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Extreme downside risk and expected stock returns

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ABSTRACT

We propose a measure for extreme downside risk (EDR) to investigate whether bearing such a risk is rewarded by higher expected stock returns. By constructing an EDR proxy with the left tail index in the classical generalized extreme value distribution, we document a significantly positive EDR premium in cross-section of stock returns even after controlling for market, size, value, momentum, and liquidity effects. The EDR premium is more prominent among glamor stocks and when high market returns are expected. High-EDR stocks are generally characterized by high idiosyncratic risk, large downside beta, lower coskewness and cokurtosis, and high bankruptcy risk. The EDR premium persists after these characteristics are controlled for. Although Value at Risk (VaR) plays a significant role in explaining the EDR premium, it cannot completely subsume the EDR effect.

1. Introduction

The literature has documented that investors generally shun positions with which they would be subject to catastrophic losses however slight probability these outcomes may carry. Such a "disaster avoidance motive" implies that investors are concerned about extreme negative scenarios and are averse to the risk of sharp price plunges (Menezes et al., 1980). Rietz (1988) and Barro (2006) have shown that rare disasters or tail events are potentially important in explaining the equity premium puzzle. These studies suggest that the potential loss from extremely undesirable returns, denoted as extreme downside risk (hereafter EDR), should be a significant factor in asset pricing. In this study, we focus on downside risk at extreme level and investigate whether EDR can indeed be priced. Specifically, we explore how EDR can be measured, as well as its ability in explaining the cross-sectional differences in expected stock returns.

EDR deserves much attention because extreme losses are encountered far more frequently than predicted by traditionally assumed return distributions (such as normal or lognormal distributions) and the influence of price plunges can be substantial. For example, for all the common stocks traded on NYSE, AMEX, and NASDAQ during July 1963 through June 2009, if the bottom 1% returns for each stock within each year are excluded, the average daily return is more than doubled, jumping from 0.09% to 0.23%. Given these facts, it is natural to expect higher returns from holding stocks with high EDRs. Despite the intuitively appealing idea, there are challenges in examining whether and how EDR is priced in asset returns. One immediate difficulty is finding a good proxy. Though the definition of EDR is conceptually straightforward, it requires estimation of the probability of rare events, sometimes outside the range of available data. That is, "estimates are often required for levels of a process that are much greater than have already been observed" (Coles, 2001).

In this study, we conduct investigation of an EDR measure and its asset pricing implications through an extreme value approach which is specifically designed to describe unusual, extreme events. We draw on the left tail index in the classical generalized extreme value (GEV) distribution as a proxy for EDR and estimate individual stock's EDR from abnormal returns relative to the Carhart (1997) four-factor model. This procedure concentrates exclusively on the far-end left tail of return distribution and captures extreme downside movements of a stock after market, size, value, and momentum factors are controlled for. We observe a significantly positive relation between firm-specific EDR and expected stock returns. This finding remains robust after we control for beta, size, book-to-market (BM) ratio, liquidity, and momentum that are well known to explain cross-sectional variation in stock returns. High-EDR stocks outperform those with low EDRs during 26 out of 36 years between July 1973 and June 2009. The EDR premium

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remains significant across firms of different sizes, and is more prominent in glamor firms. High-EDR stocks experience deeper drops in large market down months and higher expected returns when market returns are expected to be high, reflecting fundamental risks associated with extreme losses.

Our EDR measure incorporates downside and fat tail risks simultaneously. There is a large set of literature that studies risks beyond the Gaussian paradigm. In contrast to the mean–variance framework of Markowitz (1952), which assumes normal distribution and entails equal risks for both positive and negative deviations from the mean, various risk measures have been proposed. Since the safety-first rule introduced by Roy (1952) and developed by Arzac and Bawa (1977) (more recently, by Levy and Levy, 2009), different downside risk measures have been developed, including semi-variance (Markowitz, 1959), gain-confidence limit (Baumol, 1963), lower partial moment (Bawa, 1975; Fishburn, 1977), Value at Risk (VaR), conditional tail expectation, and lower partial standard deviation, among others. Some researchers adopt leptokurtic distributions such as student's t (Liesenfeld and Jung, 2000) and those with higher-order moments (Chung et al., 2006) to capture information endowed in the fat tails. The efforts made in modifying traditional measures significantly expand the understanding of risk, although most of the studies concentrate on the downside risk or fat tail risk separately.

In this paper, we focus on downside risk at extreme level for each individual stock. Our EDR measure comes directly from the extreme value theory (EVT) which provides accurate risk assessment of extreme outcomes. In addition, EDR is extracted from four-factor-adjusted returns, thus capturing information not contained in common factors. In essence, EDR is an idiosyncratic measure of extreme downside risk, following the spirit of idiosyncratic skewness in Mitton and Vorkink (2007) and Boyer et al. (2010).[1] This choice of idiosyncratic measure is motivated by Merton (1987) who suggests that in practice it is very difficult to fully diversify if the market is incomplete. Moreover, researches by Ibragimov (2009), Ibragimov and Walden (2007), and Ibragimov et al. (2008) provide theoretical evidence that diversification is not always preferable, especially for extremely heavy-tailed distributions.[2]

Recent empirical asset pricing studies have examined other risk measures from different perspectives. Ang et al. (2006a) show that downside beta helps explain the cross-sectional variation of average stock returns. Harvey and Siddique (2000) document a significant premium for conditional skewness. Moreno and Rodriguez (2009) demonstrate that adding a coskewness factor into mutual fund performance evaluation is economically and statistically significant. Dittmar (2002) introduces the fourth moment (kurtosis) into asset pricing model. All these measures are systematic in that they are based on the relation between individual stock returns and market returns. On idiosyncratic risk, Ang et al. (2006b) find that stock portfolios with high realized idiosyncratic volatility (IV) have low returns in the subsequent month while Guo and Savickas (2010) suggest that IV is a proxy of systematic risk. Mitton and Vorkink (2007) and Boyer et al. (2010) show that expected idiosyncratic skewness and returns are negatively correlated. Bali et al. (2009) measure downside risk with VaR from the empirical distribution of stock returns, and find a positive risk-return tradeoff for several stock market indices. Similarly, Bali et al. (2007) document a positive relation between VaR and expected returns on hedge funds. Our results in this paper reveal that EDR is closely related to many of these risk measures, especially VaR due to its property of reflecting downside and extreme risks. Stocks with higher EDRs normally exhibit higher idiosyncratic standard deviation, skewness, and kurtosis, higher downside beta, more negative coskewness and cokurtosis, and larger firm-specific VaR. We find that the EDR-return relation persists after controlling for all these risk measures. In particular, although VaR can substantially mitigate EDR's impact on expected stock returns, it cannot completely subsume the EDR effect. The EDR premium documented in this paper serves as an additional compensation for holding risky assets, which is beyond the rewards for exposures to standard downside or high-order moment risks.

Because firms with financial distress typically face severe downside risk, we also examine the links between EDR and firm distress measures. We observe a significant relation between EDR and Ohlson's (1980) O-score, which implies that high-EDR stocks carry high likelihood of bankruptcy. Moreover, stocks with higher leverage, lower profitability, lower prices, and larger volatility tend to have higher EDRs. Since these variables are among the firm distress predictors according to Campbell et al. (2008), EDR is also a good indictor of distress risk. Nevertheless, after we control for bankruptcy risk, high-EDR stocks still outperform low-EDR ones, which reinforces EDR's robustness in predicting stock returns.

The remainder of this paper is organized as follows: Section 2 introduces the GEV distribution and presents detailed discussion of sample selection, estimation method of EDR measures, and summary statistics. Section 3 examines the relation between EDR and expected stock returns, as well as the robustness of this relation when controlling for other characteristics variables such as size, BM, momentum, and liquidity. In Section 4, we explore the fundamental risk embedded in EDR by showing that high-EDR stocks suffer from low realized returns during large market down periods, but earn high expected returns when expected market returns are also high. Section 5 examines the relations between EDR and traditional idiosyncratic and downside risks, high-order moment risk measures, bankruptcy and distress risks. We also show the robustness of EDR premium after these variables are controlled for. Section 6 concludes.

2. Extreme value theory and extreme downside risk estimation

2.1. Classical extreme value theory: the generalized extreme value distribution

EVT plays an increasingly important role in describing the probabilistic attributes of extraordinary events. It is specifically designed to assess the shape of the extreme end of a random process and provides the best description of tail behavior among all existing statistical fat tail estimation tools. It plays a role in the sample extrema (maxima or minima) parallel to the role of the central limit theorem in the sample means. Classical EVT depicts the asymptotic distribution of the extrema (or the tail variables) in a GEV distribution with a parameter called tail index, which indicates the thickness of distribution tail. This result is very elegant and robust since it is independent of the original (parent) distribution of the random process. The left tail index becomes an appropriate proxy for EDR because it specifically focuses on the far-end tail of return distribution, providing a more accurate risk assessment of extreme outcomes. A higher EDR is revealed consistently by a higher left tail index. Compared to traditional mean-centered risk measures, EDR avoids potential distribution misspecification or higher-order moments to capture information endowed in the thickness of tails. It also considers the distribution asymmetry of stock returns.

[1] Our approach is different from some of the recent studies which examine impact of rare disasters on the stock market itself. For example, Bianchi (2010) shows that rare events are useful in explaining the cross-section of asset returns by shaping agents' expectations. Estimating expected tails with the EVT, Bollerslev and Todorov (2011) demonstrate that compensation for the fear of rare events can account for a large fraction of the equity and variance risk premia in the S&P 500 index.

[2] Perignon and Smith (2010) empirically show that the abnormally high level of aggregate VaR for US commercial banks is *not* due to a systematic underestimation of the diversification among broad risk categories.

Early applications of EVT have been largely limited to documenting fat tail evidence for market indices (Longin, 1996) or establishing the relation between tails of different stock indices (Longin, 2000; Longin and Solnik, 2001; Jondeau and Rockinger, 2003; Poon et al., 2003, 2004). EVT is also utilized to improve the estimations of VaR or expected shortfall which are influenced by the shape of tail distribution function (Danielsson and de Vries, 1997; McNeil and Frey, 2000; Bali, 2003). However, there has been little research directly incorporating EVT into asset pricing studies. An exception is Bollerslev and Todorov (2011) who measure risk through an EVT approach and report that the fear of rare events could explain much of the premium in market index. By applying a classical EVT model to financial market data at firm level, our paper investigates the role of EDR in cross-sectional variation of stock returns.

Suppose we have an independent and identically distributed (i.i.d.) random series $\{X_1, X_2, \ldots, X_n\}$, EVT provides limiting distributions for the sample maxima or minima of a normalized random variable. We take the minima case as an example.[3] Let M_n denote the minimum of the sample, then for a location parameter μ and a scale parameter σ, Fisher and Tippett (1928) and Gnedenko (1943) prove that the non-degenerate limiting distribution of the normalized random variable $\frac{M_n-\mu}{\sigma}$ must fall into one of three types: the Frechet type, the Weibull type, and the Gumbel type.[4] Jenkinson (1955) combines these three types into a generalized formula, which is the GEV distribution mentioned above:

$$H(x) = 1 - \exp\left[-\left(1-\gamma\frac{x-\mu}{\sigma}\right)^{-\frac{1}{\gamma}}\right], \quad 1-\gamma\frac{x-\mu}{\sigma} > 0, \ \gamma \neq 0, \quad (1)$$

where γ is the shape parameter, also known as tail index which indicates thickness of the left tail or the probability of extreme negative outcomes. The larger the tail index, the thicker the tail, and the higher the extreme event probability. In the GEV distribution, $\gamma > 0$ corresponds to the Frechet type, which is heavy (fat)-tailed; $\gamma < 0$ corresponds to the short-tailed Weibull distribution; $\gamma \to 0$; corresponds to the Gumbel type, a thin-tailed process.[5] For the fat-tailed case, i.e., Frechet type, the inverse of shape parameter $\frac{1}{\gamma}$ indicates the maximal order moment. Therefore only a limited number of moments are finite for very heavy-tailed distributions.

Although the asymptotic GEV distribution is derived under the i.i.d. assumption of random variables, Smith (1985) suggests that dependence of the data does not constitute a major obstacle to attaining the limiting distribution of large samples. De Haan et al. (1989) prove that the maximum or minimum of an ARCH process has a Frechet distribution. Furthermore, data property can be improved by building a series of non-overlapping block (period) extrema in the sampling process, which is the basic statistical procedure we use in this paper. Specifically, we group time-series observations into a sequence of sub-periods and select the minimal observation from each sub-period. The pool of all sub-period minima constitutes the extrema sample which follows the GEV distribution asymptotically with the expansion of sub-period length. This simple approach can largely reduce possible interdependence of extrema, which is one of the major advantages of block-extrema sampling over alternative methods.[6]

Maximum likelihood estimation (MLE) method can be applied to the extrema sample to estimate parameters in the GEV distribution, providing an unbiased estimate with minimum variance. For processes with not-too-short tails (i.e., tail index >−1/2), MLE estimate is distributed asymptotically normal, which makes it very convenient for statistical inference. In our empirical analyses, we employ the MLE method on the GEV distribution and estimate tail indexes from per-month minima of daily observations of stock return.[7] We use these tail indexes as proxy measures of EDRs in asset pricing tests.

2.2. Data and sampling

Our sample consists of all common stocks traded on NYSE, NASDAQ, and AMEX. To be included in the sample, a stock must have at least 5 years' daily information during the period between July 1963 and June 2009.[8] Daily and monthly market data are obtained from CRSP, with the corresponding accounting data from Standard & Poor's COMPUSTAT annual files. Consistent with many other asset pricing studies, we match CRSP-COMPUSTAT data following Fama and French (1992).[9] We use daily data for EDR (tail index) estimation and monthly data for asset pricing tests.

In order to capture EDR for different risk components, we extract abnormal returns or residuals from the classical four-factor model:

$$r_d^i = \alpha^i + \beta_{MKT}^i MKT_d + \beta_{SMB}^i SMB_d + \beta_{HML}^i HML_d + \beta_{MOM}^i MOM_d + \varepsilon_d^i \quad (2)$$

where r_d^i is stock i's daily excess return (raw return minus risk free rate, proxied by US 1-month. Treasury bill rate) of day d, MKT_d is the market excess return, SMB_d, HML_d, and MOM_d represent returns on portfolios formed to capture the size, BM, and momentum effects, respectively, and ε_d^i denotes regression residuals.[10] We use an AR(1)-GARCH(1,1) model to estimate the conditional mean and conditional volatility. This approach further filters out possible serial correlation and heteroskedasticity in the four-factor residuals. Our EDR measure is constructed based on the resulting innovations from this process. As Diebold et al. (1998) and McNeil and Frey (2000) indicate, there is a statistical advantage in applying EVT to model innovations and residuals rather than raw returns since the former are approximately independent over time. Therefore, the procedure adopted here could potentially improve the finite sample properties of the EDR estimator.

2.3. Estimation of EDR

Each month in the sample period, we obtain abnormal returns for each stock from the four-factor model and construct daily residuals from the AR(1)-GARCH(1,1) process using all up-to-date available data. Based on the monthly minimal residual, we use MLE to compute "pre-ranking" tail index estimates each month for each stock. In this first-stage process, we set 60 months as the minimum length of estimation window.[11]

Because tail index estimation involves using extreme daily returns, the reported daily data from CRSP may be subject to severe microstructure biases, especially for small firms, as emphasized by

[3] Similar results hold for the maxima case since $\max\{X_1, X_2, \ldots, X_3\} = -\min\{-X_1, -X_2, \ldots, -X_3\}$.

[4] Non-degenerate distribution does not put all its mass at a single point.

[5] Normal distribution, with its exponentially decaying tail, leads to Gumbel distribution for extremes, so it is thin-tailed as suggested by the tail index.

[6] Another well-known statistical methodology is to fit observations higher (or lower) than an extreme threshold into a generalized Pareto distribution.

[7] Our EDR measures are based on per-month minimum sampling. Loretan and Phillips (1994) and Longin (1996) report that tail index is very stable over different sub-period lengths.

[8] The minimum-5-year requirement is to allow enough sample observations for the empirical analyses based on monthly extrema.

[9] Monthly CRSP data from current year's July to following year's June are merged with COMPUSTAT data for the latest fiscal year ending in the preceding calendar year. This guarantees a minimum 6-month gap between fiscal yearend and stock returns.

[10] Risk factor data and US 1-month Treasury bill rates are from Kenneth French's data library at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[11] We base the MLE on an expanding window by utilizing all previous data because normally a large sample size is needed for reliable tail index estimation. Similar results are obtained when EDR is estimated from alternative rolling window schemes with window lengths of 10, 20, or 30 years.

Table 1
Summary statistics of EDR measures.

Panel A: EDR summary in full sample

	Mean	SD	Median	Fat tail (%)
Full sample	0.0672	0.0551	0.0576	95

Panel B: Characteristics of EDR sorted portfolios

	EDR		Size		BM		Beta		Momentum	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1 Low	−0.0444	−0.0304	1217.91	853.72	0.8991	0.8045	1.1922	1.1906	0.1536	0.1469
2	−0.0093	0.0025	1447.81	842.03	0.8903	0.7953	1.1978	1.1989	0.1480	0.1509
3	0.0113	0.0198	1453.25	832.63	0.9003	0.7858	1.2040	1.2059	0.1536	0.1506
4	0.0296	0.0354	1653.90	906.92	0.9089	0.8155	1.2080	1.2117	0.1488	0.1540
5	0.0453	0.0507	1781.62	914.23	0.8947	0.7933	1.2060	1.2096	0.1492	0.1488
6	0.0607	0.0668	1733.14	917.03	0.9021	0.7965	1.2144	1.2151	0.1475	0.1462
7	0.0778	0.0820	1695.92	1005.02	0.9058	0.7850	1.2160	1.2165	0.1492	0.1530
8	0.0971	0.0975	1655.33	892.22	0.9225	0.8351	1.2332	1.2341	0.1394	0.1440
9	0.1242	0.1232	1300.68	624.59	0.9396	0.8364	1.2333	1.2346	0.1337	0.1288
10 High	0.1969	0.1961	861.76	397.71	1.0643	0.9730	1.2469	1.2628	0.1318	0.1346

Note: Panel A presents full-sample summary statistics of EDRs. Average EDR of each stock is calculated for the full period from June 1973 to June 2009. Mean, standard deviation (SD), and median of EDR over the sample of all stocks are reported. "Fat Tail" column shows the proportion of stocks with positive tail indexes. Panel B reports mean and median statistics of more characteristics for decile portfolios sorted on EDR. "Size" is the market capitalization (in millions) of the preceding June, and "BM" is the book-to-market ratio of the latest fiscal year ending in the preceding calendar year. "Beta" is estimated following Fama and French (1992). "Momentum" is measured as the past 12-month return skipping the most recent month. Also reported are the mean and median EDR values of each decile.

Blume and Stambaugh (1983) and Asparouhova et al. (2010). To mitigate the liquidity biases and other error-in-variables problems, we conduct the second-stage of estimation. We first sort stocks into 100 portfolios according to their "pre-ranking" tail index estimates at the end of each month to compute weighted average daily excess returns in the following month for each percentile portfolio, where the weights are previous day's gross returns. Such a "return weighting" scheme in computing the buy-and-hold portfolio returns is proven to be effective in eliminating microstructure biases in daily returns (Asparouhova et al., 2010). We then apply the same procedure as described above to generate daily residuals for the portfolio excess return series each month starting from July 1968.[12] We also conduct per-month minima sampling to the 100 portfolio residual series utilizing all up-to-date available data as in individual stock case. MLE is applied again to these minimum residual samples (with at least 60 observations used). We thus obtain "post-ranking" tail index estimate for each portfolio in each month starting from June 1973. Finally, we assign these portfolio-level EDR measures to each stock contained in the portfolios rebalanced on a monthly basis. They serve as the final individual EDR measures used in the empirical analyses.[13]

2.4. Summary statistics of EDR estimates

Panel A of Table 1 reports basic summary statistics of the EDR estimates. Average EDR for each stock is calculated for the full study period. Mean, standard deviation, and median of EDRs for all sample stocks are reported. The last column shows that the distributions of most stocks (95% of all sample stocks) have fat left tails, based on the four-factor residual returns. A t-test indicates that mean EDR of the sample stocks is significantly positive (with an untabulated positive two-digit Newey and West (1987) robust t-statistic of 96.55), suggesting that sample stocks have fat tails on average.

We show more firm characteristics across EDR deciles in Panel B. Apparently, the range of EDR is wide. The top decile portfolio has mean and median EDRs of 0.1969 and 0.1961, respectively, while the corresponding values in the bottom decile portfolio are −0.0444 and −0.0304. Firms in the highest-EDR portfolio have the smallest mean and median sizes, but the lowest-EDR stocks do not have the largest sizes. Top-EDR decile portfolio has the highest book-to-market ratios. It also has the highest mean and median betas.[14] There is no considerable variation in momentum return across the portfolios. Put together, the evidence suggests that stocks with high EDRs are more risky on average.Fig. 1 illustrates mean and median EDRs in each month during the study period. Clearly, EDRs are above zero (indicating fat-tailed distribution) and generally show upward trends over time. Also, mean EDR starts to exceed median EDR by a large margin since early 1990s, indicating stocks are subject to more frequent and severe massive losses in the recent two decades.

3. Extreme downside risk and the cross-section of stock returns

3.1. EDR premium: portfolio analysis

To examine whether EDR commands a premium, each month between July 1973 and June 2009, we sort all sample stocks into decile portfolios based on their prior-month EDR measures and report average EDR and excess return for each portfolio in the first two rows of Table 2. The last column indicates that EDR in the highest decile is substantially larger than that in the lowest decile. On the monthly basis, the excess return spreads is 38.29 basis points (bps) with a Newey and West (1987) robust t-statistic of 3.78, which indicates an annualized return spread of 4.7%. This evidence illustrates that downside risks at extreme level are compensated with higher expected returns, even though such risks are derived from the firm-level idiosyncratic information.It is possible that results in the above analysis may be attributed to different factor loadings other than EDR. To filter out influences of other risk factors, we run time-series regressions with EDR-sorted portfolio returns as dependent variables and commonly used risk factors as explanatory variables, and report portfolio alphas. The difference in alpha between high- and low-EDR deciles reflects information components not captured

[12] This series starts from July 1968 because the valid first-stage tail index estimation for individual stocks begins from June 1968.

[13] A particular stock's EDR estimate may change over time since the stock may switch between different portfolios due to the "pre-ranking" of its tail index estimation each month.

[14] We estimate beta following the method in Fama and French (1992).

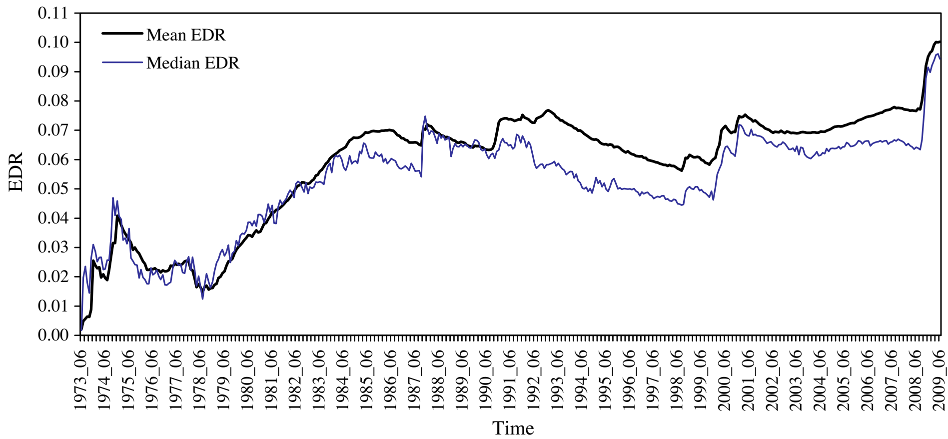

Fig. 1. Monthly mean and median EDR measures over time. *Note:* Mean and median EDRs are computed for each month in the period from June 1973 to June 2009. Vertical axis is the EDR statistics, and horizontal axis represents time.

Table 2
Average excess returns and alphas of EDR-sorted portfolios.

	EDR portfolios										
	1 Low	2	3	4	5	6	7	8	9	10 High	High–Low
EDR	−0.0444	−0.0093	0.0113	0.0296	0.0453	0.0607	0.0778	0.0971	0.1242	0.1969	0.2414
Excess return	0.8383	0.8523	0.9170	0.9032	0.8939	0.9153	0.8887	1.0071	1.0426	1.2212	0.3829 [3.78]
4-Factor alpha	0.2068	0.2116	0.2557	0.2635	0.2322	0.2531	0.2340	0.3399	0.4200	0.5586	0.3518 [4.02]

Note: Each month between July 1973 and June 2009, all stocks in the full sample are grouped into decile portfolios based on their prior-month EDRs. Row 1 reports average EDR for each portfolio. Row 2 reports average monthly excess return in percentage for each portfolio. Rows 3 reports EDR-sorted portfolio alphas measured by the intercepts in the time-series regressions from the four-factor model. The column "High–Low" represents mean differences in monthly return or alpha between the highest- and lowest-EDR decile stocks. The Newey and West (1987) robust *t*-statistics are reported in brackets for the "High–Low" column.

by existing asset pricing models. To be consistent with EDR construction, we use the four-factor model in alpha analysis. As shown in the last row of Table 2, the four-factor alpha has a monthly spread of 35.18 bps, with a Newey and West (1987) robust *t*-statistic of 4.02. The magnitude and significance level of spread in excess return and alpha are very close, implying traditional risk factors in the Carhart (1997) model have no substantial impacts on the EDR-return relation.

The 38.29 bps monthly EDR premium seems relatively small, but three observations emerge to highlight its economic importance. First, the EDR premium is compensation for taking idiosyncratic extreme risk after controlling for market, size, value, and momentum factors. In this sense, it is a reward beyond taking other commonly perceived risks. Second, untablulated calculation shows that EDR premium is 27% of size premium, 33% of book-to-market premium, and 88% of momentum premium for the same sample period.[15] This means EDR as an idiosyncratic risk measure provides additional premium beyond common risk factors by a large margin. Third, the EDR premium and difference in alpha are both highly significant and they exist in most of the sample period (as shown in next section). Also, the EDR premium is 1.35 times of beta premium (untabulated), even though beta signifies systematic risk. In summary, results from Table 2 present a significant EDR-return tradeoff which cannot be subsumed by other commonly used risk factors, suggesting that bearing high EDR is rewarded with higher expected returns.

3.2. Persistence of EDR premium

To examine whether the EDR premium is a persistent phenomenon or is caused by a few outliers by chance, we compute average monthly excess return difference between the highest- and lowest-EDR deciles for each of the 36 12-month sub-periods from July 1973 through June 2009. Fig. 2 illustrates that high-EDR firms outperform low-EDR firms in 26 out of the 36 sub-periods, indicating that the EDR premium persists throughout most of the sample periods.[16]

3.3. EDR premium in firms of different sizes and book-to-market ratios

We further examine the EDR premium in firms of different sizes and book-to-market ratios. In particular, following the spirit in Fama and French (1993), each month, we sort all stocks into two size groups (Small and Big) according to their market capitalizations of the preceding June, and three BM groups (Low-bottom 30%, Medium-middle 40%, High-top 30%) according to book-to-market ratios of last fiscal year ending in the preceding calendar year. Within each size or BM group, stocks are further sorted into deciles based on prior-month EDRs. Table 3 reports these double-sorted portfolio excess returns. Also reported are alphas from the four-factor model. The "Average" row refers to average monthly excess return or alpha of each EDR decile portfolio across all size or BM groups.

Panel A of Table 3 shows that positive and statistically significant EDR premium exists in both small and large size stocks.

[15] We compute size, book-to-market, and momentum premia (and beta premium which will be mentioned later) using the same decile portfolio approach for EDR premium calculation.

[16] We also examine the long-run persistence of EDR effect, and results (untabulated) reveal that EDR premium persists over a longer period up to at least 1 year.

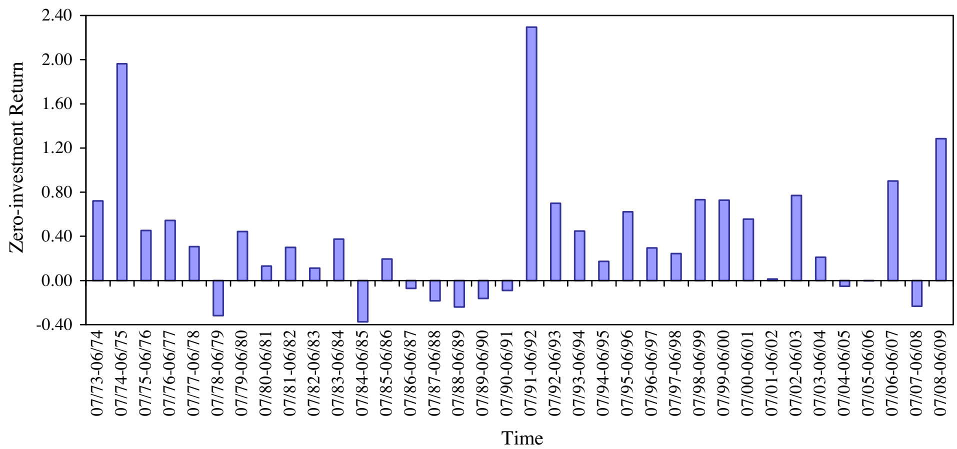

Fig. 2. Average excess return difference between high- and low-EDR portfolios over time. *Note:* Each month between July 1973 and June 2009, all stocks in the full sample are grouped into decile portfolios based on their prior-month EDRs. At the end of June of each year, average monthly percentage returns for the past 12 months (1 year) are computed for each portfolio, and average monthly excess return differences between top- and bottom-EDR deciles are depicted.

Table 3
EDR effects in different size and book-to-market portfolios.

	1 Low	2	3	4	5	6	7	8	9	10 High	High–Low
Panel A: EDR effect in different size groups											
Excess returns in EDR portfolios											
Small	1.1009	1.0311	1.136	1.0994	1.1037	1.205	1.0724	1.2782	1.3413	1.358	0.2571
											[2.31]
Large	0.6081	0.6434	0.7038	0.7029	0.7467	0.7138	0.6765	0.7693	0.7896	0.852	0.244
											[2.71]
Average	0.8545	0.8372	0.9199	0.9011	0.9252	0.9594	0.8745	1.0238	1.0655	1.105	0.2505
											[3.46]
4-Factor Alphas in EDR portfolios											
Small	0.3971	0.3341	0.386	0.3724	0.374	0.4462	0.294	0.5454	0.636	0.6451	0.248
											[2.20]
Large	0.0214	0.0336	0.1354	0.1275	0.1652	0.1346	0.1081	0.2014	0.2243	0.3347	0.3132
											[3.80]
Average	0.2093	0.1838	0.2607	0.25	0.2696	0.2904	0.201	0.3734	0.4301	0.4899	0.2806
											[3.90]
Panel B: EDR effect in different BM groups											
Excess returns in EDR portfolios											
Low	0.3666	0.403	0.6277	0.6197	0.6493	0.5759	0.5092	0.739	0.7651	0.7699	0.4033
											[4.16]
Medium	0.883	0.8527	0.9105	0.8971	0.9127	0.8856	0.9122	1.021	1.0538	1.1201	0.2372
											[2.11]
High	1.323	1.27	1.3329	1.1235	1.2036	1.3167	1.2662	1.3138	1.3888	1.4366	0.1136
											[0.83]
Average	0.8575	0.8419	0.957	0.8801	0.9219	0.9261	0.8959	1.0246	1.0692	1.1089	0.2514
											[2.65]
4-Factor Alphas in EDR portfolios											
Low	−0.0443	−0.0602	0.1715	0.1263	0.1492	0.0869	0.0861	0.2981	0.33	0.3306	0.3749
											[3.96]
Medium	0.2168	0.2141	0.2465	0.2709	0.2249	0.218	0.2234	0.3065	0.4094	0.407	0.1902
											[1.87]
High	0.5375	0.4144	0.4862	0.325	0.3761	0.4685	0.4179	0.4737	0.5731	0.7024	0.1649
											[1.23]
Average	0.2367	0.1894	0.3014	0.2407	0.2501	0.2578	0.2425	0.3594	0.4375	0.48	0.2433
											[3.66]

Note: In Panel A, stocks are sorted into two size groups (Small and Big) according to their market capitalizations of the preceding June. In Panel B, stocks are sorted into three book-to-market (BM) groups (Low-bottom 30%, Medium-middle 40%, High-top 30%) according to book-to-market ratio of last fiscal year ending in the preceding calendar year. Within each size or book-to-market group, stocks are further sorted into deciles based on prior-month EDRs. Monthly average excess percentage return and intercept of the time-series regressions from four-factor model (4-factor Alpha) are reported for each size-EDR- or BM-EDR-sorted portfolio. "High–Low" in the last column refers to mean differences in monthly return or alpha between the highest- and lowest-EDR decile stocks. The "Average" row indicates average monthly return or alpha of each EDR decile across all size or book-to-market groups. The Newey and West (1987) robust *t*-statistics are reported in brackets for the "High–Low" column.

Conditioning on firm size, the highest-EDR portfolio still has average excess return higher than that of the lowest-EDR portfolio with an average spread of 25.05 bps per month. Consistently, alphas from the highest-EDR decile are significantly greater than those from the lowest-EDR decile in both size portfolios. Therefore, EDR premium is not sensitive to firm size. Similarly, Panel B indicates that the positive EDR premium is still significant after controlling for book-to-market ratios. The average spread between

Table 4
Cross-sectional regressions with EDR as one explanatory variable.

Model	EDR	Beta	Size	BM	Momentum	Liquidity beta
Panel A: Full sample regressions						
1	1.4352					
	[3.78]					
2	0.9703	0.0648	−0.1238	0.2383		
	[3.22]	[0.24]	[−3.54]	[2.82]		
3	0.8517	0.0639	−0.1364	0.2267	0.2781	−0.0308
	[3.42]	[0.25]	[−3.93]	[2.73]	[1.44]	[−0.30]
Panel B: Regressions after excluding top EDR decile stocks						
4	0.9941					
	[2.55]					
5	1.0388	0.0650	−0.1195	0.2451		
	[2.88]	[0.24]	[−3.42]	[2.99]		
6	0.9806	0.0587	−0.1326	0.2338	0.2783	−0.0250
	[3.00]	[0.23]	[−3.84]	[2.89]	[1.45]	[−0.22]

Note: Fama and MacBeth (1973) cross-sectional regressions are run each month between July 1973 and June 2009 with individual stock return as the dependent variable. The explanatory variables are prior-month EDR and traditional risk measures including beta, size, and book-to-market (BM) ratio, as well as momentum and liquidity beta. "Beta" is estimated following Fama and French (1992), "Size" is the logarithm of the market capitalization (in millions) of the preceding June, and "BM" is the logarithm of book-to-market ratio of the latest fiscal year ending in the preceding calendar year. "Momentum" is measured as the past 12-month return skipping the most recent month. "Liquidity Beta" is constructed following Pastor and Stambaugh (2003). Regressions are based on full sample data each month in Panel A, and in Panel B, regressions are run after stocks in the top EDR decile are excluded each month. Time-series averages of the slopes are reported along with the Newey and West (1987) robust *t*-statistics in brackets.

the highest- and lowest-EDR decile stocks across three BM portfolios is 25.14 bps. Meanwhile, the spread is substantially larger in low-BM portfolio (40.33 bps) than in high-BM portfolio (11.36 bps). Thus the positive relation between EDR and expected returns is stronger among glamor stocks. Alphas from the four-factor model show same patterns. Overall, results in Table 3 suggest that size and book-to-market affects EDR premium to some extent, but they cannot fully explain it.

3.4. EDR premium in cross-sectional regressions

To further explore the relation between EDR and expected stock returns, we run Fama and MacBeth (1973) cross-sectional regressions with different explanatory variables. This allows us to examine the robustness of EDR premium while controlling for multiple variables simultaneously. Each month during the sample period, we use all individual stock returns as dependent variable and prior-month EDR as one of the explanatory variables. We control for various firm characteristics known to influence cross-sectional asset returns, including beta, (log) size, (log) BM, momentum, and liquidity. Following Jegadeesh and Titman (1993), we calculate momentum as past year return skipping the most recent month. Liquidity is measured by the liquidity beta from Pastor and Stambaugh (2003). Time-series averages of the cross-sectional regression coefficients for explanatory variables are reported in Table 4 Panel A with the Newey and West (1987) robust *t*-statistics.

The overall findings indicate that coefficients of EDR are significantly positive in each model, even after controlling for other explanatory variables. This confirms the results from portfolio analyses that the explanatory power of EDR is not subsumed by size and value effects. Furthermore, after controlling for additional variables including momentum and liquidity beta, a significant EDR premium remains.

Portfolio analyses in the previous section reveal that stocks in top decile exhibit substantially higher EDRs and expected returns, generating a large amount of EDR premia. In order to examine whether the EDR-return relation is driven by issues with very high EDRs, we conduct Fama and MacBeth (1973) analyses after excluding stocks in the top decile from the full sample each month. The results in Panel B of Table 4 show that the coefficients of EDR remain significantly positive, suggesting that EDR premium is not driven by stocks with very high EDRs.

4. Risk implication of EDR-return relation

The significantly positive EDR-expected return relation demonstrated above suggests that investors demand a risk premium for bearing EDR. If EDR captures a risk that needs to be priced, we should observe deeper price drops of high-EDR stocks along with severe market downs, i.e., stocks with high EDRs experience low returns (relative to low-EDR stocks) when extremely bad market returns are realized and marginal utility of wealth is high. On the other hand, when market returns are *expected* to be high (marginal utility of wealth is expected to be low), high-EDR securities should be associated with higher *expected* returns. Such behaviors would lead to a less smooth wealth path and a poor hedge against low wealth, implying high-EDR stocks are fundamentally riskier.

We adopt the model-independent approach in Bali et al. (2010) to examine the performance of high-EDR stocks when *realized* market returns are extremely low, as well as the *expected* returns associated with high-EDR stocks when *expected* market returns are extremely high. We define the time of extreme market down as the months when the lowest 20% of market returns are realized during the sample period. To represent the period of high expected market returns, we use the months with top 20% term or default premia since recession times are characterized by high expected market returns.[17,18]

Panel A of Table 5 reports average *realized* returns for the top and bottom EDR decile portfolios during extreme market down months and the rest sample period. High-EDR stocks drop more during worst market performance time and top EDR decile's average excess return is 70.55 bps *lower* than that of the bottom EDR decile. Even though this difference is not significant at the 5% level, we do observe high-EDR stocks tend to experience poor returns along with poor market performance. In Panels B and C, we examine whether high-EDR investments are accompanied by higher *expected* returns during large term and default premia periods when market returns are *expected* to be high. We form EDR deciles based on prior month EDRs, and observe substantially larger EDR premia during the high expected market return periods (79.35 bps for large term premium months and

[17] Term premium is measured by the difference between 10-year and 1-year Treasury bond yields with constant maturity; default premium is calculated as the difference between BAA- and AAA-rated corporate bond yields.

[18] We are grateful to the anonymous referee for suggesting this analysis.

Table 5
Risk implication of EDR-return relation.

	Low EDR	High EDR	High–Low	t-Statistic
	Realized excess returns			
Panel A: Realized excess returns of EDR portfolios in normal and large market down months				
Large market down months	−5.7461	−6.4516	−0.7055	[−1.53]
Other month	2.6177	2.7824	0.1647	[1.19]
	Expected excess returns			
Panel B: Expected excess returns of EDR portfolios in normal and high term premium months				
High term premium months	1.4215	2.2150	0.7935	[2.33]
Other months	0.6933	0.9742	0.2809	[3.16]
	Expected excess returns			
Panel C: Expected excess returns of EDR portfolios in normal and high default premium months				
High default premium months	1.3390	2.0185	0.6796	[2.51]
Other months	0.7139	1.0231	0.3092	[2.91]

Note: In Panel A, the full sample period is separated into months of extreme market downs when the lowest 20% of market returns are realized and other months. Decile portfolios are constructed according to current month EDRs, and average realized excess returns in percentage for the top and bottom EDR deciles and their difference are reported for the extreme market down and other months, with the Newey and West (1987) robust *t*-statistics in brackets. In Panels B and C, the full sample period is separated into months with high expected market returns indicated by the highest 20% term (Panel B) or default premia (Panel C) and other months. Term premium is the difference between 10-year and 1-year treasury constant maturity rates, and default premium is the difference between BAA- and AAA-rated corporate bond yields. Decile portfolios are constructed according to prior month EDRs, and average excess returns for the top and bottom EDR deciles and their difference are reported for high term (default) premium and other months, with the Newey and West (1987) robust *t*-statistics in brackets.

Table 6
Correlations between EDR and other risk measures.

	Correlation	t-Statistic
Idiosyncratic volatility	0.0791	[8.54]
Idiosyncratic skewness	0.0270	[3.32]
Idiosyncratic kurtosis	0.0814	[10.10]
Value at risk	0.0935	[7.36]
Right tail index	0.1663	[6.61]
Downside beta	0.0182	[1.67]
Coskewness	−0.0032	[−0.51]
Cokurtosis	−0.0800	[−10.99]
Bankruptcy risk	0.0413	[7.69]
Leverage	0.0317	[6.75]
Profitability	−0.0240	[−6.79]
Price	−0.0120	[−2.60]
Volatility	0.0549	[4.65]
Delist	0.0483	[6.86]

Note: Cross-sectional correlation coefficients between EDR and other risk measures are computed each month between June 1973 and June 2009. “Idiosyncratic volatility”, “Idiosyncratic skewness”, and “Idiosyncratic kurtosis” are measured as the standard deviation, third, and fourth moments of residuals from the four-factor model. “Downside beta” is estimated following Ang et al. (2006a). “Coskewness” and “Cokurtosis” are constructed as in Harvey and Siddique (2000) and Ang et al. (2006a), respectively. All of the above risk measures are computed each month utilizing up-to-date monthly information with a minimum window length of 5 years. “Value at Risk” is the parametric 1% VaR based on the fourth-order Cornish-Fisher expansion using daily four-factor return residuals over the past 100 days. “Right tail index” is estimated from the same approach as EDR, but is based on the maxima of daily four-factor return residuals in each month. “Bankruptcy risk” is defined according to Ohlson (1980). “Leverage” is defined as total liabilities over total assets. “Profitability” is defined as net income over total assets. “Price” is the logarithm of past month’s market closing price. “Volatility” refers to standard deviation of daily returns in the previous month. “Delist” is an exchange delisting dummy variable that equals one when a particular stock is delisted from NYSE, AMEX, or NASDAQ, and zero otherwise. Accounting related variables are calculated using data of the latest fiscal year ending in the preceding calendar year. Time-series averages of the monthly correlations are reported, with the Newey and West (1987) robust *t*-statistics in brackets.

67.96 bps for large default premium months), which are twice as much in magnitude as the premia in the rest of the sample period. Moreover, EDR premia in all cases are significantly positive, indicating EDR effect is robust to general business conditions and becomes stronger when the economy is expected to be good. Table 5 hence provides further evidence that there is fundamental risk embedded in EDR that requires to be priced in the cross-section of stock returns.

5. Extreme downside risk and other risk measures

Results so far indicate that EDR may capture different risk components other than those endowed in existing risk proxies. It is thus of interest to study the characteristics of stocks with different EDR levels by directly examining their relations with EDR, and whether EDR premium can be explained by other risk measures. The fact that EDR is estimated from idiosyncratic return residuals motivates us to investigate the links between EDR and firm-specific risk measures, such as idiosyncratic volatility, skewness, kurtosis, VaR, and firm-specific right tail index. In addition, we examine the connections between EDR and risk measures that reflect comovements with the market, such as downside beta, coskewness, and cokurtosis. Finally, firms in financial distress typically carry a high probability of extremely negative returns, and we also check the relations between EDR and bankruptcy risk and other firm distress indicators.

5.1. Correlations between EDR and other risk measures

In Table 6, we compute cross-sectional correlation coefficients between EDR and traditional risk measures and other characteristic variables each month, and report time-series averages of the correlations. Among the various measures related to idiosyncratic risk, idiosyncratic volatility is calculated as the standard deviation of residuals from the Carhart (1997) four-factor model, and idiosyncratic skewness and kurtosis are the third and fourth moments, respectively. We estimate volatility and high moment measures using up-to-date monthly information. Another popular downside risk proxy at extreme level is VaR. To make a fair comparison with EDR, we estimate a parametric 1% VaR based on the fourth-order Cornish–Fisher expansion using daily four-factor return residuals over the past 100 days, follow Bali et al. (2008).[19] Table 6 shows that firm-specific returns exhibit large fluctuation for high-EDR stocks, which are also accompanied by large deviations from normal distribution tails, as indicated by high idiosyncratic kurtosis.

[19] The Cornish–Fisher expansion is an accurate approximation of the quantiles of a distribution provided by Cornish and Fisher (1937). Applied to our specific case here, the fourth-order Cornish–Fisher expansion expresses the lowest daily return residual (i.e., the 1% empirical distribution-based VaR since exactly 100 daily observations are used) as a nonlinear function of the mean, standard deviation, skewness, and kurtosis of the residuals. Refer to Bali et al. (2008, p. 772) for details.

Moreover, high EDR is also associated with large asymmetry in idiosyncratic return distribution reflected in the skewness measure. It is interesting to see that firm-specific return distribution is skewed more to the right when EDR (which is a measure of the left tail) is high. This is probably due to the significantly positive correlation (0.1663) between EDR and the right tail index estimated using the same procedure as EDR based on the maxima of daily four-factor return residuals in each month. EDR also has a close connection with other tail-based downside risk measure, as confirmed by the significantly positive correlation with VaR. This is not surprising due to VaR's properties of reflecting downside and extreme risks and predicting stock returns. In fact, EDR and VaR have the second largest correlation coefficient among all reported correlation values (only smaller than the correlation between EDR and right tail index), suggesting that VaR may have significant impact on EDR premium.

The next set of risk measures concentrates on comovements with the market. Downside beta is calculated as in Ang et al. (2006a). The CAPM-based coskewness is a third moment measure constructed according to Harvey and Siddique (2000). We also consider a cokurtosis measure following Ang et al. (2006a). These systematic measures of risk are estimated using up-to-date monthly information. It can be observed from Table 6 that EDR is positively related to downside beta and negatively correlated with coskewness, but these relations are insignificant. EDR has a significantly negative relation with cokurtosis, which is surprising given Dittmar's (2002) finding that kurtosis captures the probability of large negative outcomes.[20]

Also included in the risk measure list are bankruptcy risk and a set of firm distress indicators. The direct bankruptcy risk proxy is represented by Ohlson's (1980) O-score.[21] A higher O-score implies higher bankruptcy possibility. The distress indicators are from Campbell et al. (2008) who show that firms with higher leverage, lower profitability, lower stock prices, and higher return volatility suffer more from the risk of going bankruptcy, being delisted from exchanges, or receiving a D-rating. Among these distress risk related variables, leverage is the ratio of total liabilities to total assets, profitability is the ratio of net income to total assets, price is defined as the logarithm of last month closing price, return volatility refers to standard deviation of daily stock returns in the previous month. To directly check delisting risk, we also include a dummy variable which equals one when a particular stock is delisted from NYSE, AMEX, or NASDAQ, and zero otherwise. Not surprisingly, EDR is closely related to bankruptcy probability as evidenced by its significantly positive correlation with O-score. High EDR is also associated with firms with high leverage, low profitability, low stock prices, and more volatile past return performances. The positive and significant correlation coefficient with the delisting dummy variable suggests that stocks delisted from exchanges generally show thicker left tails. In summary, evidence here suggests that high-EDR stocks are more likely to be issues of financially distressed companies or firms with high bankruptcy risk.

Notably, even though most of the reported correlations are statistically significant, their values are relatively low. The highest correlation coefficient (in absolute value) is less than 0.17, and all others are below 0.10. This feature implies that the EDR effect cannot be completely subsumed by other risk measures, as further demonstrated in the following section.

[20] The negative relation could be caused by the fact that EDR is measured from the residuals of stock returns while cokurtosis in Ang et al. (2006a) is a mean-centered measure from raw returns.

[21] We do not adjust the GNP price-level index in Ohlson's (1980) O-score equation since in monthly regression analysis the index is unchanged. Furthermore, because Ohlson (1980) model is based on industrials, we exclude stocks with COMPUSTAT Standard Industrial Classification (SIC) codes between 4000 and 4999, and those above 6000.

Table 7
Average excess returns of EDR-sorted portfolios after controlling for other risk measures.

	Excess returns			
	Low EDR	High EDR	High–Low	*t*-Statistic
Idiosyncratic volatility	0.8782	1.0768	0.1987	[2.47]
Idiosyncratic skewness	0.8428	1.1964	0.3536	[3.60]
Idiosyncratic kurtosis	0.8410	1.1919	0.3510	[3.70]
Value at risk	0.8726	1.0537	0.1811	[2.46]
Right tail index	0.8478	1.1805	0.3327	[3.52]
Downside beta	0.8390	1.1718	0.3328	[3.25]
Coskewness	0.8591	1.1889	0.3298	[3.00]
Cokurtosis	0.8621	1.2122	0.3501	[3.48]
Bankruptcy risk	0.8936	1.1941	0.3005	[3.55]

Note: Each month between July 1973 and June 2009, all stocks in the full sample are grouped into decile portfolios based on each of the risk measures in column one (as defined in Table 6) known before the month-end, and within each portfolio, stocks are further sorted into deciles according to prior month EDRs. Average excess return in percentage of each EDR decile across the ten control variable portfolios is computed, along with the difference in mean excess return between the highest- and lowest-EDR deciles. This table reports time-series average excess returns of top and bottom EDR deciles ("High EDR" and "Low EDR" columns) and the difference between them ("High–Low" column) with the Newey and West (1987) robust *t*-statistics in brackets.

5.2. EDR premium after controlling for other risk measures

Evidence above indicates that high-EDR stocks are more likely to have high idiosyncratic risks (volatility, skewness, kurtosis, VaR), large right tail index, large downside beta, low coskewness and cokurtosis, and high bankruptcy risk (represented by O-score). To further investigate whether the EDR premium still exists after controlling for these variables, we sort stocks into decile portfolios ranked according to each of these nine risk measures known before the end of each month, then within each portfolio, further form deciles based on prior month's EDR. Such a bivariate portfolio setting is constructed every month and average excess return of each EDR decile across each of the control variable sorted portfolios is computed, along with the difference in mean excess return between the highest- and lowest-EDR deciles. We report time-series average excess returns of top and bottom EDR deciles ("High EDR" and "Low EDR" columns) and the difference between them ("High–Low" column) in Table 7, corresponding to each control variable.[22]

Bivariate portfolio results indicate that controlling for idiosyncratic volatility cannot eliminate the EDR premium even though the premium magnitude is reduced (from 38.29 bps without controlling for other variables in Table 2 to 19.87 bps after idiosyncratic volatility is controlled for). The remaining EDR premium is still positive and statistically significant. This suggests that idiosyncratic volatility has some overlapping effects on expected returns with EDR, but it cannot fully account for the EDR premium. When idiosyncratic skewness and idiosyncratic kurtosis are controlled for, the monthly EDR premium is over 35 bps in both cases, which is very close to the 38.29 bps premium before controlling for other risk measures. Since both EDR and VaR estimated from four-factor residuals are measuring downside risk at the distribution tail, controlling for VaR substantially affects the premium on EDR and reduces the magnitude to 18.11 bps, which is the largest reduction in EDR premium in the table. Nevertheless, the EDR-return tradeoff is not merely a reflection of VaR effect since VaR can only explain about 53% of EDR premium, and EDR is still significantly and positively related to expected returns even after VaR's influence is factored out. Since VaR is positively associated with expected stock returns, the additional premium on EDR beyond the compensation on VaR can be treated as evidence of EDR's

[22] We thank the anonymous referee for suggesting this bivariate portfolio approach.

supplementary role in predicting stock returns.[23] Overall, EDR reflects more information beyond those traditional idiosyncratic risk measures. This further reinforces the robustness of the EDR premium.

There is still a significantly positive relation between EDR and expected stock returns after controlling for right tail index, and the EDR premium is similar to that before right tail is considered. This implies even though fat right tails may be attractive due to the potential to provide extremely desirable outcomes, investors still require compensation for bearing extreme risk on the downside. Good upside potential cannot dominate downside risk and therefore cannot subsume the EDR effect.

The relation between EDR and cross-section expected stock returns is generally unchanged when downside beta, coskewness, or cokurtosis are controlled for. The EDR premia are at a significant level of around or above 33 bps per month after the influences of these systematic risk indicators are taken into consideration. This is consistent with the evidence of weak EDR-downside beta and EDR-coskewness correlations, and negative EDR-cokurtosis correlation as documented in Table 6. After all, by construction, EDR reflects firm-specific information around the far left tail of return distribution, while the systematic risk measures represent comovements with the market, which should have limited impacts on the EDR-return relation. Furthermore, as demonstrated by Poti and Wang (2010), while coskewness and cokurtosis help price a number of stock portfolios, the three- and four-moment versions of CAPM cannot provide an exhaustive account of asset returns. Our evidence here implies EDR may represent part of the orthogonal risk component with respect to coskewness and cokurtosis which has a significant predictive power for expected returns.

Similarly, controlling for bankruptcy risk cannot substantially alter the significance and magnitude of EDR premium. This evidence once again suggests that, although high-EDR stocks normally have high bankruptcy risk, the latter does not explain the positive relation between EDR and expected returns. Moreover, Dichev (1998), Griffin and Lemmon (2002), and Campbell et al. (2008), among others, have documented that firms with high bankruptcy risk are not rewarded by higher returns, which implies EDR has distinctively different risk implications from traditional bankruptcy and distress risk measures.[24]

6. Conclusion

We propose a risk measure associated with catastrophic losses and examine how this extreme downside risk (EDR) is related to expected stock returns on a cross-sectional basis. We use maximum likelihood estimation of the left tail index from classical GEV distribution to measure EDR, and apply the method to return residuals from the Carhart (1997) four-factor model to estimate EDRs for individual stocks.

We find a significant return premium for EDR even after controlling for size, book-to-market ratio, momentum, and liquidity effects. The EDR premium is larger for glamor stocks but is not sensitive to firm size. High-EDR stocks provide higher expected returns during periods when market returns are expected to be high, and underperform low-EDR stocks when the market is experiencing deep drops, suggesting that EDR reflects certain fundamental components of risk. Firms with high EDRs generally have high idiosyncratic volatility, skewness, kurtosis, firm-specific VaR, fat right tails, large downside beta, low coskewness and cokurtosis, and high bankruptcy risk. Although some of them (especially VaR) can substantially affect the EDR premium, the significantly positive EDR-return relation remains robust after these effects are controlled for.

EDR is a measure beyond the traditional mean–variance framework. Derived from the EVT model, it benefits from its ability in detecting potential extreme risks. On the other hand, EVT concentrates on the extremes and does not provide inferences for sample means. In addition, EDR in this paper is constructed from residuals after adjusting common risk factors. For all these reasons, EDR renders a new risk component of stock returns. A direction in future study is to explore the mechanism through which extreme downside movement of stock returns can be captured in general asset pricing process. An asset pricing model inclusive of EDR will contribute to the literature on risk-return tradeoff and help in a more comprehensive understanding of various risk components.

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[23] Among the VaR deciles, most (eight) have positive mean return differences between the highest- and lowest-EDR portfolios, three of which are statistically significant with magnitudes of 23.19–46.56 bps and the Newey and West (1987) robust t-statistics of 1.88–2.95. This confirms VaR's significant role in affecting the EDR premium, and also provides evidence that EDR still exhibits its own power in predicting stock returns which cannot be fully explained by VaR. Actually, in a Fama and MacBeth (1973) regression with stock return as dependent variable and EDR and VaR as independent variables, the coefficients of EDR and VaR are both significantly positive (even after controlling for other firm characteristics and risk measures), suggesting that they have their distinct effects on expected stock returns despite their close relation.

[24] We also conduct Fama and MacBeth (1973) regression analyses with stock return as dependent variable and the nine traditional risk measures and other firm characteristics as independent variables. The coefficient of EDR is significantly positive in all models, even when all the risk measures are included. The results are available from the authors upon request.

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