sort funds into portfolios, we find these betas have no power to explain future fund returns (full results are available upon request).

Fung-Hsieh alpha is 0.96% per month (with a t-statistic of 2.6).[31]

7.5 Different Hedge Fund Databases

No single database completely covers the hedge fund universe. Our main results rely on hedge funds in the Lipper TASS database, but we also examine hedge funds covered by the HFR and CISDM databases. Our baseline results remain unchanged using 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 a 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 we got using the Lipper TASS database. We report details in the Internet Appendix (Tables IA-10 and IA-11).

7.6 Different Performance Metrics

Finally, in specification (8) of Table 15, we examine the performance of hedge fund portfolios sorted on SED using manipulation-proof performance measure (MPPM) developed by Goetzmann et al. (2007), the Sharpe ratio, and the 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 ratios and information ratios (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 outperform low-SED funds by a significant margin. For example, under the MPPM measure with a penalizing coefficient of three, we find that high-SED funds have an average MPPM of 0.065 (with a Newey-West t-statistic of 6.0), low-SED funds have an average MPPM of -0.015 (with a t-statistic of -0.5), and the difference is 0.08 (with a t-statistic of 2.5). Using Sharpe ratios and information ratios 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.

[31] 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 for a rare disaster concern index are similar to those using only sector index options.

8 Conclusions

We provide novel evidence that hedge funds with managers who have better skills in exploiting rare disaster concerns (SED) deliver superior future fund performance while 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 often contains 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 existence and magnitude of fear premium in the *ex ante* disaster concerns, and/or identifying the investors who are willing to pay higher fear premiums.

We develop a rare disaster concern index that equals the price of a disaster insurance contract that reflects the *ex ante* disaster concerns. 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.

Who buys the insurance against rare disaster events? Are the buyers of the insurance the same investors who also invest in the hedge funds selling such insurance? Answers to these questions may reveal agency issues within the organization of institutional investors, and agency issues between hedge funds and investors. We leave them for future research.

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

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

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).[32] 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

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

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

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

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

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

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

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

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

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

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

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

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

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

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Table 1: 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 2: 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 3: 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 in 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 level 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 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 likelihoods 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 4: Persistence of hedge fund skills in 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 5: Determinants of hedge fund skills in 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, including Fung-Hsieh alpha and R-squared, strategy distinctiveness index (SDI), downside return measure, and timing ability on market liquidity, market return, and market volatility (see Table 3 for details). The market-timing variables also contain extreme good (Bull) and extreme bad (Bear) market timing, estimated by the 18-24 month rolling-window regression for individual funds as follows: $R_{i,t+1} = a_i + b_i * MKT_{t+1} + c_i * MKT_{t+1}^2 * Bull_{t+1} + d_i * MKT_{t+1}^2 * Bear_{t+1} + \varepsilon_{i,t+1}$, where Bull and Bear are dummy variables, equal to to one for months in which the CRSP value-weighted market excess returns (MKT) are the top and bottom quintiles of the monthly returns over the hedge fund sample period. We report regression estimates in addition to robust *t*-statistics (in parenthese).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minimal Investment	0.029	0.020	0.0187	0.010				
	(2.25)	(1.58)	(1.49)	(0.80)				
Management Fee (%)	-5.7253	-3.604	-5.1803	-3.146				
	(-1.99)	(-1.27)	(-1.82)	(-1.13)				
Incentive Fee (%)	0.0077	-0.067	-0.1361	-0.184				
	(0.03)	(-0.27)	(-0.56)	(-0.75)				
Redemption Notice Period	0.0002	0.000	-0.0002	0.000				
	(0.40)	(0.80)	(-0.38)	(0.01)				
Lockup Period	-0.0022	-0.003	-0.0011	-0.002				
	(-1.29)	(-1.67)	(-0.63)	(-1.02)				
High Water Mark	0.0541	0.052	0.0571	0.056				
	(1.62)	(1.58)	(1.72)	(1.70)				
Personal Capital Invested	-0.0157	-0.008	-0.0087	-0.002				
	(-0.51)	(-0.25)	(-0.28)	(-0.05)				
Leverage	0.0509	0.031	0.0476	0.029				
	(1.85)	(1.14)	(1.75)	(1.07)				
AUM	-0.0291	-0.023	-0.0225	-0.017	-0.092	-0.087	-0.0514	-0.049
	(-2.49)	(-2.03)	(-1.99)	(-1.56)	(-3.13)	(-2.87)	(-1.84)	(-1.68)
AGE	0.0195	0.015	0.0066	0.005	0.0044	0.007	-0.0912	-0.075
	(0.64)	(0.50)	(0.22)	(0.17)	(0.07)	(0.11)	(-0.81)	(-0.68)

Fund Flow (past 1 year)	0.0164	0.011	0.0059	0.001	-0.0111	-0.012	-0.0368	-0.037
	(1.18)	(0.83)	(0.40)	(0.07)	(-0.23)	(-0.27)	(-0.69)	(-0.73)
Return Volatility (past 2 years)	1.7971	2.737	0.6537	1.541	6.5084	8.006	2.9691	4.251
	(0.69)	(1.04)	(0.25)	(0.57)	(2.00)	(2.58)	(0.81)	(1.23)
Return Skewness (past 2 years)	0.1032	0.079	0.0791	0.059	0.1703	0.140	0.1358	0.110
	(4.66)	(3.47)	(3.54)	(2.57)	(6.96)	(5.44)	(5.22)	(4.03)
Return Kurtosis (past 2 years)	0.0206	0.024	0.0069	0.010	0.0043	0.008	-0.0010	0.003
	(2.47)	(2.83)	(0.81)	(1.13)	(0.44)	(0.86)	(-0.11)	(0.31)
Alpha (F-H factor model)	-11.1859	-10.656	-10.2262	-9.833	-14.922	-14.227	-13.8962	-13.325
	(-3.95)	(-3.81)	(-3.61)	(-3.50)	(-4.20)	(-4.04)	(-3.85)	(-3.70)
R-squared (F-H factor model)	0.5228	0.409	0.4406	0.340	0.4021	0.341	0.3107	0.253
	(5.67)	(4.56)	(5.00)	(3.94)	(3.27)	(2.86)	(2.73)	(2.27)
SDI	0.458	0.362	0.3408	0.251	0.3079	0.268	0.2646	0.224
	(4.96)	(4.05)	(3.70)	(2.80)	(2.28)	(2.08)	(1.99)	(1.75)
Downside Return	7.2535	7.440	9.451	9.631	4.7459	5.544	6.7865	7.461
	(1.93)	(1.98)	(2.43)	(2.50)	(1.53)	(1.85)	(2.13)	(2.42)
Liquidity Timing	-0.0073	-0.008	-0.0178	-0.017	-0.0122	-0.013	-0.0186	-0.018
	(-0.62)	(-0.73)	(-1.44)	(-1.45)	(-0.76)	(-0.86)	(-1.15)	(-1.18)
Volatility Timing	-0.2435	0.500	0.0319	0.697	-0.4652	0.557	-0.3144	0.628
	(-0.82)	(1.30)	(0.10)	(1.81)	(-1.38)	(1.37)	(-0.88)	(1.53)
Market Timing	0.0118		0.0104		0.0116		0.0113	
	(2.53)		(2.24)		(1.75)		(1.70)	
Extreme Market Timing (Bullish)		0.009		0.010		0.002		0.004
		(2.57)		(2.84)		(0.52)		(0.96)
Extreme Market Timing (Bearish)		0.027		0.026		0.030		0.029
		(7.21)		(6.91)		(6.99)		(6.93)
Constant	Included	Included	Included	Included	Included	Included	Included	Included
Year FEs	No	No	Yes	Yes	No	No	Yes	Yes
Fund FEs	No	No	No	No	Yes	Yes	Yes	Yes
Observations	10,330	10,245	10,330	10,245	10,330	10,313	10,330	10,313
Adjusted R-squared	0.0346	0.079	0.0921	0.134	0.2114	0.246	0.2550	0.286

Table 6: 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 in exploiting rare disaster concerns (SED). Decile 1 (10) consists of funds with the lowest (highest) skills (see Table 3 for details). We hold decile portfolios for one month and calculate equally weighted returns. Monthly mean returns (in percent) and Newey-West (1987) *t*-statistics (in parentheses) are reported for each decile and the high-minus-low SED portfolio. We also report regression intercepts (monthly alphas) from the Fung-Hsieh 8-factor model and the Namvar-Phillips-Pukthuanthong-Rau 10-factor model, adjusted for hedge fund return smoothing as in Getmansky, Lo, and Makarov (2004). Four sets of results are presented: (1) the baseline hedge fund sample requires funds to have at least $10 million in assets under management (AUM) at the time portfolio formation (each decile on average has 147-149 funds); (2) the broader hedge fund sample has no restrictions on fund AUM (each decile on average has 264-266 funds); (3) we use the date that a fund was added into TASS database to correct for backfilling bias in hedge fund returns (each decile on average has 118-120 funds); and (4) we assume large negative returns (i.e., -100%) for all exiting funds after they are delisted in TASS database and enter into "graveyard" fund sample (each decile on average has 147-149 funds).

Exploit Rare Disaster Concerns	(1) Baseline Results			(2) No AUM Restriction			(3) Correct Backfilling Bias			(4) Delisting Fund Return		
	Excess Ret	F-H Alpha	NPPR Alpha	Excess Ret	F-H Alpha	NPPR Alpha	Excess Ret	F-H Alpha	NPPR Alpha	Excess Ret	F-H Alpha	NPPR Alpha
1 - Low Skill	-0.058	-0.628	-0.088	0.073	-0.466	0.045	-0.233	-0.900	-0.276	-0.970	-1.560	-0.912
	(-0.14)	(-2.81)	(-0.33)	(0.18)	(-2.40)	(0.19)	(-0.52)	(-3.40)	(-0.90)	(-2.04)	(-6.02)	(-3.03)
2	0.195	-0.117	0.129	0.229	-0.047	0.112	0.016	-0.365	-0.007	-0.613	-0.984	-0.679
	(0.81)	(-0.93)	(0.77)	(0.96)	(-0.34)	(0.63)	(0.06)	(-2.66)	(-0.04)	(-2.00)	(-5.18)	(-3.07)
3	0.294	0.008	0.241	0.292	0.024	0.204	0.229	-0.047	0.177	-0.218	-0.514	-0.219
	(1.45)	(0.07)	(1.59)	(1.48)	(0.22)	(1.33)	(1.05)	(-0.36)	(1.19)	(-0.91)	(-3.20)	(-1.30)
4	0.296	0.044	0.246	0.281	0.031	0.224	0.174	-0.120	0.155	-0.279	-0.517	-0.362
	(1.69)	(0.37)	(2.06)	(1.61)	(0.30)	(1.82)	(0.88)	(-0.91)	(1.23)	(-1.22)	(-3.54)	(-2.48)
5	0.264	-0.001	0.241	0.277	0.057	0.217	0.172	-0.144	0.180	-0.290	-0.567	-0.314
	(1.47)	(-0.01)	(1.98)	(1.73)	(0.54)	(1.91)	(0.87)	(-0.72)	(1.45)	(-1.35)	(-3.19)	(-2.17)
6	0.280	0.090	0.228	0.272	0.073	0.227	0.206	-0.000	0.132	-0.300	-0.445	-0.328
	(1.87)	(0.84)	(2.45)	(1.82)	(0.70)	(2.42)	(1.33)	(-0.00)	(1.23)	(-1.62)	(-3.15)	(-2.49)
7	0.337	0.150	0.270	0.330	0.146	0.277	0.300	0.113	0.227	-0.155	-0.355	-0.227
	(2.40)	(1.70)	(2.85)	(2.40)	(1.79)	(3.11)	(2.03)	(1.19)	(2.26)	(-0.79)	(-2.73)	(-1.79)
8	0.419	0.233	0.332	0.570	0.417	0.514	0.380	0.184	0.286	-0.243	-0.454	-0.305
	(3.01)	(2.56)	(3.35)	(2.89)	(2.36)	(2.43)	(2.45)	(1.72)	(2.69)	(-1.23)	(-3.37)	(-2.26)
9	0.568	0.347	0.465	0.585	0.374	0.478	0.487	0.280	0.411	-0.019	-0.255	-0.125
	(3.15)	(2.43)	(3.19)	(3.47)	(3.14)	(3.62)	(2.78)	(2.03)	(3.19)	(-0.08)	(-1.64)	(-0.75)
10 - High Skill	0.905	0.668	0.735	0.967	0.752	0.825	0.724	0.498	0.547	0.334	0.098	0.160
	(4.17)	(3.44)	(3.35)	(4.47)	(3.97)	(3.96)	(3.12)	(2.51)	(2.40)	(1.46)	(0.52)	(0.74)
High - Low	0.963	1.267	0.804	0.894	1.184	0.757	0.957	1.372	0.798	1.303	1.619	1.051
	(2.76)	(3.78)	(2.82)	(2.70)	(3.70)	(2.67)	(2.66)	(3.86)	(2.63)	(3.12)	(4.34)	(3.17)

Table 7: Risk exposure of SED hedge fund portfolios

We monthly form hedge fund decile portfolios based on their skills in 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 disaster risk 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 factors: (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 market excess return itself, and the market excess return and one of the following factors: (1) volatility skew that is the implied volatility difference between the S&P 500 index OTM put and ATM call as in Xing, Zhang, and Zhao (2010); (2) high-order moment risk of volatility, skewness, and kurtosis based on the S&P 500 index options as in Bakshi, Kapadia, and Madan (2003); and (3) the option return spread between the S&P 500 index OTM and ATM puts.

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: Disaster risk factor loadings

Exploit Rare Disaster Concerns	Market Return	Volatility Skew	High Mom. (Vola.)	High Mom. (Skew.)	High Mom. (Kurt.)	Option Return Spread
1 - Low Skill	0.558	-0.091	-0.862	-0.004	0.000	-0.328
	(8.09)	(-1.25)	(-4.01)	(-0.79)	(0.71)	(-6.83)
2	0.362	-0.042	-0.543	-0.003	0.000	-0.187
	(8.48)	(-1.14)	(-5.65)	(-0.74)	(0.61)	(-3.63)
3	0.303	-0.036	-0.392	-0.003	0.000	-0.194
	(7.94)	(-1.13)	(-3.50)	(-1.16)	(1.04)	(-6.00)
4	0.250	-0.021	-0.418	-0.003	0.000	-0.181
	(7.35)	(-0.69)	(-5.12)	(-1.59)	(1.29)	(-7.85)
5	0.249	-0.049	-0.497	-0.003	0.000	-0.245
	(5.54)	(-1.45)	(-5.38)	(-1.52)	(1.12)	(-5.11)
6	0.212	-0.021	-0.369	-0.001	0.000	-0.155
	(7.11)	(-0.79)	(-4.30)	(-0.75)	(0.26)	(-7.90)
7	0.200	-0.025	-0.336	-0.000	0.000	-0.128
	(7.27)	(-1.03)	(-4.19)	(-0.29)	(0.14)	(-4.44)
8	0.216	0.016	-0.289	-0.001	0.000	-0.115
	(10.77)	(0.58)	(-4.08)	(-0.80)	(0.78)	(-6.50)
9	0.262	0.008	-0.083	-0.000	-0.000	-0.052
	(8.68)	(0.19)	(-0.52)	(-0.09)	(-0.16)	(-0.97)
10 - High Skill	0.282	0.095	-0.060	-0.000	0.000	-0.008
	(5.77)	(1.37)	(-0.21)	(-0.08)	(0.02)	(-0.10)
High - Low	-0.276	0.186	0.801	0.004	-0.000	0.320
	(-2.94)	(1.74)	(2.13)	(0.62)	(-0.57)	(3.10)

Table 8: SED hedge fund portfolios using rare disaster concerns purged of disaster risk premiums

We use Seo-Wachter (2013) stochastic disaster risk model to adjust our original measure of rare disaster concerns. The purged rare disaster concern index (RIXC) is the difference between our original RIX and the Seo-Wachter model-implied RIX. Then we estimate each fund's SEDs from 24-month rolling-window regressions of excess monthly returns on the market excess returns and the RIXC factor (we require at least 18 months of available fund returns in estimation). 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 (Newey-West *t*-statistics are in parentheses). 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%.

	Full sample (07/1997 - 07/2010)	(1) Group months by market excess returns		(2) Rank months by market excess returns (quintiles)		(3) Group months by NBER recession dates		(4) Rank months by market excess returns (deciles)	
Exploit Rare Disaster Concerns	All 157 Months	Lost 10% or More	Others	Lowest Quintile	Others	Stressful Times	Normal Times	Lowest Decile	Highest Decile
1 - Low Skill	-0.187	-8.856	0.157	-4.310	0.868	-2.217	0.253	-6.265	2.447
	(-0.46)	(-2.90)	(0.57)	(-5.27)	(3.18)	(-2.34)	(0.79)	(-4.56)	(2.10)
2	0.202	-4.832	0.402	-2.596	0.918	-1.080	0.480	-3.474	1.686
	(0.81)	(-2.95)	(2.26)	(-5.59)	(5.53)	(-1.85)	(2.43)	(-4.39)	(1.40)
3	0.270	-3.434	0.417	-1.927	0.833	-0.978	0.541	-2.671	1.193
	(1.36)	(-2.95)	(2.90)	(-5.24)	(6.35)	(-2.00)	(3.67)	(-4.36)	(2.86)
4	0.253	-3.202	0.390	-1.598	0.726	-0.569	0.431	-2.268	1.304
	(1.38)	(-2.60)	(3.11)	(-4.46)	(6.22)	(-1.33)	(3.12)	(-3.52)	(2.58)
5	0.272	-2.673	0.389	-1.302	0.675	-0.523	0.445	-2.058	1.240
	(1.77)	(-2.15)	(3.68)	(-3.82)	(7.12)	(-1.27)	(4.00)	(-3.40)	(2.67)
6	0.275	-2.309	0.378	-1.261	0.668	-0.479	0.438	-1.810	1.214
	(1.89)	(-2.08)	(3.62)	(-4.17)	(7.04)	(-1.27)	(4.01)	(-3.38)	(2.47)
7	0.354	-1.815	0.440	-1.104	0.727	-0.264	0.488	-1.605	1.389
	(2.54)	(-1.90)	(4.19)	(-3.99)	(7.51)	(-0.73)	(4.48)	(-3.30)	(3.74)
8	0.466	-1.844	0.557	-1.060	0.856	-0.054	0.578	-1.423	1.749
	(3.05)	(-2.22)	(4.62)	(-4.22)	(7.07)	(-0.16)	(4.37)	(-3.14)	(3.49)
9	0.579	-2.032	0.683	-1.289	1.057	0.289	0.642	-1.426	2.025
	(3.38)	(-1.97)	(4.70)	(-5.18)	(7.03)	(1.03)	(3.73)	(-3.13)	(2.38)
10 - High Skill	1.023	-1.539	1.124	-0.952	1.528	0.815	1.068	-0.967	2.907
	(4.24)	(-1.24)	(5.05)	(-2.43)	(6.33)	(1.66)	(4.28)	(-1.50)	(2.95)
High - Low	1.210	7.317	0.967	3.358	0.660	3.032	0.814	5.298	0.460
	(3.51)	(2.56)	(4.23)	(4.12)	(2.87)	(3.59)	(3.29)	(3.87)	(0.47)

Table 9: SED hedge fund portfolios with versus without short credit hedge funds

Our sample of credit-style hedge funds from the TASS database consists of funds in the following investment styles: event driven, fixed income arbitrage, and convertible arbitrage. We estimate each fund's credit exposure by regressing its past 18-24 monthly returns on the U.S. credit spread (the yield difference between Moody's Aaa and Baa corporate bonds). A short credit fund is defined as the fund with positive and significant (at 10% level or better) exposure to this credit factors. Such a fund has positive payoffs when disaster shocks are realized in the credit market and essentially purchases credit protections before stressful market times. At the end of each month from June 1997 through June 2010, we rank our sample of credit-style hedge funds into decile portfolios according to their skills in exploiting rare disaster concerns (SED). We hold portfolios for one month and calculate equally weighted returns. Monthly mean returns (in percent) and Newey-West (1987) *t*-statistics (in parentheses) are reported, in addition to alphas from the Fung-Hsieh 8-factor model and the Namvar-Phillips-Pukthuanthong-Rau 10-factor model. The first (second) section presents results of portfolios including (excluding) short credit funds, and the last section tests the return difference. On average, each SED decile has 35-36 funds when short credit funds are included, and 26-32 funds when short credit funds are excluded.

Exploit Rare Disaster Concerns	(1) Include Short Credit Funds			(2) Exclude Short Credit Funds			Difference (2) - (1)		
	Excess Ret	F-H Alpha	NPPR Alpha	Excess Ret	F-H Alpha	NPPR Alpha	Excess Ret	F-H Alpha	NPPR Alpha
1 - Low Skill	0.044	-0.215	-0.013	-0.020	-0.303	-0.069	-0.064	-0.088	-0.056
	(0.12)	(-0.98)	(-0.06)	(-0.05)	(-1.36)	(-0.29)	(-1.82)	(-2.57)	(-1.60)
2	0.294	0.148	0.210	0.262	0.113	0.181	-0.032	-0.035	-0.029
	(1.09)	(0.96)	(1.11)	(0.97)	(0.73)	(0.96)	(-1.84)	(-1.78)	(-1.76)
3	0.299	0.135	0.206	0.285	0.131	0.180	-0.014	-0.005	-0.026
	(1.19)	(1.02)	(1.25)	(1.13)	(1.01)	(1.08)	(-0.76)	(-0.18)	(-1.61)
4	0.321	0.200	0.217	0.301	0.177	0.199	-0.020	-0.022	-0.018
	(1.58)	(1.93)	(1.53)	(1.45)	(1.69)	(1.37)	(-1.75)	(-1.93)	(-1.38)
5	0.230	0.119	0.194	0.207	0.094	0.178	-0.023	-0.026	-0.017
	(1.38)	(1.13)	(1.70)	(1.24)	(0.86)	(1.54)	(-1.73)	(-1.67)	(-1.51)
6	0.216	0.130	0.161	0.212	0.125	0.164	-0.005	-0.005	0.003
	(1.35)	(1.35)	(1.44)	(1.34)	(1.29)	(1.53)	(-0.36)	(-0.43)	(0.21)
7	0.283	0.207	0.252	0.291	0.215	0.256	0.008	0.008	0.004
	(2.01)	(2.55)	(2.61)	(2.03)	(2.56)	(2.55)	(0.76)	(0.84)	(0.36)
8	0.472	0.360	0.383	0.466	0.345	0.368	-0.006	-0.014	-0.015
	(2.96)	(4.04)	(3.38)	(2.90)	(3.95)	(3.25)	(-0.31)	(-0.64)	(-0.64)
9	0.551	0.447	0.489	0.527	0.419	0.473	-0.024	-0.028	-0.017
	(3.96)	(4.18)	(4.60)	(3.74)	(3.73)	(4.20)	(-0.61)	(-0.76)	(-0.46)
10 - High Skill	0.813	0.633	0.731	0.926	0.737	0.855	0.113	0.105	0.124
	(3.76)	(4.15)	(4.40)	(3.82)	(4.14)	(4.54)	(1.98)	(2.05)	(2.20)
High - Low	0.769	0.848	0.744	0.946	1.040	0.924	0.177	0.192	0.180
	(2.58)	(3.12)	(3.02)	(3.00)	(3.58)	(3.49)	(2.59)	(2.99)	(2.59)

Table 10: 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 two columns of each panel reports alphas (in percent) of high-minus-low SED portfolios based on the Fung-Hsieh 8-factor model and the Namvar-Phillips-Pukthuanthong-Rau 10-factor model. 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 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). For brevity, we only report the results of the top and bottom quintiles (see Internet Appendix for full details).

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 Alpha	NPPR Alpha
1 - low	0.228	0.257	0.343	0.377	0.594	0.366	0.619	0.266
	(1.15)	(2.44)	(4.93)	(4.12)	(4.09)	(1.93)	(3.53)	(1.42)
5 - High	-0.041	0.195	0.248	0.383	0.752	0.793	0.729	0.655
	(-0.13)	(0.82)	(1.23)	(1.78)	(2.73)	(3.27)	(2.92)	(2.70)
Average	0.118	0.274	0.306	0.350	0.694	0.576	0.753	0.497
	(0.49)	(1.83)	(2.56)	(2.90)	(3.98)	(3.41)	(5.15)	(3.22)

Panel B: 5×5 portfolios on SDI and SED

SDI	SED 1 - Low	2	3	4	SED 5 - High	SED 5-1	F-H Alpha	NPPR Alpha
1 - low	-0.480	0.097	0.220	0.525	0.884	1.364	1.656	1.156
	(-1.10)	(0.36)	(0.88)	(2.29)	(3.06)	(3.68)	(4.98)	(3.45)
5 - High	0.359	0.284	0.341	0.251	0.596	0.236	0.374	0.184
	(2.95)	(3.67)	(7.14)	(3.55)	(6.21)	(1.87)	(3.07)	(1.46)
Average	0.138	0.287	0.329	0.431	0.777	0.639	0.793	0.568
	(0.59)	(1.85)	(2.47)	(3.34)	(4.20)	(3.83)	(5.26)	(3.56)

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 Alpha	NPPR Alpha
1 - low	0.099	0.095	0.401	0.472	0.818	0.719	1.143	0.585
	(0.23)	(0.35)	(1.67)	(2.04)	(2.78)	(2.51)	(4.32)	(2.29)
5 - High	0.047	0.300	0.376	0.639	0.867	0.820	1.124	0.817
	(0.15)	(1.41)	(1.83)	(3.37)	(3.59)	(3.25)	(4.68)	(3.42)
Average	0.122	0.248	0.303	0.393	0.651	0.529	0.755	0.484
	(0.47)	(1.45)	(1.97)	(2.73)	(3.40)	(3.43)	(5.58)	(3.60)

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 Alpha	NPPR Alpha
1 - low	-0.279	0.035	0.328	0.482	0.784	1.063	1.406	0.898
	(-0.64)	(0.11)	(1.13)	(1.67)	(2.06)	(3.60)	(4.89)	(3.06)
5 - High	0.371	0.332	0.411	0.449	0.777	0.406	0.474	0.414
	(2.06)	(2.87)	(4.94)	(4.28)	(4.45)	(2.01)	(2.32)	(2.01)
Average	0.170	0.237	0.292	0.381	0.620	0.450	0.536	0.406
	(0.83)	(1.57)	(2.19)	(2.85)	(3.53)	(3.41)	(4.16)	(3.07)

Table 11: 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. The last two columns of each panel report high-minus-low SED portfolios' alphas based on the Fung-Hsieh 8-factor model and the Namvar-Phillips-Pukthuanthong-Rau 10-factor model.

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	F-H Alpha	NPPR Alpha
1 - low	0.111	0.330	0.505	0.941	1.183	1.073	1.158	0.892
	(0.36)	(1.47)	(2.32)	(3.58)	(3.36)	(4.30)	(4.41)	(3.52)
2	0.067	0.277	0.259	0.479	0.639	0.572	0.729	0.528
	(0.29)	(2.06)	(1.77)	(3.59)	(3.19)	(3.40)	(4.56)	(3.17)
3	0.103	0.194	0.297	0.359	0.629	0.526	0.586	0.509
	(0.58)	(1.54)	(2.79)	(3.69)	(4.35)	(3.71)	(4.21)	(3.67)
4	0.137	0.279	0.242	0.260	0.566	0.429	0.556	0.364
	(0.72)	(2.23)	(2.19)	(2.45)	(4.82)	(3.19)	(4.67)	(3.10)
5 - High	-0.092	0.032	0.107	0.286	0.524	0.616	0.818	0.648
	(-0.30)	(0.17)	(0.61)	(2.02)	(3.29)	(2.47)	(3.65)	(2.73)
Average	0.065	0.223	0.282	0.465	0.708	0.643	0.770	0.588
	(0.30)	(1.56)	(2.06)	(3.50)	(4.14)	(4.44)	(5.65)	(4.29)

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	F-H Alpha	NPPR Alpha
1 - Low Skill	-0.260	0.137	0.125	0.003	0.017	0.277	0.312	0.208
	(-0.83)	(0.65)	(0.69)	(0.01)	(0.06)	(0.97)	(1.13)	(0.73)
2	0.116	0.287	0.213	0.308	0.334	0.218	0.262	0.232
	(0.57)	(2.09)	(1.74)	(2.65)	(2.65)	(1.36)	(1.70)	(1.55)
3	0.201	0.245	0.264	0.320	0.419	0.218	0.276	0.240
	(1.04)	(1.94)	(2.45)	(3.34)	(3.92)	(1.65)	(2.48)	(2.34)
4	0.389	0.371	0.388	0.429	0.513	0.124	0.220	0.117
	(1.92)	(2.56)	(3.09)	(3.72)	(4.22)	(0.85)	(1.80)	(0.93)
5 - High Skill	1.035	0.799	0.660	0.680	0.752	-0.283	-0.242	-0.226
	(2.90)	(3.08)	(3.09)	(3.68)	(3.61)	(-1.10)	(-0.96)	(-0.95)
Average	0.296	0.368	0.330	0.348	0.407	0.111	0.166	0.114
	(1.27)	(2.29)	(2.43)	(2.78)	(2.91)	(0.73)	(1.26)	(0.89)

Table 12: Fama-MacBeth regressions of hedge fund returns

This table reports results from Fama-MacBeth (1973) cross-sectional regressions of hedge funds' excess returns in month $t+1$ on their 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 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 13: Persistence of 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 in exploiting rare disaster concerns (SED). Decile 1 (10) consists of funds with the lowest (highest) skills (see Table 3 for details). Portfolio returns are equally weighted. We report results for the portfolio holding period of 3 months, 6 months, 12 months, and 18 months. For these 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 8-factor model and the Namvar-Phillips-Pukthuanthong-Rau 10-factor model. On average, the number of funds in each decile ranges from 126 to 147.

Exploit Rare Disaster Concerns	Holding Period = 3 months			6 months			12 months			18 months		
	Excess Ret	F-H Alpha	NPPR Alpha	Excess Ret	F-H Alpha	NPPR Alpha	Excess Ret	F-H Alpha	NPPR Alpha	Excess Ret	F-H Alpha	NPPR Alpha
1 - Low Skill	0.005	-0.435	-0.064	0.040	-0.410	-0.050	0.205	-0.194	0.052	0.302	-0.063	0.136
	(0.01)	(-2.09)	(-0.27)	(0.10)	(-1.69)	(-0.20)	(0.61)	(-0.95)	(0.21)	(0.92)	(-0.35)	(0.57)
2	0.202	-0.052	0.144	0.251	0.004	0.179	0.280	0.034	0.192	0.307	0.065	0.215
	(0.84)	(-0.53)	(1.15)	(1.04)	(0.04)	(1.48)	(1.29)	(0.31)	(1.50)	(1.44)	(0.66)	(1.77)
3	0.288	0.071	0.238	0.296	0.087	0.231	0.323	0.122	0.251	0.327	0.124	0.255
	(1.44)	(0.75)	(2.24)	(1.46)	(0.94)	(2.20)	(1.81)	(1.21)	(2.32)	(1.85)	(1.30)	(2.40)
4	0.294	0.125	0.231	0.284	0.113	0.218	0.276	0.105	0.209	0.292	0.117	0.224
	(1.65)	(1.29)	(2.23)	(1.60)	(1.18)	(2.18)	(1.77)	(1.01)	(2.03)	(1.87)	(1.10)	(2.17)
5	0.273	0.097	0.227	0.275	0.105	0.228	0.270	0.104	0.215	0.277	0.111	0.220
	(1.60)	(0.91)	(2.41)	(1.62)	(1.02)	(2.42)	(1.80)	(0.94)	(2.13)	(1.85)	(0.99)	(2.12)
6	0.283	0.142	0.235	0.258	0.114	0.213	0.257	0.111	0.214	0.265	0.120	0.220
	(1.85)	(1.58)	(2.71)	(1.65)	(1.24)	(2.45)	(1.88)	(1.15)	(2.39)	(1.91)	(1.16)	(2.32)
7	0.281	0.136	0.235	0.261	0.118	0.215	0.271	0.125	0.227	0.271	0.120	0.232
	(1.94)	(1.66)	(2.85)	(1.80)	(1.55)	(2.78)	(2.04)	(1.53)	(2.75)	(2.01)	(1.38)	(2.66)
8	0.384	0.228	0.328	0.383	0.231	0.334	0.340	0.180	0.306	0.322	0.156	0.288
	(2.72)	(3.09)	(3.80)	(2.77)	(3.40)	(4.29)	(2.54)	(2.41)	(3.52)	(2.33)	(1.89)	(3.16)
9	0.502	0.325	0.434	0.478	0.302	0.421	0.423	0.231	0.387	0.394	0.197	0.360
	(2.86)	(3.13)	(3.63)	(2.82)	(3.22)	(3.84)	(2.71)	(2.87)	(3.63)	(2.49)	(2.39)	(3.35)
10 - High Skill	0.841	0.647	0.737	0.775	0.587	0.702	0.649	0.436	0.595	0.572	0.342	0.509
	(4.03)	(4.58)	(4.38)	(3.91)	(4.39)	(4.44)	(3.26)	(3.90)	(4.00)	(2.91)	(3.14)	(3.68)
High - Low	0.836	1.082	0.801	0.735	0.998	0.752	0.444	0.629	0.543	0.270	0.405	0.373
	(2.61)	(4.16)	(3.47)	(2.31)	(3.39)	(3.05)	(1.86)	(2.76)	(2.43)	(1.21)	(1.88)	(1.65)

Table 14: 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 in exploiting rare disaster concerns (SED). In Panel A, we form quintiles within each 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 two columns report monthly alphas of high-minus-low SED portfolios using the Fung-Hsieh 8-factor model and the Namvar-Phillips-Pukthuanthong-Rau 10-factor model.

	1 - Low Skill	2	3	4	5 - High Skill	5-1	F-H Alpha	NPPR 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	0.758	0.487
	(0.88)	(2.18)	(2.84)	(2.49)	(3.25)	(3.12)	(3.70)	(2.47)
Equity Market Neutral	0.188	0.069	0.212	0.347	0.614	0.427	0.595	0.352
	(1.16)	(0.76)	(3.08)	(5.23)	(4.35)	(2.28)	(3.15)	(1.89)
Dedicated Short Bias	0.060	-0.483	-0.079	-0.003	-0.291	-0.351	-0.292	-0.178
	(0.10)	(-0.99)	(-0.17)	(-0.01)	(-0.54)	(-0.71)	(-0.55)	(-0.35)
Global Macro	0.144	0.379	0.227	0.331	0.383	0.240	0.357	0.180
	(0.58)	(2.16)	(1.82)	(3.01)	(1.99)	(0.92)	(1.44)	(0.72)
Emerging Markets	0.236	0.361	0.439	0.586	1.186	0.951	1.467	0.737
	(0.42)	(0.91)	(1.29)	(1.91)	(2.84)	(2.25)	(3.58)	(1.75)
Event Driven	0.236	0.446	0.328	0.398	0.731	0.494	0.564	0.508
	(1.12)	(2.85)	(2.69)	(3.30)	(4.98)	(3.29)	(3.86)	(3.41)
Fund of Funds	-0.004	0.226	0.227	0.234	0.387	0.391	0.536	0.399
	(-0.02)	(1.60)	(1.84)	(2.06)	(3.10)	(2.86)	(4.91)	(3.45)
Fixed Income Arbitrage	0.064	0.071	0.112	0.244	0.546	0.481	0.490	0.442
	(0.32)	(0.45)	(1.12)	(3.01)	(4.10)	(2.40)	(2.41)	(2.19)
Convertible Arbitrage	-0.110	0.101	0.359	0.452	0.656	0.766	0.859	0.687
	(-0.33)	(0.50)	(2.32)	(2.77)	(3.26)	(2.69)	(3.38)	(2.55)
Managed Futures	0.364	0.394	0.374	0.415	0.714	0.350	0.309	0.550
	(1.18)	(1.63)	(1.59)	(1.71)	(2.20)	(1.14)	(1.00)	(1.80)
Multi Strategy	0.191	0.318	0.307	0.400	0.807	0.616	0.741	0.592
	(0.90)	(2.58)	(3.02)	(4.00)	(5.29)	(3.83)	(4.61)	(3.68)
Options Strategy	-0.081	0.542	0.534	0.126	0.675	0.804	1.550	0.853
	(-0.27)	(2.34)	(3.94)	(0.77)	(2.68)	(1.69)	(2.97)	(1.82)
Panel B: Fund size based on net asset value								
NAV - Low	-0.164	0.073	0.239	0.261	0.794	0.959	1.319	0.859
	(-0.49)	(0.41)	(1.86)	(1.96)	(3.95)	(3.49)	(5.61)	(3.49)
2	0.103	0.280	0.250	0.424	0.743	0.640	0.854	0.526
	(0.41)	(1.71)	(1.62)	(2.88)	(3.79)	(3.06)	(4.44)	(2.66)
3	0.096	0.274	0.220	0.323	0.520	0.424	0.464	0.431
	(0.46)	(2.24)	(1.96)	(3.43)	(3.68)	(2.28)	(2.74)	(2.37)
4	0.299	0.447	0.294	0.368	0.694	0.395	0.518	0.386
	(1.29)	(3.13)	(2.59)	(3.61)	(4.21)	(2.34)	(3.34)	(2.39)
NAV - High	0.119	0.283	0.458	0.471	0.865	0.746	0.848	0.646
	(0.42)	(1.33)	(2.60)	(3.23)	(3.74)	(3.27)	(4.10)	(3.05)

Table 15: Robustness checks on SED hedge fund portfolios

We present the following results: (1) value-weighted portfolio returns in our baseline sample (see Table 3 for details of portfolio formation and Table 6 for the baseline result); (2) monthly portfolio returns in non-December months; (3) monthly portfolio returns in December; (4) fund's SED estimated using the RIX constructed by the 90-day OTM puts of sector indicies; (5) fund's SED estimated using the RIX constructed by the 30-day OTM puts of the S&P 500 index; (6) the sample of hedge funds covered in HFR database; (7) the sample of hedge funds covered in CISDM database; and (8) alternative measures of hedge fund performance. For cases (1) - (7), we present both monthly mean returns and the Fung-Hsieh 8-factor alphas (in percent). For cases (2) - (7), we report equal-weighted portfolio returns (results are similar for value-weighted portfolio returns). Alternative performance measures include: (i) the manipulation-proof performance measure (MPPM) with the rho coefficient to penalize hedge fund return equal to 3 (see details in Goetzmann et al., (2007)); (ii) the Sharpe ratio adjusted for hedge fund return smoothing (see details in Getmansky, Lo, and Makarov (2004); and (iii) the 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 factor-based abnormal return using its past 24 months of returns. Newey-West (1987) *t*-statistics are in parentheses.

	(1) Portfolio Value Weight		(2) Non December Return		(3) Only December Return		(4) RIX: 90-Day OTM Puts		(5) RIX: S&P 500 Index OTM Puts		(6) HFR Database		(7) CISDM Database		(8) Alternative Measures of Fund Performance		
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	MPPM	Sharpe Ratio	Inform. Ratio
1 - Low Skill	-0.165	-0.606	-0.181	-0.530	1.297	-0.230	-0.128	-0.562	-0.093	-0.576	0.080	-0.335	-0.005	-0.236	-0.015	0.148	0.173
	(-0.43)	(-2.49)	(-0.42)	(-2.35)	(2.54)	(-0.47)	(-0.33)	(-2.78)	(-0.26)	(-2.19)	(0.20)	(-1.78)	(-0.01)	(-1.24)	(-0.46)	(1.04)	(1.00)
2	0.127	-0.179	0.096	-0.077	1.290	0.899	0.186	-0.055	0.353	0.050	0.263	0.024	0.284	0.185	0.026	0.221	0.189
	(0.44)	(-1.05)	(0.38)	(-0.75)	(3.28)	(1.31)	(0.80)	(-0.48)	(1.54)	(0.34)	(1.06)	(0.25)	(1.09)	(1.34)	(1.55)	(1.56)	(1.41)
3	0.276	0.054	0.191	0.039	1.439	0.439	0.287	0.078	0.087	-0.184	0.325	0.118	0.388	0.289	0.033	0.320	0.248
	(1.28)	(0.42)	(0.91)	(0.40)	(4.11)	(1.40)	(1.44)	(0.76)	(0.36)	(-1.01)	(1.56)	(1.19)	(1.79)	(2.42)	(2.65)	(2.28)	(1.69)
4	0.382	0.231	0.226	0.100	1.064	0.526	0.225	0.033	0.359	0.143	0.295	0.114	0.272	0.185	0.036	0.320	0.355
	(2.25)	(2.10)	(1.25)	(0.94)	(3.90)	(1.46)	(1.28)	(0.31)	(2.10)	(1.36)	(1.65)	(1.31)	(1.54)	(2.02)	(3.28)	(2.24)	(2.69)
5	0.267	0.042	0.180	0.027	1.189	0.816	0.248	0.103	0.217	0.055	0.264	0.081	0.232	0.134	0.037	0.413	0.420
	(1.38)	(0.28)	(0.97)	(0.20)	(4.61)	(2.33)	(1.57)	(1.15)	(1.37)	(0.52)	(1.52)	(0.77)	(1.27)	(1.19)	(3.75)	(3.02)	(3.36)
6	0.270	0.119	0.201	0.105	1.160	0.422	0.320	0.176	0.342	0.180	0.283	0.134	0.327	0.256	0.039	0.454	0.525
	(1.81)	(1.18)	(1.31)	(1.12)	(3.62)	(1.82)	(2.18)	(2.12)	(2.03)	(1.39)	(1.78)	(1.45)	(2.11)	(2.67)	(4.26)	(3.18)	(4.50)
7	0.404	0.257	0.261	0.162	1.170	0.362	0.324	0.187	0.275	0.183	0.373	0.225	0.326	0.251	0.040	0.516	0.621
	(2.72)	(2.51)	(1.86)	(2.04)	(3.35)	(1.42)	(2.23)	(2.19)	(1.27)	(1.33)	(2.53)	(2.72)	(2.26)	(2.91)	(4.25)	(3.60)	(4.47)
8	0.434	0.291	0.340	0.240	1.299	0.840	0.503	0.349	0.348	0.256	0.418	0.280	0.410	0.336	0.044	0.576	0.653
	(3.19)	(3.17)	(2.40)	(3.15)	(4.57)	(4.17)	(3.17)	(3.64)	(2.94)	(3.32)	(2.82)	(3.56)	(3.16)	(4.18)	(3.70)	(3.45)	(5.25)
9	0.362	0.255	0.444	0.337	1.949	1.141	0.605	0.428	0.365	0.190	0.568	0.414	0.583	0.426	0.054	0.496	0.570
	(1.44)	(1.72)	(2.60)	(2.83)	(3.02)	(3.15)	(3.34)	(3.77)	(2.25)	(1.46)	(3.58)	(4.47)	(3.89)	(3.60)	(5.04)	(3.26)	(5.83)
10 - High Skill	0.845	0.600	0.725	0.595	2.897	1.709	0.927	0.689	0.548	0.386	0.918	0.681	0.935	0.694	0.065	0.580	0.535
	(3.59)	(2.80)	(3.55)	(3.99)	(3.60)	(3.15)	(3.55)	(3.73)	(2.30)	(1.62)	(4.03)	(4.46)	(4.43)	(3.91)	(5.95)	(4.61)	(5.10)
High - Low	1.010	1.206	0.906	1.125	1.600	1.939	1.055	1.251	0.641	0.963	0.838	1.016	0.940	0.930	0.080	0.433	0.362
	(2.78)	(3.65)	(2.51)	(3.96)	(2.14)	(3.37)	(3.17)	(4.40)	(1.78)	(2.61)	(2.58)	(3.93)	(2.32)	(3.72)	(2.49)	(3.69)	(2.04)

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

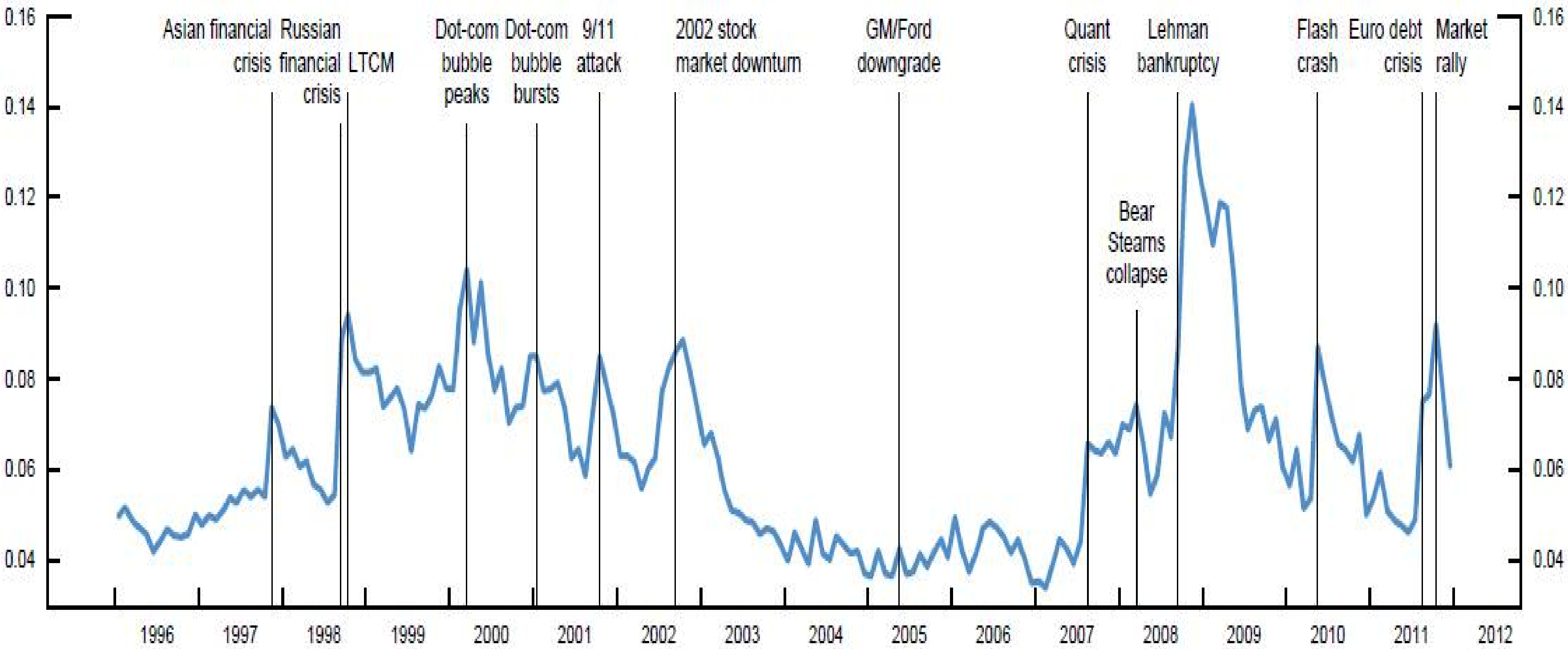


Figure 2: Time-series plot of the high-minus-low SED portfolio returns

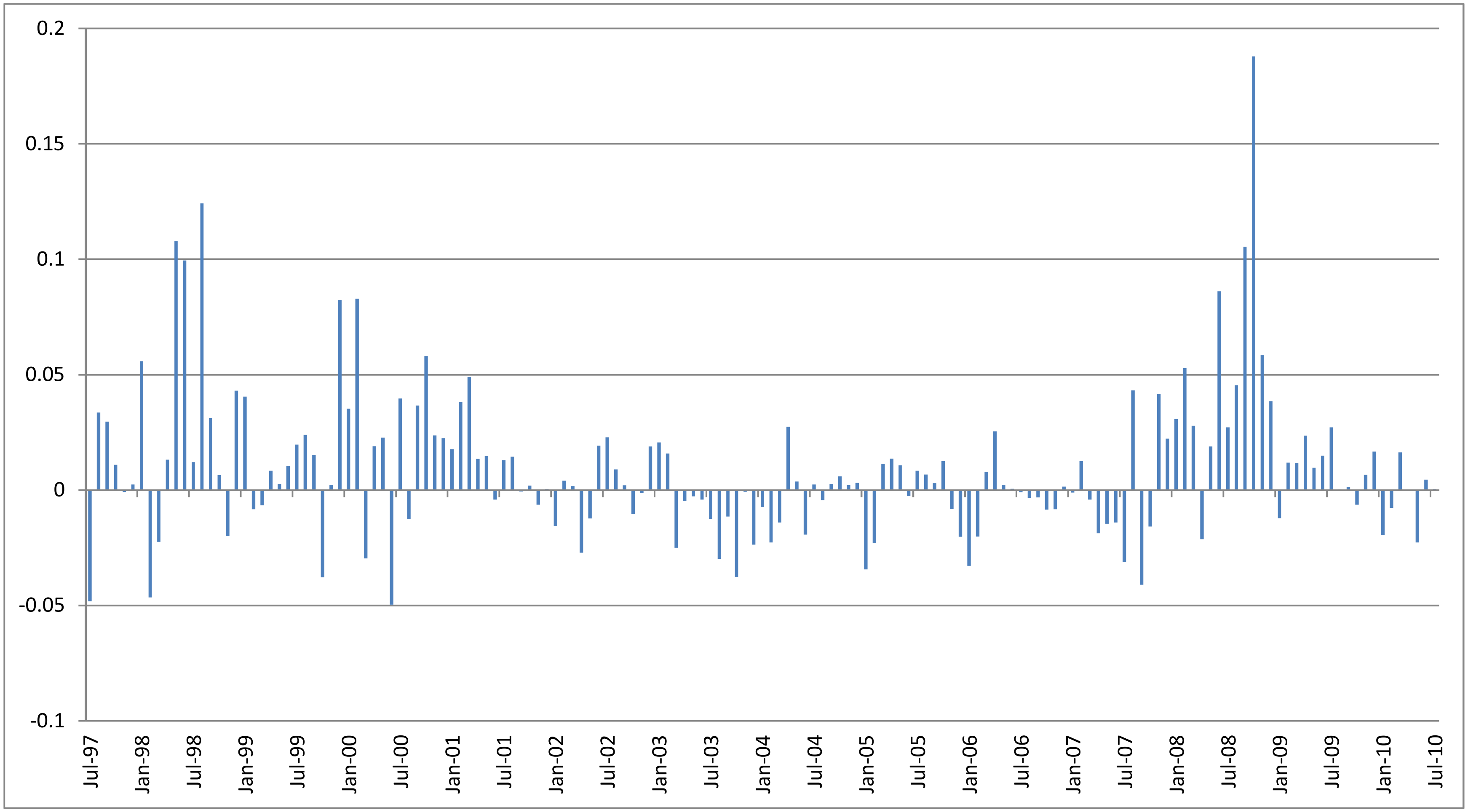
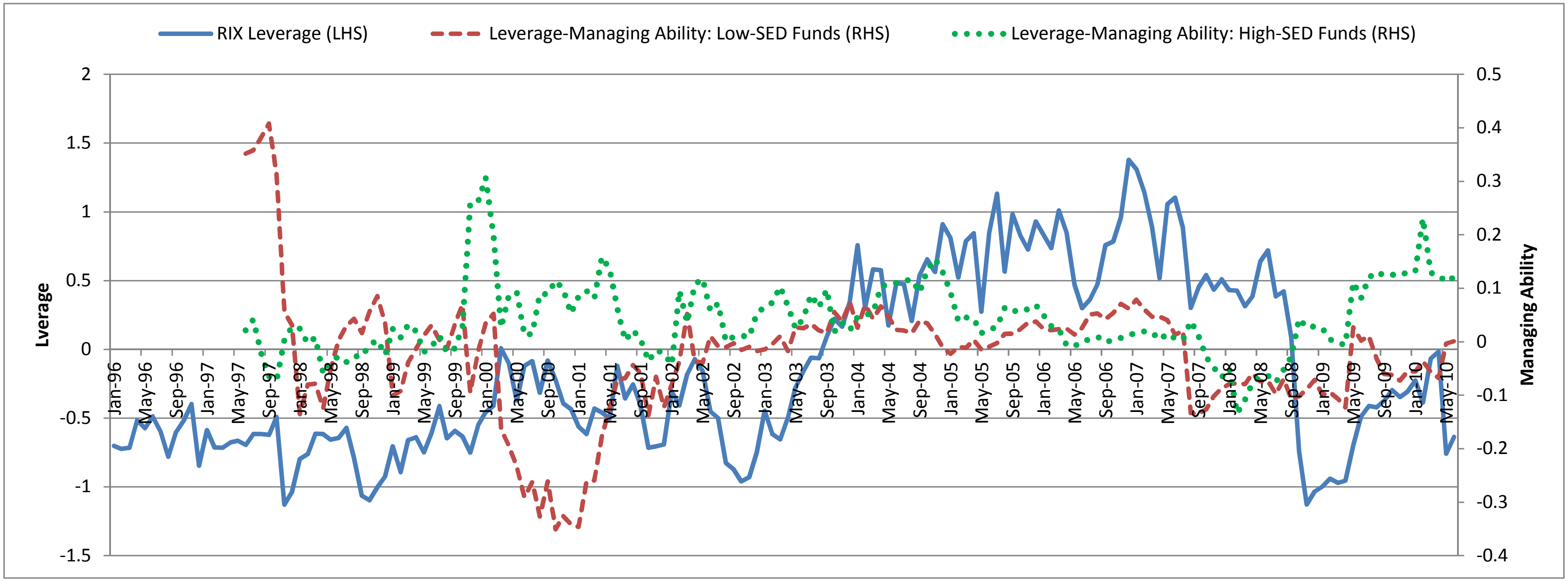


Figure 3: RIX-implied leverage and leverage-managing ability of high- and low-SED funds

We standardize the leverage implied from each sector's RIX over its full sample (with mean equal to zero and standard deviation equal to one) and then average them across sectors to get the RIX-implied leverage. At the end of each month of forming SED hedge fund portfolios, we also estimate fund's leverage-managing ability by performing 24-month rolling-window regressions of fund return on the market return, the RIX leverage, the change in RIX leverage, and the maximum between zero and the negative of the change in RIX leverage. The (positive) regression coefficient of the last maximum term captures the fund's ability to managing leverage.



Do Hedge Funds Exploit Rare Disaster Concerns?

Internet Appendix: Additional Analyses and Robustness Checks

Table IA-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 in the main text 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 IA-2: Factor loadings of SED hedge fund portfolios

This table reports regression intercepts and factor loadings of monthly formed SED hedge fund deciles in our baseline analysis (see Table 6 in the main text). In Panel A, we use the Fung-Hsieh 8-factor model, including the market factor (MKTRF), the emerging market factor (EMI), 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 used in Table 7 in the main text because of the negative relation between yield and price. In Panel B, we use the Namvar Phillips-Pukthuanthong-Rau 10-factor model that is constructed using 10 return-based global principal components extracted from 251 assets across various markets and asset classes.

Panel A: Fung-Hsieh 8-factor model

Exploit Rare Disaster Concerns	Intercept	MKT	EMI	SMB	TERM	DEF	PTFSBD	PTFSFX	PTFSCOM
Equal-weighted portfolio returns									
1 - Low Skill	-0.628	0.108	0.451	0.075	0.304	0.247	-0.017	0.011	0.019
	(-2.81)	(1.01)	(7.71)	(1.23)	(2.05)	(1.10)	(-0.83)	(0.83)	(1.22)
2	-0.117	0.123	0.222	0.096	0.233	0.325	0.003	-0.000	0.023
	(-0.93)	(2.07)	(7.75)	(2.95)	(2.43)	(2.17)	(0.40)	(-0.01)	(2.59)
3	0.008	0.133	0.176	0.075	0.252	0.303	-0.001	0.008	0.014
	(0.07)	(2.24)	(6.09)	(2.03)	(2.77)	(2.15)	(-0.07)	(1.20)	(1.65)
4	0.044	0.117	0.144	0.075	0.177	0.225	-0.009	0.006	0.007
	(0.37)	(2.63)	(5.43)	(1.87)	(2.47)	(1.72)	(-0.90)	(1.09)	(0.98)
5	-0.001	0.090	0.144	0.095	0.166	0.217	-0.018	0.005	0.003
	(-0.01)	(2.10)	(4.55)	(3.05)	(2.30)	(1.82)	(-0.83)	(0.72)	(0.39)
6	0.090	0.108	0.106	0.067	0.114	0.186	-0.009	0.005	0.008
	(0.84)	(2.95)	(4.44)	(1.71)	(1.71)	(1.77)	(-0.83)	(0.95)	(1.08)
7	0.150	0.091	0.098	0.092	0.142	0.201	-0.002	0.006	0.003
	(1.70)	(2.58)	(4.66)	(1.71)	(2.21)	(2.26)	(-0.30)	(1.23)	(0.47)
8	0.233	0.092	0.108	0.090	0.119	0.193	-0.000	0.007	0.004
	(2.56)	(2.77)	(4.73)	(3.79)	(1.62)	(2.10)	(-0.05)	(1.30)	(0.69)
9	0.347	0.230	0.092	0.184	0.052	-0.013	-0.005	0.011	0.016
	(2.43)	(3.46)	(2.73)	(2.26)	(0.44)	(-0.07)	(-0.41)	(1.01)	(1.80)
10 - High Skill	0.668	0.127	0.153	0.258	-0.029	-0.043	0.006	0.024	0.018
	(3.44)	(1.78)	(3.00)	(2.50)	(-0.16)	(-0.18)	(0.48)	(1.66)	(1.30)
High - Low	1.267	0.026	-0.293	0.230	-0.340	-0.284	0.021	0.019	0.003
	(3.78)	(0.23)	(-3.13)	(1.72)	(-1.20)	(-0.77)	(0.68)	(0.87)	(0.15)
Value-weighted portfolio returns									
1 - Low Skill	-0.701	0.071	0.394	0.054	0.362	0.365	-0.029	0.006	0.027
	(-2.25)	(0.54)	(5.77)	(0.64)	(1.61)	(1.45)	(-1.03)	(0.35)	(1.12)
2	-0.272	0.085	0.215	0.225	0.337	0.416	-0.012	-0.007	0.023
	(-1.12)	(0.88)	(4.84)	(3.42)	(1.55)	(1.64)	(-0.87)	(-0.43)	(1.31)
3	-0.059	0.161	0.181	0.081	0.304	0.347	-0.017	0.008	0.023
	(-0.34)	(1.69)	(3.72)	(1.84)	(2.29)	(1.83)	(-1.05)	(0.91)	(1.93)
4	0.167	0.093	0.114	0.048	0.148	0.234	-0.018	0.007	0.016
	(1.15)	(1.73)	(2.42)	(0.95)	(1.48)	(1.69)	(-1.72)	(0.99)	(1.77)
5	-0.049	0.065	0.144	0.127	0.229	0.228	-0.029	0.004	0.004
	(-0.26)	(1.45)	(3.92)	(2.80)	(2.38)	(1.50)	(-1.24)	(0.56)	(0.39)
6	0.047	0.081	0.114	0.057	0.160	0.197	-0.019	0.003	0.008
	(0.34)	(1.83)	(4.05)	(1.69)	(1.85)	(1.45)	(-1.35)	(0.51)	(0.94)
7	0.210	0.076	0.102	0.130	0.159	0.179	0.001	-0.005	0.011
	(1.62)	(1.41)	(3.50)	(1.59)	(1.61)	(1.17)	(0.11)	(-0.56)	(1.22)
8	0.256	0.089	0.090	0.087	0.106	0.153	-0.008	0.005	0.008
	(2.12)	(2.08)	(2.76)	(3.72)	(1.28)	(1.47)	(-1.04)	(0.70)	(1.03)
9	0.210	0.285	0.028	0.178	-0.239	0.053	-0.044	0.014	0.019
	(0.98)	(2.93)	(0.63)	(1.64)	(-1.12)	(0.21)	(-2.16)	(0.93)	(1.23)
10 - High Skill	0.590	0.014	0.111	0.346	0.041	0.062	-0.010	0.016	0.031
	(2.42)	(0.15)	(1.77)	(2.75)	(0.24)	(0.28)	(-0.52)	(1.08)	(1.50)
High - Low	1.224	-0.032	-0.252	0.348	-0.291	-0.325	0.015	0.013	0.015
	(3.02)	(-0.26)	(-2.56)	(2.33)	(-1.04)	(-0.91)	(0.39)	(0.61)	(0.65)

Panel B: Namvar-Phillips-Pukthuanthong-Rau 10-factor model

Exploit Rare Disaster Concerns	Intercept	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
Equal-weighted portfolio returns											
1 - Low Skill	-0.088	0.036	-0.020	0.002	-0.009	0.035	0.012	-0.001	-0.023	0.002	0.043
	(-0.33)	(7.16)	(-1.56)	(0.26)	(-0.58)	(2.97)	(0.74)	(-0.07)	(-1.45)	(0.14)	(2.34)
2	0.129	0.024	-0.012	-0.002	0.002	0.025	-0.008	-0.008	-0.014	0.004	0.022
	(0.77)	(8.72)	(-2.15)	(-0.36)	(0.26)	(2.83)	(-1.12)	(-0.94)	(-1.35)	(0.40)	(2.42)
3	0.241	0.020	-0.009	-0.001	0.001	0.016	-0.002	-0.003	-0.014	0.003	0.015
	(1.59)	(7.20)	(-1.76)	(-0.19)	(0.09)	(2.01)	(-0.27)	(-0.35)	(-1.52)	(0.32)	(1.89)
4	0.246	0.017	-0.005	0.002	0.002	0.016	0.000	0.003	-0.016	0.001	0.015
	(2.06)	(7.31)	(-0.95)	(0.42)	(0.33)	(2.14)	(0.02)	(0.42)	(-2.01)	(0.07)	(2.16)
5	0.241	0.016	-0.000	0.001	0.004	0.015	0.006	-0.000	-0.018	-0.001	0.017
	(1.98)	(6.27)	(-0.06)	(0.19)	(0.59)	(2.24)	(0.50)	(-0.07)	(-1.82)	(-0.10)	(2.12)
6	0.228	0.014	-0.001	0.005	0.003	0.016	-0.001	0.003	-0.007	-0.001	0.012
	(2.45)	(6.80)	(-0.16)	(0.95)	(0.61)	(2.34)	(-0.17)	(0.49)	(-0.91)	(-0.18)	(2.06)
7	0.270	0.014	-0.002	0.004	0.000	0.010	-0.003	-0.001	-0.008	0.003	0.010
	(2.85)	(5.66)	(-0.55)	(0.91)	(0.02)	(1.48)	(-0.70)	(-0.20)	(-1.24)	(0.47)	(1.51)
8	0.332	0.014	-0.002	0.006	-0.003	0.010	-0.000	-0.000	-0.008	0.007	0.011
	(3.35)	(7.50)	(-0.53)	(1.50)	(-0.55)	(1.92)	(-0.02)	(-0.02)	(-1.50)	(1.15)	(2.01)
9	0.465	0.018	-0.001	0.006	-0.002	0.008	0.001	0.001	-0.012	0.009	0.011
	(3.19)	(4.97)	(-0.11)	(0.87)	(-0.22)	(0.90)	(0.13)	(0.06)	(-1.49)	(0.93)	(1.35)
10 - High Skill	0.735	0.019	-0.005	0.011	-0.002	0.003	-0.001	-0.010	-0.008	0.019	0.007
	(3.35)	(3.47)	(-0.84)	(1.30)	(-0.19)	(0.30)	(-0.08)	(-0.90)	(-0.79)	(1.53)	(0.56)
High - Low	0.804	-0.015	0.015	0.008	0.010	-0.032	-0.014	-0.008	0.014	0.019	-0.035
	(2.82)	(-2.75)	(1.32)	(0.66)	(0.63)	(-2.08)	(-0.95)	(-0.46)	(1.00)	(0.91)	(-1.72)
Value-weighted portfolio returns											
1 - Low Skill	-0.237	0.033	-0.012	0.000	-0.013	0.038	-0.001	0.001	-0.021	0.007	0.038
	(-0.69)	(5.54)	(-0.87)	(0.01)	(-0.68)	(2.33)	(-0.02)	(0.06)	(-1.05)	(0.29)	(1.99)
2	-0.076	0.027	-0.005	-0.010	0.010	0.034	-0.005	-0.021	-0.028	0.033	0.018
	(-0.23)	(6.80)	(-0.46)	(-1.06)	(0.59)	(2.09)	(-0.39)	(-0.87)	(-1.49)	(1.38)	(1.35)
3	0.229	0.023	-0.011	-0.000	-0.001	0.019	-0.001	-0.003	-0.015	0.005	0.021
	(1.31)	(6.05)	(-1.49)	(-0.04)	(-0.11)	(1.83)	(-0.12)	(-0.28)	(-1.20)	(0.33)	(1.79)
4	0.280	0.015	-0.006	0.005	0.004	0.016	0.000	-0.001	-0.014	0.008	0.010
	(1.94)	(5.83)	(-0.96)	(0.66)	(0.44)	(1.95)	(0.01)	(-0.18)	(-1.42)	(0.83)	(1.16)
5	0.242	0.015	-0.001	0.000	0.007	0.017	0.008	0.000	-0.022	0.002	0.019
	(1.70)	(5.29)	(-0.10)	(0.01)	(0.89)	(2.02)	(0.62)	(0.04)	(-2.00)	(0.16)	(2.10)
6	0.232	0.012	-0.000	0.004	0.006	0.018	0.001	0.003	-0.009	-0.006	0.009
	(2.14)	(6.07)	(-0.02)	(0.82)	(0.87)	(2.33)	(0.12)	(0.40)	(-0.84)	(-0.67)	(1.18)
7	0.285	0.014	-0.001	0.001	-0.004	0.012	-0.001	-0.000	-0.012	0.017	0.011
	(2.19)	(4.30)	(-0.21)	(0.12)	(-0.46)	(1.30)	(-0.16)	(-0.04)	(-1.32)	(1.53)	(1.32)
8	0.363	0.012	-0.000	0.004	-0.001	0.008	-0.004	0.002	-0.006	0.008	0.014
	(3.16)	(6.30)	(-0.06)	(0.80)	(-0.10)	(1.45)	(-0.66)	(0.31)	(-0.97)	(0.97)	(2.09)
9	0.186	0.022	-0.004	0.004	0.000	0.010	0.008	-0.003	-0.022	0.019	0.004
	(0.77)	(3.56)	(-0.45)	(0.44)	(0.02)	(0.79)	(0.80)	(-0.17)	(-1.37)	(1.12)	(0.31)
10 - High Skill	0.620	0.012	0.002	0.005	-0.001	0.013	-0.009	-0.007	-0.003	0.027	-0.002
	(2.43)	(2.41)	(0.28)	(0.68)	(-0.13)	(1.16)	(-0.98)	(-0.49)	(-0.22)	(1.75)	(-0.13)
High - Low	0.822	-0.015	0.014	0.006	0.011	-0.020	-0.009	-0.008	0.016	0.024	-0.036
	(2.27)	(-2.87)	(1.09)	(0.49)	(0.61)	(-1.17)	(-0.48)	(-0.42)	(0.97)	(0.90)	(-1.55)

Table IA-3: SED hedge fund portfolios using rare disaster concerns purged of diaster risk premium

The purged rare disaster concerns (RIX^C) are the difference between our original RIX measure and various model-implied rare disaster concern measures (RIX^M). We use various disaster risk models to generate model-implied option prices, calculate disaster-risk-model-implied rare disaster concerns by applying the RIX methodology, and form decile hedge fund portfolios. CDR stands for constant disaster risk model and SDR stands for stochastic disaster risk model. The model parameters and option prices are based on the results in Seo and Wachter (2014).

Exploit Purged Rare Disaster Concerns (RIX^C = RIX - RIX^M)	(1) RIX^M = CDR (10% Jump Size)		(2) RIX^M = CDR (20% Jump Size)		(3) RIX^M = SDR (10% Jump Size)		(4) RIX^M = SDR (20% Jump Size)		(5) RIX^M = Seo-Wachter SDR (22% Jump Size)	
	Excess Return	NPPR Alpha	Excess Return	NPPR Alpha	Excess Return	NPPR Alpha	Excess Return	NPPR Alpha	Excess Return	NPPR Alpha
1 - Low Skill	-0.243	-0.246	-0.195	-0.214	-0.185	-0.199	-0.188	-0.208	-0.187	-0.213
	(-0.57)	(-0.98)	(-0.46)	(-0.84)	(-0.44)	(-0.84)	(-0.46)	(-0.91)	(-0.46)	(-0.94)
2	0.226	0.166	0.229	0.165	0.195	0.148	0.219	0.167	0.202	0.156
	(0.93)	(1.28)	(0.93)	(1.28)	(0.77)	(1.09)	(0.86)	(1.20)	(0.81)	(1.18)
3	0.277	0.222	0.293	0.228	0.312	0.239	0.292	0.238	0.270	0.233
	(1.44)	(2.02)	(1.54)	(2.14)	(1.64)	(2.22)	(1.49)	(2.19)	(1.36)	(2.15)
4	0.249	0.199	0.264	0.211	0.246	0.192	0.249	0.187	0.253	0.184
	(1.42)	(2.05)	(1.49)	(2.12)	(1.36)	(1.91)	(1.38)	(1.75)	(1.38)	(1.66)
5	0.313	0.258	0.285	0.236	0.270	0.222	0.274	0.232	0.272	0.238
	(1.85)	(2.66)	(1.75)	(2.42)	(1.67)	(2.22)	(1.72)	(2.58)	(1.77)	(2.74)
6	0.264	0.220	0.276	0.237	0.312	0.262	0.287	0.236	0.275	0.226
	(1.82)	(2.60)	(1.73)	(2.58)	(2.10)	(3.08)	(1.97)	(2.75)	(1.89)	(2.66)
7	0.378	0.333	0.353	0.311	0.334	0.285	0.344	0.289	0.354	0.299
	(2.54)	(3.68)	(2.35)	(3.40)	(2.39)	(3.37)	(2.46)	(3.31)	(2.54)	(3.46)
8	0.481	0.393	0.493	0.405	0.463	0.382	0.467	0.380	0.466	0.376
	(3.19)	(4.10)	(3.42)	(4.39)	(2.96)	(3.74)	(3.07)	(3.85)	(3.05)	(3.74)
9	0.605	0.501	0.574	0.476	0.616	0.507	0.605	0.498	0.579	0.466
	(3.47)	(4.13)	(3.28)	(3.98)	(3.63)	(4.16)	(3.44)	(4.00)	(3.38)	(3.84)
10 - High Skill	1.005	0.860	0.983	0.850	0.993	0.869	1.009	0.889	1.023	0.897
	(4.32)	(4.59)	(4.30)	(4.57)	(4.22)	(4.64)	(4.33)	(4.75)	(4.24)	(4.61)
High - Low	1.249	1.106	1.178	1.064	1.178	1.068	1.198	1.097	1.210	1.110
	(3.38)	(4.49)	(3.22)	(4.40)	(3.35)	(4.41)	(3.48)	(4.58)	(3.51)	(4.57)

Table IA-4: Subsample analysis of return performance of SED hedge fund portfolios

We monthly form hedge fund decile portfolios based on their skills in 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 IA-5: The alternative story on fund's purchasing/selling disaster insurance

We estimate each TASS hedge fund's exposure to rare disaster concerns by regressing the fund's monthly excess returns at t-1 on the RIX factor at month t. The selection of funds and 18-24 month rolling-window regression specification are the same as those reported in the baseline result of the paper (see Tables 3 and 6 in detail). Then at the end of month t-1, we rank hedge funds into ten deciles using their RIX exposure. Decile 1 (10) contains funds with the low (high) exposure. This table presents both equal-weighted (EW) and value-weighted (VW) fund portfolio returns over the three-month holding period after portfolio formation.

Fund's covariation between return(t-1) and RIX(t)	The 1st month after portfolio formation		The 2nd month after portfolio formation		The 3rd month after portfolio formation	
	EW	VW	EW	VW	EW	VW
1 - Low Expousre	0.068	0.161	0.077	0.137	0.111	0.238
	(0.13)	(0.33)	(0.15)	(0.28)	(0.21)	(0.48)
2	0.168	0.016	0.136	-0.073	0.139	0.020
	(0.52)	(0.04)	(0.40)	(-0.20)	(0.43)	(0.06)
3	0.257	0.189	0.240	0.136	0.281	0.160
	(1.04)	(0.77)	(1.03)	(0.49)	(1.14)	(0.61)
4	0.221	0.168	0.261	0.252	0.307	0.152
	(1.03)	(0.78)	(1.29)	(1.21)	(1.60)	(0.68)
5	0.269	0.388	0.237	0.270	0.231	0.308
	(1.53)	(2.08)	(1.39)	(1.45)	(1.26)	(1.58)
6	0.215	0.100	0.267	0.223	0.283	0.243
	(1.29)	(0.56)	(1.70)	(1.26)	(1.85)	(1.32)
7	0.264	0.298	0.213	0.254	0.192	0.274
	(1.86)	(2.20)	(1.47)	(1.61)	(1.22)	(1.92)
8	0.298	0.239	0.230	0.184	0.236	0.193
	(2.11)	(1.42)	(1.52)	(1.13)	(1.70)	(1.33)
9	0.303	0.288	0.244	0.071	0.211	-0.088
	(1.94)	(1.27)	(1.39)	(0.25)	(1.21)	(-0.28)
10 - High Exposure	0.338	0.284	0.149	0.121	0.037	-0.075
	(1.37)	(0.93)	(0.54)	(0.38)	(0.14)	(-0.25)
High - Low	0.270	0.123	0.072	-0.017	-0.074	-0.313
	(0.51)	(0.25)	(0.14)	(-0.04)	(-0.15)	(-0.73)

Table IA-6: SED portfolios with versus without short credit hedge funds (CDS factor included)

This table reports equal-weighted SED hedge fund portfolio returns and alphas when we identify short credit funds using both the U.S. credit spread factor and a CDS factor. Our CDS factor is the average of five CDS indices across different regions and is related to both corporate and sovereign credit risks. We collect the CDS index data from Markit. When constructing the CDS factor, we use the average of five CDS indices whenever they become available. These indices are: (1) North America Corporate (High Yield), starting from 11/2001; (2) North America Corporate (Investment Grade), starting from 04/2003; (3) Europe Corporate, starting from 04/2002; (4) Europe Sovereign, starting from 10/2004; and (5) Emerging Market Corporate, starting from 10/2004. A short credit fund is defined as the fund with positive and significant (at 10% level or better) exposures to these credit factors whenever its credit beta estimates become available. Panel A presents results of the full sample period, and each SED decile on average has 35-36 (24-32) funds when short credit funds are included (excluded); Panel B presents post-2003 subsample results when most of CDS indices become available, and each SED decile on average has 42-43 (25-40) funds when short credit funds are included (excluded).

Panel A: Full sample period (1996-2010)

Exploit Rare Disaster Concerns	(1) Include Short Credit Funds			(2) Exclude Short Credit Funds			Difference (2) - (1)		
	Excess Ret	F-H Alpha	NPPR Alpha	Excess Ret	F-H Alpha	NPPR Alpha	Excess Ret	F-H Alpha	NPPR Alpha
1 - Low Skill	0.044	-0.215	-0.013	-0.021	-0.304	-0.070	-0.064	-0.089	-0.057
	(0.12)	(-0.98)	(-0.06)	(-0.06)	(-1.37)	(-0.29)	(-1.84)	(-2.59)	(-1.61)
2	0.294	0.148	0.210	0.262	0.113	0.181	-0.032	-0.035	-0.029
	(1.09)	(0.96)	(1.11)	(0.97)	(0.73)	(0.96)	(-1.86)	(-1.79)	(-1.78)
3	0.299	0.135	0.206	0.285	0.131	0.180	-0.013	-0.004	-0.026
	(1.19)	(1.02)	(1.25)	(1.13)	(1.01)	(1.08)	(-0.76)	(-0.18)	(-1.61)
4	0.321	0.200	0.217	0.302	0.178	0.200	-0.020	-0.022	-0.018
	(1.58)	(1.93)	(1.53)	(1.45)	(1.69)	(1.37)	(-1.72)	(-1.90)	(-1.36)
5	0.230	0.119	0.194	0.208	0.095	0.179	-0.023	-0.025	-0.016
	(1.38)	(1.13)	(1.70)	(1.24)	(0.87)	(1.55)	(-1.67)	(-1.61)	(-1.43)
6	0.216	0.130	0.161	0.213	0.126	0.165	-0.003	-0.004	0.004
	(1.35)	(1.35)	(1.44)	(1.34)	(1.30)	(1.53)	(-0.26)	(-0.35)	(0.29)
7	0.283	0.207	0.252	0.291	0.214	0.255	0.008	0.007	0.003
	(2.01)	(2.55)	(2.61)	(2.03)	(2.54)	(2.54)	(0.72)	(0.67)	(0.29)
8	0.472	0.360	0.383	0.482	0.359	0.383	0.010	-0.001	-0.000
	(2.96)	(4.04)	(3.38)	(2.96)	(4.04)	(3.33)	(0.38)	(-0.04)	(-0.01)
9	0.551	0.447	0.489	0.541	0.432	0.486	-0.009	-0.015	-0.003
	(3.96)	(4.18)	(4.60)	(3.81)	(3.87)	(4.31)	(-0.24)	(-0.40)	(-0.09)
10 - High Skill	0.813	0.633	0.731	0.983	0.784	0.903	0.170	0.151	0.172
	(3.76)	(4.15)	(4.40)	(3.75)	(4.19)	(4.30)	(1.94)	(2.08)	(1.92)
High - Low	0.769	0.848	0.744	1.003	1.088	0.973	0.234	0.240	0.229
	(2.58)	(3.12)	(3.02)	(3.10)	(3.65)	(3.49)	(2.46)	(2.89)	(2.31)

Panel B: Subsample period (2003-2010)

Exploit Rare Disaster Concerns	(1) Include Short Credit Funds			(2) Exclude Short Credit Funds			Difference (2) - (1)		
	Excess Ret	F-H Alpha	NPPR Alpha	Excess Ret	F-H Alpha	NPPR Alpha	Excess Ret	F-H Alpha	NPPR Alpha
1 - Low Skill	0.046	-0.382	-0.168	0.016	-0.421	-0.205	-0.030	-0.039	-0.037
	(0.08)	(-1.17)	(-0.57)	(0.03)	(-1.27)	(-0.67)	(-1.22)	(-1.55)	(-1.29)
2	0.226	-0.107	0.043	0.239	-0.102	0.056	0.013	0.005	0.013
	(0.51)	(-0.42)	(0.18)	(0.55)	(-0.41)	(0.24)	(0.90)	(0.31)	(1.01)
3	0.272	-0.086	0.086	0.260	-0.105	0.071	-0.012	-0.019	-0.016

	(0.66)	(-0.41)	(0.39)	(0.63)	(-0.50)	(0.31)	(-1.20)	(-1.61)	(-1.52)
4	0.216	-0.100	0.020	0.204	-0.105	0.007	-0.012	-0.005	-0.013
	(0.63)	(-0.71)	(0.11)	(0.59)	(-0.75)	(0.04)	(-1.54)	(-0.64)	(-1.54)
5	0.122	-0.188	0.028	0.102	-0.196	0.021	-0.019	-0.008	-0.007
	(0.44)	(-1.20)	(0.21)	(0.37)	(-1.24)	(0.16)	(-1.48)	(-0.58)	(-0.73)
6	0.167	-0.074	0.054	0.154	-0.082	0.049	-0.013	-0.008	-0.005
	(0.62)	(-0.42)	(0.39)	(0.57)	(-0.46)	(0.35)	(-0.93)	(-0.54)	(-0.41)
7	0.179	-0.085	0.094	0.168	-0.106	0.075	-0.011	-0.021	-0.020
	(0.77)	(-0.66)	(0.79)	(0.71)	(-0.82)	(0.59)	(-0.65)	(-1.28)	(-1.13)
8	0.458	0.361	0.292	0.489	0.364	0.297	0.030	0.002	0.005
	(1.75)	(3.05)	(1.70)	(1.81)	(2.96)	(1.72)	(0.71)	(0.06)	(0.19)
9	0.530	0.443	0.349	0.570	0.518	0.410	0.040	0.074	0.061
	(2.68)	(2.78)	(2.77)	(2.75)	(2.82)	(2.95)	(0.65)	(1.52)	(1.27)
10 - High Skill	0.902	0.717	0.761	1.194	1.002	1.038	0.292	0.285	0.277
	(3.20)	(3.62)	(3.91)	(3.32)	(3.78)	(4.20)	(1.94)	(2.50)	(2.17)
High - Low	0.856	1.099	0.928	1.178	1.422	1.243	0.322	0.324	0.314
	(1.79)	(2.48)	(2.86)	(2.34)	(2.98)	(3.27)	(2.11)	(2.79)	(2.41)

Table IA-7: SED portfolios excluding disaster-insurance-purchase funds

This table reports both equal-weighted (EW) and value-weighted (VW) SED hedge fund portfolio returns and alphas after we exclude the sample of funds that is likely to purchase disaster insurance. We identify disaster-insurance-purchase funds as follows: (1) estimate the rolling-window regression of fund excess returns at month t - 1 on the RIX and market factors at month t; (2) select funds with significant (at 10% level or better) and negative RIX exposure. After excluding these funds, we sort the remaining funds into deciles based on their skills in exploiting disaster concerns (each decile on average has 105 funds).

Exploit Rare Disaster Concerns	Equal-Weighted Portfolios			Value-Weighted Portfolios		
	Excess Ret	F-H Alpha	NPPR Alpha	Excess Ret	F-H Alpha	NPPR Alpha
1 - Low Skill	-0.127	-0.576	-0.066	0.077	-0.379	0.062
	(-0.40)	(-2.64)	(-0.33)	(0.22)	(-1.36)	(0.26)
2	0.184	-0.026	0.136	-0.004	-0.366	-0.119
	(0.94)	(-0.19)	(0.96)	(-0.01)	(-1.61)	(-0.49)
3	0.311	0.103	0.304	0.385	0.180	0.409
	(1.80)	(0.98)	(2.84)	(2.08)	(1.16)	(3.26)
4	0.334	0.165	0.309	0.400	0.243	0.367
	(2.05)	(1.47)	(3.03)	(2.83)	(2.17)	(3.66)
5	0.303	0.114	0.273	0.328	0.110	0.305
	(2.01)	(1.02)	(3.00)	(2.11)	(0.89)	(3.02)
6	0.343	0.217	0.307	0.374	0.228	0.354
	(2.73)	(1.87)	(3.33)	(2.97)	(1.70)	(3.61)
7	0.384	0.254	0.341	0.456	0.309	0.376
	(3.22)	(3.05)	(4.23)	(3.31)	(2.88)	(3.50)
8	0.439	0.317	0.356	0.418	0.291	0.347
	(3.45)	(3.68)	(3.79)	(3.26)	(3.00)	(3.53)
9	0.589	0.449	0.502	0.358	0.270	0.231
	(3.36)	(3.78)	(3.88)	(1.35)	(1.59)	(1.22)
10 - High Skill	0.914	0.717	0.774	0.889	0.643	0.662
	(4.13)	(4.53)	(4.41)	(3.71)	(3.05)	(3.07)
High - Low	1.040	1.293	0.840	0.812	1.022	0.600
	(3.60)	(5.13)	(3.83)	(2.46)	(3.39)	(2.21)

Table IA-8: Additional results of double-sorted portfolios

We present detailed and additional results of double-sorted hedge fund portfolios. In Panels A - G, we rank funds sequentially into 25 portfolios first on a fund skill variable then on SED. The set of fund skill variables contains R-squared from the Fung-Hsieh factor regression in Titman and Tiu (2011), the strategy distinctiveness index (SDI) in Sun, Wang, and Zheng (2012), the ability of timing market return, liquidity, and volatility in Cao et al. (2013), the conditional performance measure of upside and downside returns in Sun, Wang, and Zheng (2013). In Panels H - K, 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 L - N, 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 two columns of each panel report alphas of high-minus-low SED portfolios with respect to F-H 8-factor and NPPR 10-factor models. In the context of sequentially sorted portfolios (Panels A - K), the last two rows of each panel reports the average return performance of SED quintiles. In the context of independently sorted portfolios (Panels L - N), 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. (2013). We follow Bali et al. (2011) to construct the macroeconomic risk factors of default premium and inflation.

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 Alpha	NPPR Alpha
1 - low	0.228	0.257	0.343	0.377	0.594	0.366	0.619	0.266
	(1.15)	(2.44)	(4.93)	(4.12)	(4.09)	(1.93)	(3.53)	(1.42)
2	0.287	0.335	0.321	0.426	0.704	0.417	0.649	0.413
	(1.14)	(2.36)	(3.04)	(4.49)	(4.40)	(2.06)	(3.73)	(2.18)
3	-0.019	0.265	0.259	0.285	0.625	0.644	1.012	0.593
	(-0.06)	(1.74)	(2.05)	(2.36)	(3.59)	(2.57)	(4.78)	(2.61)
4	0.138	0.317	0.357	0.278	0.796	0.658	0.756	0.561
	(0.49)	(1.79)	(2.47)	(1.94)	(3.30)	(2.82)	(3.39)	(2.40)
5 - High	-0.041	0.195	0.248	0.383	0.752	0.793	0.729	0.655
	(-0.13)	(0.82)	(1.23)	(1.78)	(2.73)	(3.27)	(2.92)	(2.70)
Average	0.118	0.274	0.306	0.350	0.694	0.576	0.753	0.497
	(0.49)	(1.83)	(2.56)	(2.90)	(3.98)	(3.41)	(5.15)	(3.22)

Panel B: 5×5 portfolios on SDI and SED

SDI	SED 1 - Low	2	3	4	SED 5 - High	SED 5-1	F-H Alpha	NPPR Alpha
1 - low	-0.480	0.097	0.220	0.525	0.884	1.364	1.656	1.156
	(-1.10)	(0.36)	(0.88)	(2.29)	(3.06)	(3.68)	(4.98)	(3.45)
2	0.158	0.350	0.330	0.502	0.903	0.745	0.799	0.674
	(0.52)	(1.55)	(1.72)	(2.79)	(3.47)	(3.21)	(3.53)	(2.89)
3	0.399	0.342	0.391	0.435	0.752	0.353	0.534	0.302
	(1.57)	(2.02)	(2.49)	(3.12)	(3.36)	(1.73)	(2.78)	(1.45)
4	0.254	0.363	0.365	0.444	0.750	0.496	0.602	0.521
	(1.36)	(3.33)	(4.73)	(4.30)	(4.13)	(2.64)	(3.20)	(2.64)
5 - High	0.359	0.284	0.341	0.251	0.596	0.236	0.374	0.184
	(2.95)	(3.67)	(7.14)	(3.55)	(6.21)	(1.87)	(3.07)	(1.46)
Average	0.138	0.287	0.329	0.431	0.777	0.639	0.793	0.568
	(0.59)	(1.85)	(2.47)	(3.34)	(4.20)	(3.83)	(5.26)	(3.56)

Panel C: 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 Alpha	NPPR Alpha
1 - low	0.010	0.307	0.400	0.522	0.912	0.903	1.232	0.928
	(0.03)	(1.54)	(2.16)	(2.54)	(3.85)	(3.88)	(5.89)	(4.16)
2	0.228	0.333	0.314	0.317	0.578	0.349	0.480	0.359
	(1.07)	(2.31)	(2.59)	(2.44)	(3.90)	(2.37)	(3.64)	(2.72)
3	0.277	0.252	0.264	0.280	0.489	0.212	0.251	0.194
	(1.41)	(1.92)	(2.37)	(2.74)	(3.00)	(1.76)	(2.06)	(1.62)
4	0.126	0.150	0.151	0.373	0.528	0.402	0.594	0.409
	(0.50)	(0.83)	(0.92)	(2.84)	(3.19)	(2.58)	(4.40)	(3.10)
5 - High	0.009	0.115	0.404	0.437	0.829	0.821	1.241	0.680
	(0.02)	(0.39)	(1.88)	(1.89)	(2.82)	(2.64)	(4.56)	(2.46)
Average	0.130	0.231	0.306	0.386	0.667	0.537	0.760	0.514
	(0.50)	(1.30)	(2.07)	(2.59)	(3.64)	(3.37)	(5.59)	(3.75)

Panel D: 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 Alpha	NPPR Alpha
1 - low	0.099	0.095	0.401	0.472	0.818	0.719	1.143	0.585
	(0.23)	(0.35)	(1.67)	(2.04)	(2.78)	(2.51)	(4.32)	(2.29)
2	0.141	0.245	0.158	0.248	0.443	0.303	0.412	0.321
	(0.65)	(1.67)	(1.12)	(1.88)	(2.57)	(2.37)	(3.30)	(2.58)
3	0.229	0.249	0.220	0.255	0.493	0.263	0.460	0.205
	(1.05)	(1.61)	(1.83)	(2.42)	(3.19)	(1.84)	(3.56)	(1.74)
4	0.094	0.352	0.363	0.351	0.635	0.541	0.638	0.494
	(0.45)	(2.44)	(2.76)	(2.94)	(3.66)	(3.55)	(4.34)	(3.44)
5 - High	0.047	0.300	0.376	0.639	0.867	0.820	1.124	0.817
	(0.15)	(1.41)	(1.83)	(3.37)	(3.59)	(3.25)	(4.68)	(3.42)

Average	0.122	0.248	0.303	0.393	0.651	0.529	0.755	0.484
	(0.47)	(1.45)	(1.97)	(2.73)	(3.40)	(3.43)	(5.58)	(3.60)

Panel E: 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 Alpha	NPPR Alpha
1 - low	0.092	0.262	0.400	0.448	0.922	0.830	1.098	0.765
	(0.29)	(1.17)	(1.93)	(2.18)	(3.38)	(3.45)	(4.62)	(3.22)
2	0.156	0.194	0.389	0.296	0.671	0.516	0.620	0.497
	(0.73)	(1.22)	(2.99)	(2.57)	(3.91)	(3.45)	(4.29)	(3.62)
3	0.180	0.235	0.239	0.276	0.494	0.314	0.414	0.299
	(0.93)	(1.81)	(2.05)	(2.51)	(3.08)	(2.37)	(3.17)	(2.41)
4	0.166	0.309	0.269	0.298	0.666	0.500	0.673	0.487
	(0.72)	(2.10)	(2.16)	(2.42)	(4.03)	(3.13)	(4.39)	(3.36)
5 - High	-0.046	0.145	0.326	0.495	0.721	0.768	1.193	0.580
	(-0.11)	(0.51)	(1.38)	(2.42)	(2.46)	(2.43)	(4.09)	(2.09)
Average	0.110	0.229	0.325	0.363	0.695	0.586	0.800	0.525
	(0.42)	(1.31)	(2.15)	(2.57)	(3.57)	(3.65)	(5.44)	(3.73)

Panel F: 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 Alpha	NPPR Alpha
1 - low	-0.037	-0.106	0.078	0.113	0.457	0.494	0.484	0.484
	(-0.23)	(-0.93)	(1.10)	(1.65)	(3.45)	(2.73)	(2.78)	(2.66)
2	0.072	0.140	0.211	0.241	0.359	0.287	0.347	0.313
	(0.49)	(1.44)	(2.42)	(2.99)	(3.23)	(2.65)	(3.52)	(2.95)
3	0.258	0.288	0.322	0.363	0.512	0.254	0.288	0.278
	(1.58)	(2.26)	(2.41)	(2.81)	(3.89)	(2.02)	(2.32)	(2.32)
4	0.003	0.342	0.363	0.544	0.735	0.732	0.883	0.714
	(0.01)	(1.77)	(1.82)	(2.86)	(3.68)	(4.79)	(5.86)	(4.58)
5 - High	0.012	0.504	0.733	0.928	1.244	1.232	1.620	1.055
	(0.02)	(1.28)	(2.09)	(2.68)	(3.23)	(3.40)	(4.83)	(3.08)
Average	0.062	0.234	0.341	0.438	0.661	0.600	0.724	0.569
	(0.30)	(1.39)	(2.21)	(3.00)	(4.40)	(4.28)	(5.87)	(4.30)

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

Downside Return	SED 1 - Low	2	3	4	SED 5 - High	SED 5-1	F-H Alpha	NPPR Alpha
1 - low	-0.279	0.035	0.328	0.482	0.784	1.063	1.406	0.898
	(-0.64)	(0.11)	(1.13)	(1.67)	(2.06)	(3.60)	(4.89)	(3.06)
2	0.132	0.260	0.174	0.333	0.597	0.465	0.426	0.470
	(0.61)	(1.47)	(0.98)	(1.99)	(2.68)	(2.87)	(2.57)	(2.84)
3	0.264	0.283	0.270	0.271	0.378	0.114	0.116	0.068
	(1.37)	(2.20)	(2.31)	(2.28)	(2.28)	(0.76)	(0.77)	(0.47)
4	0.360	0.276	0.276	0.367	0.561	0.201	0.259	0.179
	(2.35)	(2.30)	(3.36)	(4.21)	(4.51)	(1.89)	(2.52)	(1.66)

5 - High	0.371	0.332	0.411	0.449	0.777	0.406	0.474	0.414
	(2.06)	(2.87)	(4.94)	(4.28)	(4.45)	(2.01)	(2.32)	(2.01)
Average	0.170	0.237	0.292	0.381	0.620	0.450	0.536	0.406
	(0.83)	(1.57)	(2.19)	(2.85)	(3.53)	(3.41)	(4.16)	(3.07)

Panel H: 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 Alpha	NPPR Alpha
1 - low	0.113	0.198	0.226	0.271	0.281	0.168	0.245	0.179
	(1.21)	(2.69)	(3.49)	(5.71)	(4.93)	(2.33)	(3.66)	(2.50)
2	0.206	0.212	0.227	0.207	0.405	0.199	0.207	0.260
	(1.76)	(1.78)	(2.02)	(2.03)	(4.74)	(2.14)	(2.22)	(2.84)
3	0.323	0.317	0.313	0.364	0.490	0.167	0.207	0.179
	(2.20)	(1.97)	(2.06)	(2.65)	(4.32)	(1.55)	(1.88)	(1.69)
4	0.161	0.229	0.394	0.565	0.737	0.576	0.601	0.578
	(0.80)	(1.16)	(2.01)	(2.83)	(4.25)	(3.29)	(3.61)	(3.29)
5 - High	-0.113	0.162	0.527	0.760	1.144	1.257	1.673	1.065
	(-0.26)	(0.44)	(1.49)	(2.29)	(3.81)	(3.39)	(5.21)	(3.22)
Average	0.138	0.224	0.338	0.433	0.612	0.474	0.587	0.452
	(0.75)	(1.31)	(2.04)	(2.83)	(4.82)	(3.64)	(5.05)	(3.71)

Panel I: 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 Alpha	NPPR Alpha
1 - low	0.497	0.500	0.633	0.946	1.111	0.614	0.677	0.485
	(1.50)	(2.08)	(2.65)	(3.74)	(3.85)	(2.36)	(2.61)	(1.86)
2	0.172	0.341	0.311	0.428	0.611	0.439	0.479	0.375
	(0.90)	(2.34)	(2.25)	(3.22)	(3.50)	(2.78)	(3.11)	(2.36)
3	0.174	0.292	0.248	0.298	0.574	0.400	0.480	0.381
	(0.96)	(2.30)	(2.31)	(3.06)	(4.27)	(3.05)	(3.76)	(2.90)
4	-0.041	0.157	0.218	0.326	0.445	0.486	0.622	0.396
	(-0.20)	(1.25)	(2.18)	(3.54)	(3.36)	(3.09)	(4.39)	(2.81)
5 - High	-0.437	-0.086	0.111	0.372	0.520	0.957	1.393	0.844
	(-1.28)	(-0.49)	(0.69)	(2.47)	(2.86)	(3.19)	(5.77)	(3.27)
Average	0.073	0.241	0.304	0.474	0.652	0.579	0.730	0.496
	(0.32)	(1.61)	(2.25)	(3.70)	(3.99)	(3.60)	(5.12)	(3.38)

Panel J: 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 Alpha	NPPR Alpha
1 - low	-0.307	0.022	0.255	0.290	0.490	0.797	1.000	0.678
	(-0.97)	(0.10)	(1.36)	(1.63)	(2.12)	(2.84)	(3.99)	(2.62)
2	0.003	0.132	0.189	0.302	0.455	0.452	0.558	0.438
	(0.01)	(0.88)	(1.59)	(3.05)	(3.19)	(2.95)	(3.89)	(3.07)
3	0.148	0.212	0.255	0.296	0.498	0.349	0.404	0.338
	(0.87)	(1.68)	(2.51)	(3.19)	(3.95)	(2.83)	(3.33)	(2.79)
4	0.256	0.355	0.274	0.455	0.674	0.418	0.573	0.389

	(1.26)	(2.59)	(2.09)	(3.76)	(4.65)	(2.76)	(4.35)	(2.78)
5 - High	0.521	0.701	0.610	0.667	0.982	0.461	0.738	0.490
	(1.50)	(3.04)	(3.08)	(3.14)	(3.82)	(1.87)	(3.51)	(2.24)
Average	0.124	0.284	0.316	0.402	0.620	0.496	0.655	0.467
	(0.54)	(1.80)	(2.37)	(3.19)	(4.02)	(3.24)	(5.29)	(3.50)

Panel K: 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 Alpha	NPPR Alpha
1 - low	0.195	0.596	0.385	0.544	0.978	0.783	1.045	0.765
	(0.61)	(2.85)	(2.03)	(2.96)	(4.33)	(2.86)	(4.46)	(2.94)
2	0.188	0.281	0.305	0.378	0.565	0.376	0.500	0.363
	(0.93)	(2.22)	(2.92)	(4.17)	(4.32)	(2.27)	(3.36)	(2.37)
3	0.183	0.212	0.235	0.271	0.458	0.276	0.399	0.259
	(1.05)	(1.85)	(2.31)	(2.83)	(3.80)	(2.26)	(3.59)	(2.31)
4	0.070	0.194	0.222	0.393	0.638	0.568	0.703	0.484
	(0.33)	(1.26)	(1.65)	(2.82)	(3.94)	(3.73)	(4.77)	(3.33)
5 - High	-0.232	0.240	0.482	0.315	0.619	0.850	1.180	0.621
	(-0.63)	(0.92)	(2.43)	(1.31)	(2.11)	(2.98)	(4.61)	(2.45)
Average	0.081	0.305	0.325	0.380	0.652	0.571	0.765	0.499
	(0.35)	(1.96)	(2.53)	(2.90)	(4.15)	(3.42)	(5.48)	(3.37)

Panel L: 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 Alpha	NPPR Alpha
1 - low	0.395	0.176	0.094	0.240	0.420	0.025	0.074	0.030
	(1.61)	(1.26)	(1.01)	(2.89)	(2.81)	(0.10)	(0.28)	(0.11)
2	0.174	0.290	0.210	0.297	0.523	0.350	0.450	0.345
	(0.93)	(3.18)	(2.52)	(4.03)	(4.57)	(1.91)	(2.48)	(1.82)
3	0.242	0.238	0.202	0.303	0.510	0.268	0.266	0.285
	(1.48)	(1.73)	(1.50)	(2.35)	(3.31)	(1.59)	(1.65)	(1.64)
4	0.255	0.341	0.443	0.479	0.790	0.536	0.547	0.486
	(1.17)	(1.78)	(2.31)	(2.69)	(3.27)	(2.86)	(3.09)	(2.54)
5 - High	0.143	0.547	0.570	0.681	0.946	0.803	1.133	0.684
	(0.33)	(1.47)	(1.54)	(1.81)	(2.38)	(3.15)	(4.76)	(2.68)
5-1	-0.252	0.372	0.476	0.442	0.527	0.778	1.059	0.654
	(-0.47)	(0.92)	(1.27)	(1.14)	(1.16)	(2.17)	(2.86)	(1.79)

Panel M: 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 Alpha	NPPR Alpha
1 - low	0.140	0.205	0.143	0.275	0.353	0.213	0.374	0.136
	(0.69)	(1.60)	(1.26)	(2.82)	(2.54)	(1.10)	(2.00)	(0.70)
2	-0.099	0.235	0.245	0.288	0.417	0.515	0.729	0.396
	(-0.46)	(2.20)	(2.63)	(4.01)	(3.35)	(2.83)	(4.09)	(2.33)
3	0.291	0.232	0.248	0.304	0.780	0.490	0.669	0.384
	(1.49)	(1.70)	(2.19)	(2.75)	(4.54)	(2.57)	(3.44)	(1.99)

4	0.235	0.363	0.347	0.471	0.681	0.447	0.499	0.357
	(1.04)	(2.13)	(1.85)	(2.48)	(2.75)	(2.80)	(3.13)	(2.19)
5 - High	0.059	0.419	0.591	0.715	0.916	0.857	1.065	0.670
	(0.15)	(1.28)	(1.76)	(2.09)	(2.37)	(3.51)	(4.41)	(2.70)
5-1	-0.081	0.213	0.448	0.440	0.563	0.644	0.691	0.534
	(-0.21)	(0.66)	(1.34)	(1.28)	(1.38)	(2.44)	(2.52)	(1.98)

Panel N: 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 Alpha	NPPR Alpha
1 - low	-0.008	0.359	0.325	0.523	0.909	0.916	1.068	0.807
	(-0.03)	(1.93)	(1.76)	(2.87)	(3.67)	(3.42)	(4.29)	(3.12)
2	0.056	0.216	0.238	0.369	0.652	0.596	0.665	0.526
	(0.27)	(1.72)	(2.21)	(3.33)	(3.61)	(3.31)	(3.75)	(3.09)
3	0.116	0.210	0.213	0.372	0.666	0.550	0.691	0.511
	(0.52)	(1.63)	(1.95)	(3.41)	(3.95)	(2.92)	(3.72)	(2.86)
4	0.145	0.377	0.353	0.363	0.711	0.566	0.718	0.538
	(0.66)	(2.71)	(2.32)	(2.88)	(3.90)	(2.94)	(4.10)	(2.85)
5 - High	0.116	0.386	0.328	0.523	0.728	0.612	0.885	0.515
	(0.36)	(1.64)	(1.41)	(2.43)	(3.53)	(2.58)	(4.37)	(2.52)
5-1	0.123	0.027	0.003	0.000	-0.181	-0.304	-0.183	-0.291
	(0.54)	(0.15)	(0.01)	(0.00)	(-0.90)	(-1.21)	(-0.70)	(-1.17)

Table IA-9: SED relation to RIX-leverage-managing ability

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. Explanatory variables are the same as those in Table 5. Each hedge fund's RIX-leverage-managing ability is estimated by performing 24-month rolling-window regressions of fund return on the market return, the RIX leverage, the change in RIX leverage, and the maximum between zero and the negative of the change in RIX leverage (we require at least 18 months of fund returns available). The full sample consists all funds in TASS database that is used in our baseline analysis. We also choose two subsamples based on whether funds report leverage use in the TASS database. Robust *t*-statistics are reported in parenthese.

	(1) All HFs in the TASS Database (Baseline Sample)			(2) HF Reporting Leverage Use (NO)		(3) HF Reporting Leverage Use (YES)	
RIX-Leverage Managing	0.386	0.352	1.057	0.188	0.148	0.446	0.415
	(2.12)	(1.88)	(4.44)	(0.61)	(0.47)	(2.03)	(1.84)
Minimal Investment		0.019			0.014		0.020
		(2.65)			(2.23)		(1.52)
Management Fee (%)		-5.209			-9.665		-2.943
		(-2.17)			(-3.31)		(-0.95)
Incentive Fee (%)		0.583			0.769		0.505
		(3.31)			(4.49)		(1.67)
Redemption Notice Period		-0.001			0.000		-0.001
		(-1.61)			(0.53)		(-2.16)
Lockup Period		-0.001			-0.004		0.000
		(-1.12)			(-2.07)		(0.28)
High Water Mark		0.047			-0.060		0.119
		(1.67)			(-1.96)		(2.67)
Personal Capital Invested		-0.019			-0.014		-0.021
		(-0.76)			(-0.45)		(-0.57)
Leverage		0.025					
		(1.15)					
AUM			-0.047				
			(-1.65)				
AGE			-0.083				
			(-0.74)				
Fund Flow (past 1 year)			-0.043				
			(-0.75)				
Return Volatility (past 2 years)			3.294				
			(0.97)				
Return Skewness (past 2 years)			0.135				
			(5.26)				
Return Kurtosis (past 2 years)			0.001				
			(0.16)				
Alpha (F-H factor model)			-11.669				
			(-3.25)				
R-squared (F-H factor model)			0.319				
			(2.71)				
SDI			0.249				
			(1.86)				
Downside Return			5.433				
			(1.84)				

Liquidity Timing			-0.024				
			(-1.48)				
Market Timing			0.008				
			(1.30)				
Volatility Timing			-0.277				
			(-0.80)				
Year FEs	No	Yes	Yes	No	Yes	No	Yes
Fund FEs	No	No	Yes	No	No	No	No
Constant	Included	Included	Included	Included	Included	Included	Included
Observations	20,331	20,155	10,326	8,286	8,161	12,045	11,994
Adjusted R-squared	0.002	0.004	0.265	0.000	0.007	0.002	0.005

Table IA-10: SED portfolio results using CISDM database

We report results using hedge funds from HFR 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. Portfolios are monthly formed and returns are equal weighted. On average, there are 143-145 funds in each decile.

Panel A: Alphas and loadings based on the Fung-Hsieh 8-factor model

Exploit Rare Disaster Concerns	Alpha	MKTRF	EMI	SMB	TERM	DEF	PTFSBD	PTFSFX	PTFSCOM
1 - Low Skill	-0.236	0.049	0.338	0.007	0.304	0.648	0.009	0.019	0.016
	(-1.24)	(0.63)	(6.80)	(0.15)	(2.24)	(3.94)	(0.65)	(1.79)	(1.24)
2	0.185	0.043	0.146	0.003	0.308	0.607	0.008	0.006	0.017
	(1.34)	(0.97)	(4.73)	(0.07)	(2.99)	(4.87)	(0.55)	(0.81)	(1.84)
3	0.289	0.007	0.148	0.010	0.213	0.413	0.011	0.009	0.011
	(2.42)	(0.19)	(5.22)	(0.27)	(2.53)	(4.17)	(0.83)	(1.59)	(1.42)
4	0.185	0.004	0.114	0.042	0.163	0.383	0.004	0.011	0.005
	(2.02)	(0.14)	(5.67)	(1.71)	(2.77)	(4.54)	(0.66)	(2.35)	(0.78)
5	0.134	0.043	0.093	0.039	0.155	0.323	-0.011	0.007	0.005
	(1.19)	(1.28)	(4.19)	(1.69)	(2.72)	(3.82)	(-1.40)	(2.06)	(0.77)
6	0.256	0.028	0.085	0.041	0.120	0.295	-0.004	0.005	0.001
	(2.67)	(1.12)	(4.73)	(1.91)	(2.50)	(3.90)	(-0.63)	(1.36)	(0.28)
7	0.251	0.048	0.072	0.051	0.115	0.261	-0.002	0.011	0.001
	(2.91)	(1.73)	(4.00)	(2.24)	(2.36)	(3.79)	(-0.30)	(3.03)	(0.15)
8	0.336	0.036	0.073	0.084	0.067	0.191	0.006	0.013	0.002
	(4.18)	(1.17)	(3.91)	(2.84)	(1.49)	(3.67)	(1.29)	(2.71)	(0.41)
9	0.426	0.018	0.089	0.136	0.109	0.047	0.003	0.028	0.000
	(3.60)	(0.37)	(3.20)	(4.42)	(1.46)	(0.48)	(0.37)	(3.62)	(0.05)
10 - High Skill	0.694	-0.026	0.172	0.242	0.067	-0.096	0.022	0.039	0.008
	(3.91)	(-0.36)	(3.82)	(5.56)	(0.59)	(-0.65)	(1.57)	(4.65)	(0.65)
High - Low	0.930	-0.075	-0.166	0.236	-0.237	-0.744	0.012	0.020	-0.008
	(3.72)	(-0.81)	(-2.75)	(3.91)	(-1.57)	(-2.77)	(0.59)	(1.66)	(-0.49)

Panel B: Alphas and loadings based on the Namvar-Phillips-Pukthuanthong-Rau 10-factor model

Exploit Rare Disaster Concerns	Alpha	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
1 - Low Skill	0.006	0.026	-0.014	0.005	-0.003	0.030	-0.006	-0.004	-0.013	-0.001	0.039
	(0.03)	(8.35)	(-2.44)	(0.75)	(-0.27)	(2.87)	(-0.70)	(-0.42)	(-2.04)	(-0.07)	(3.13)
2	0.238	0.015	-0.011	0.002	0.005	0.019	-0.012	-0.006	-0.009	0.003	0.015
	(1.39)	(6.46)	(-2.94)	(0.38)	(0.72)	(2.33)	(-2.13)	(-0.99)	(-2.13)	(0.30)	(2.21)
3	0.348	0.012	-0.013	0.002	0.002	0.015	-0.011	-0.004	-0.004	0.002	0.008
	(2.51)	(6.65)	(-3.90)	(0.64)	(0.31)	(2.34)	(-2.50)	(-0.78)	(-1.25)	(0.25)	(1.51)
4	0.241	0.010	-0.006	0.001	0.004	0.013	-0.008	-0.004	-0.008	0.002	0.010
	(2.08)	(6.97)	(-2.94)	(0.31)	(0.95)	(2.72)	(-2.21)	(-0.98)	(-2.55)	(0.25)	(2.14)
5	0.201	0.010	-0.002	0.006	0.005	0.014	0.000	-0.001	-0.008	-0.001	0.008
	(1.79)	(6.58)	(-0.70)	(1.60)	(1.26)	(2.62)	(0.04)	(-0.23)	(-2.06)	(-0.17)	(1.61)
6	0.302	0.008	-0.002	0.003	0.005	0.015	-0.000	-0.004	-0.007	0.001	0.009
	(3.02)	(6.87)	(-0.88)	(0.86)	(1.39)	(3.40)	(-0.16)	(-1.06)	(-2.00)	(0.19)	(2.37)
7	0.320	0.009	-0.003	-0.002	0.002	0.008	-0.004	0.000	-0.006	0.001	0.011
	(3.47)	(8.56)	(-1.78)	(-0.89)	(0.61)	(2.10)	(-1.53)	(0.07)	(-2.08)	(0.25)	(2.76)
8	0.372	0.009	-0.001	-0.001	0.002	0.004	-0.005	-0.002	-0.006	0.005	0.005
	(3.68)	(7.15)	(-0.32)	(-0.29)	(0.50)	(0.85)	(-1.99)	(-0.44)	(-1.80)	(0.91)	(0.97)
9	0.582	0.006	0.000	-0.003	0.008	0.007	-0.002	-0.007	-0.006	-0.001	0.008
	(3.89)	(3.39)	(0.14)	(-0.64)	(1.08)	(1.18)	(-0.50)	(-1.08)	(-1.35)	(-0.08)	(1.19)
10 - High Skill	0.949	0.009	0.000	0.001	0.014	0.002	0.001	-0.013	-0.003	-0.004	0.008
	(4.44)	(2.75)	(0.03)	(0.08)	(1.34)	(0.18)	(0.12)	(-1.49)	(-0.47)	(-0.32)	(0.77)
High - Low	0.943	-0.017	0.015	-0.004	0.017	-0.028	0.007	-0.009	0.010	-0.003	-0.030
	(3.28)	(-3.99)	(2.37)	(-0.63)	(1.36)	(-1.93)	(0.63)	(-0.75)	(1.28)	(-0.16)	(-2.06)

Panel C: 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)

Table IA-11: 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. Portfolios are monthly formed and returns are equal weighted. On average, there are 242-245 funds in each decile.

Panel A: Alphas and loadings based on the Fung-Hsieh 8-factor model

Exploit Rare Disaster Concerns	Alpha	MKTRF	EMI	SMB	TERM	DEF	PTFSBD	PTFSFX	PTFSCOM
1 - Low Skill	-0.335	0.114	0.301	0.146	0.211	0.405	-0.005	0.007	0.013
	(-1.78)	(1.38)	(6.39)	(3.30)	(1.77)	(2.79)	(-0.40)	(0.71)	(1.03)
2	0.024	0.102	0.165	0.073	0.157	0.351	-0.000	0.004	0.011
	(0.25)	(2.46)	(6.65)	(2.73)	(2.07)	(3.72)	(-0.01)	(0.66)	(1.79)
3	0.118	0.087	0.126	0.068	0.115	0.271	-0.010	0.005	0.008
	(1.19)	(2.43)	(5.56)	(2.69)	(1.93)	(3.23)	(-1.53)	(0.98)	(1.41)
4	0.114	0.088	0.104	0.058	0.111	0.245	-0.008	0.005	0.003
	(1.31)	(2.90)	(5.37)	(2.87)	(2.37)	(3.99)	(-1.41)	(1.59)	(0.66)
5	0.081	0.072	0.094	0.066	0.109	0.249	-0.013	0.005	-0.001
	(0.77)	(2.31)	(4.43)	(3.44)	(2.32)	(3.73)	(-1.51)	(1.68)	(-0.18)
6	0.134	0.073	0.078	0.051	0.091	0.250	-0.010	0.005	0.001
	(1.45)	(2.81)	(4.59)	(2.00)	(1.97)	(3.72)	(-1.59)	(1.66)	(0.23)
7	0.225	0.094	0.067	0.080	0.104	0.205	-0.004	0.006	-0.001
	(2.72)	(3.55)	(4.14)	(2.81)	(2.39)	(3.29)	(-0.75)	(1.96)	(-0.14)
8	0.280	0.085	0.081	0.082	0.074	0.189	0.002	0.006	0.003
	(3.56)	(3.17)	(4.96)	(2.61)	(1.71)	(3.99)	(0.44)	(1.50)	(0.54)
9	0.414	0.144	0.072	0.139	0.024	0.070	-0.000	0.012	0.004
	(4.47)	(3.87)	(3.78)	(3.99)	(0.45)	(0.78)	(-0.07)	(2.62)	(0.93)
10 - High Skill	0.681	0.133	0.143	0.238	0.011	0.006	0.007	0.024	0.012
	(4.46)	(2.34)	(4.04)	(3.90)	(0.10)	(0.03)	(0.64)	(2.98)	(1.20)
High - Low	1.016	0.019	-0.157	0.092	-0.200	-0.399	0.012	0.018	-0.001
	(3.93)	(0.23)	(-2.74)	(1.10)	(-1.28)	(-1.44)	(0.86)	(1.57)	(-0.07)

Panel B: Alphas and loadings based on the Namvar-Phillips-Pukthuanthong-Rau 10-factor model

Exploit Rare Disaster Concerns	Alpha	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
1 - Low Skill	0.027	0.027	-0.013	-0.000	-0.002	0.031	0.001	-0.006	-0.012	-0.000	0.026
	(0.11)	(8.78)	(-1.88)	(-0.01)	(-0.17)	(3.00)	(0.13)	(-0.63)	(-1.48)	(-0.01)	(2.11)
2	0.195	0.018	-0.010	-0.000	0.002	0.021	-0.005	-0.002	-0.010	0.004	0.015
	(1.47)	(9.32)	(-3.12)	(-0.10)	(0.25)	(3.03)	(-1.14)	(-0.38)	(-2.11)	(0.59)	(2.83)
3	0.265	0.014	-0.006	-0.000	0.002	0.015	-0.003	-0.001	-0.009	0.004	0.012
	(2.27)	(8.49)	(-1.92)	(-0.04)	(0.44)	(2.54)	(-0.63)	(-0.27)	(-2.08)	(0.62)	(2.60)
4	0.251	0.012	-0.004	0.002	0.004	0.013	0.001	-0.001	-0.008	0.002	0.011
	(2.64)	(9.51)	(-1.63)	(0.54)	(0.85)	(2.74)	(0.20)	(-0.23)	(-2.10)	(0.38)	(2.71)
5	0.234	0.011	-0.000	0.004	0.004	0.013	0.003	-0.001	-0.009	-0.002	0.011
	(2.45)	(7.85)	(-0.05)	(1.27)	(1.01)	(2.55)	(0.76)	(-0.30)	(-2.02)	(-0.36)	(2.80)
6	0.232	0.010	-0.000	0.003	0.004	0.011	0.001	-0.000	-0.006	0.002	0.008
	(2.63)	(7.23)	(-0.11)	(1.13)	(0.89)	(2.21)	(0.29)	(-0.10)	(-1.52)	(0.31)	(2.16)
7	0.330	0.010	-0.001	0.001	0.000	0.009	-0.000	0.001	-0.006	0.002	0.008
	(3.84)	(7.36)	(-0.65)	(0.36)	(0.01)	(1.97)	(-0.18)	(0.26)	(-1.82)	(0.55)	(2.49)
8	0.329	0.011	-0.001	0.004	-0.002	0.008	-0.002	-0.001	-0.006	0.010	0.008
	(3.60)	(8.63)	(-0.32)	(1.20)	(-0.48)	(1.91)	(-0.50)	(-0.24)	(-1.75)	(2.19)	(2.59)
9	0.494	0.013	-0.001	0.002	-0.004	0.006	0.000	0.002	-0.008	0.009	0.009
	(4.63)	(7.16)	(-0.34)	(0.53)	(-0.64)	(1.10)	(0.00)	(0.37)	(-1.72)	(1.63)	(2.14)
10 - High Skill	0.788	0.016	-0.004	0.009	0.001	0.007	0.001	-0.008	-0.006	0.013	0.007
	(4.45)	(5.35)	(-0.79)	(1.48)	(0.09)	(0.74)	(0.10)	(-1.12)	(-0.95)	(1.30)	(0.95)
High - Low	0.761	-0.010	0.010	0.009	0.003	-0.024	-0.000	-0.002	0.006	0.013	-0.018
	(3.09)	(-2.96)	(1.37)	(1.58)	(0.24)	(-2.02)	(-0.06)	(-0.25)	(0.72)	(0.95)	(-1.50)

Panel C: 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)