Extreme Downside Liquidity Risk

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Keywords: Asset Pricing, Asymmetric dependence, Copulas, Liquidity Risk, Downside Risk, Tail Risk, Crash Aversion

JEL Classification Numbers: C12, G01, G11, G12, G17.

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Abstract

We investigate whether investors receive compensation for extreme downside liquidity (EDL) risk. The joint EDL risk of a stock is decomposed into clustering in the lower left tail of the bivariate distribution between (i) individual stock liquidity and market liquidity, (ii) the individual stock return and market liquidity, and (iii) individual stock liquidity and the market return. We capture these lower tail dependencies with copulas and show that the cross-section of expected stock returns reflects a premium for EDL risk. From 1968 through 2009, the average return on stocks with high sensitivities to EDL risk exceeds that for stocks with low sensitivities by 3.6 percent annually. This premium is different from linear liquidity risk (as in Acharya and Pedersen (2005)'s liquidity-adjusted CAPM) and cannot be explained by traditional risk- and firm characteristics. Our results show that investors care about extreme joint realizations in systematic liquidity risk and that asset pricing models that rely on linear correlation sensitivities alone might be misspecified.

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1 Introduction

There is strong empirical evidence that investors are sensitive to downside risk (Ang, Chen, and Xing (2006)). In a recent paper, Ruenzi and Weigert (2011) show that the cross-section of expected stock returns reflects a premium for a stock's sensitivity to market crashes. In particular, they document that stocks that realize their lowest payoff in times of extreme market downward movements have high average returns. In this paper we investigate a new dimension of downside risk: a stock's extreme downside liquidity (EDL) risk. Investors might not worry about liquidity risk in normal market conditions, but it might become a main concern in case of extreme market downturns.

Our approach is based on Acharya and Pedersen (2005)'s liquidity-adjusted CAPM. In their model, an asset's joint liquidity risk consists of three different risk components: (i) the sensitivity of an asset's liquidity to market liquidity, (ii) the sensitivity of an asset's return to market liquidity, and (iii) the sensitivity of an asset's liquidity to the market return.

Acharya and Pedersen (2005) measure these different sensitivities based on linear correlations. However, when dealing with non-normally distributed random variables (such as the empirical distributions of stock liquidity and stock returns), linear correlations fail to account for extreme risks, i.e. dependence structures in the tails of the distribution (see Embrechts, McNeil, and Straumann (2002)). Thus, the liquidity-adjusted CAPM cannot account for a stock's EDL risk and might be misspecified if investors care about extreme joint realizations.

The idea of a premium for EDL risk is related to a recent working paper by Menkveld and Wang (2011). They document a premium for liquileaks; the probability that a security hits an illiquid state and is trapped in it, so that waiting a day will not restore liquidity. We differ from their study in analyzing extreme events in *systematic* liquidity risk (instead of liquileak risk). While Menkveld and Wang (2011) focus on the impact of extreme illiquidity levels on an individual stock level, we focus on the likelihood that an individual stock is extremely illiquid (has an extremely low return) when market liquidity (the market return) is extremely low. Focusing on the joint realization of individual and market variables is motivated by the findings of Lou and Sadka (2010), which document that in times of financial crises the performance of stocks can be explained better by systematic liquidity risk than the liquidity level.

We examine whether EDL risk can explain the cross-section of expected stock returns. Similar to Acharya and Pedersen (2005), we decompose the joint EDL risk of a stock into three different EDL risk components with associated return premiums:

(i) Clustering in the lower left tail of the bivariate distribution between individual stock liquidity and market liquidity (EDL_1 risk) due to investors looking for compensation for holding a security that becomes illiquid in times of extreme market liquidity downturns.

(ii) Clustering in the lower left tail of the bivariate distribution between the individual stock return and market liquidity (EDL_2 risk). Investors who face margin or solvency constraints usually have to liquidate some assets to raise cash when their wealth drops critically. If they hold assets with strong EDL_2 risk, such liquidations will occur in times of extreme market liquidity downturns. Liquidation in those times leads to additional costs, which are especially unwelcome to investors whose wealth has already dropped (see also Pastor and Stambaugh (2003)).

(iii) Clustering in the lower left tail of the bivariate distribution between individual stock liquidity and the market return (EDL_3 risk). In times of market return crashes, institutional investors (such as mutual fund managers) are often forced to sell because market participants engage in asset fire sales (Coval and Stafford (2007)) or financial intermediaries withdraw from providing liquidity (Brunnermeier and Pedersen (2009)). If a selling investor holds securities with strong EDL_3 risk, he will suffer from high transaction costs at the precise moment when his wealth has already dropped and additional losses are particularly painful.

We capture the three distinct EDL risk components based on lower tail dependence coefficients (see Sibuya (1960)). The lower tail dependence coefficient reflects the probability that a realization of one random variable is in the extreme lower tail of its distribution conditional on the realization of the other random variable also being in the extreme lower tail of its distribution. Subsequently, we define the joint EDL risk of a stock as the sum of the three different EDL risk components. All else being equal, assets that exhibit strong EDL risk are unattractive assets to hold: they tend to realize the lowest liquidity (return) exactly when the market also realizes its lowest liquidity (return) level. Hence, investors who are sensitive to EDL risk will require a return premium for holding those stocks.

Our liquidity measure is based on the Amihud (2002) illiquidity measure. Based on weekly data from 1968 to 2009 we estimate lower tail dependence coefficients for (i) individual stock liquidity and market liquidity (EDL_1 risk), (ii) individual stock return and market liquidity (EDL_2 risk), and (iii) individual stock liquidity and market return (EDL_3) for each stock i and week t in our sample.[1]

We investigate the time series of aggregate EDL risk (defined as the value-weighted average of EDL risk over all stocks in the sample) and its three risk components. Aggregate EDL risk peaks around 1978-1979 (Second US Oil Crisis), after 1987 (Black Monday Stock Market

[1] We also calculate (and later include as a control variable) the tail dependence between individual returns and market returns as in Ruenzi and Weigert (2011).

Crash), 1997-1998 (Asian Financial Crisis) as well as in the years of the recent financial crisis 2007-2009. However, we see different patterns in the behaviour of the EDL risk components. In the 1987 crash, the main driver of the spike is EDL_2 (stock return and market liquidity) risk. In the 2007-2009 crisis, the peak is caused by increasing EDL_1 (liquidity and market liquidity) and EDL_3 (liquidity and market return) risk.

To detect a premium for EDL risk in the cross-section of stock returns, we relate EDL risk (and the EDL risk components) to future returns. Our empirical analysis - based on portfolio sorts, factor regressions, and Fama and MacBeth (1973) regressions on the individual firm level - reveals that there exists a positive impact of EDL risk on future returns.

Univariate equal-weighted portfolio sorts show that a trading strategy that is long in stocks with strong EDL risk and short in stocks with weak EDL risk yields a significant average excess return of approximately 3.60% p.a. in the period from 1968 to 2009. We find that this premium is driven by EDL_2 (stock return and market liquidity) risk and EDL_3 (stock liquidity and market return) risk. In addition, we document that the premium for EDL risk has increased over time. While we do not find a significant premium for EDL risk in the time period from 1968-1987, there is a large premium for EDL risk after 1987: During 1988-2009, a portfolio consisting of the 20% stocks with the strongest EDL risk delivers an excess return which is 5.72% p.a. higher than that of a portfolio consisting of the 20% stocks with the weakest EDL risk.

We show that the premium for EDL risk cannot be explained by linear liquidity risk nor various risk- and firm characteristics. First, we perform equal-weighted portfolio double sorts based on linear liquidity risk and EDL risk. Our results reveal that the average spread between stocks with strong EDL risk and weak EDL risk controlling for linear liquidity risk is 3.11% p.a., which is statistically significant at the 5% significance level. Second, we find that the return premium for EDL risk is robust to different factor model specifications (among others, the market model by Sharpe (1964), the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and an alternative three-factor model by Chen, Novy-Marx, and Zhang (2011)). Third, in Fama and MacBeth (1973) regressions on the firm level, we investigate the impact of EDL risk on future returns controlling for a large number of firm characteristics. EDL risk remains a statistically and economically significant explanatory variable when we control for size (Banz (1981)), book-to-market (Basu (1983)), momentum (Jegadeesh and Titman (1993)), lower tail dependence (LTD) in returns (Ruenzi and Weigert (2011)), linear liquidity risk (Acharya and Pedersen (2005)), idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang (2006)), and lottery characteristics (Bali, Cakici, and Whitelaw (2011)) of a stock. Our results suggest that EDL risk is an important determinant of the cross-section of expected stock returns and that asset pricing models that rely on linear liquidity risk alone might be misspecified.

We conduct robustness tests to confirm the stability of our results. Results are confirmed if we change the weighting scheme of our portfolio sorts from equal-weighted to value-weighted (see section 4.1). We also show that our results are similar when we apply different regression estimation techniques to measure the impact of EDL risk on future returns (see section 4.2).

Our study is related to three strands of literature. First, our paper relates to the literature on downside risk and asset pricing. Downside risk aversion is already discussed in Roy (1952) who argues that investors display 'safety-first' preferences and dislike downside losses more than they like upside gains. Kahneman and Tversky (1979) argue that individuals evaluate outcomes relative to reference points and show that individuals strongly prefer avoiding losses to acquiring gains.[2] Although aversion to losses, i.e. downside risk, is discussed extensively, only a few papers investigate the effect of loss- or disappointment aversion of investors on expected asset returns.[3] In a similar vein, Ang, Chen, and Xing (2006) propose an equilibrium model based on Gul (1992)'s disappointment preferences in which investors demand an additional risk premium for holding stocks with high downside beta. Finally, Kelly (2009) and Ruenzi and Weigert (2011) investigate the impact of extreme downside risk and tail risk on the cross-section of expected stock returns. They find that investors demand additional compensation for stocks that are crash-prone, i.e. stocks that have particularly bad returns exactly when the market crashes.

Second, we contribute to the literature on the impact of liquidity risk on the cross-section of stock returns. Numerous studies investigate whether systematic liquidity risk is a priced factor. Pastor and Stambaugh (2003) find that stocks with high loadings on the market liquidity factor outperform stocks with low loadings by 7.5% annually. Acharya and Pedersen (2005) derive an equilibrium model for returns that includes the liquidity level and a stock's liquidity covariation with market liquidity and the market return. They find that liquidity risk is a priced factor in the cross-section of stock returns. In contrast to the latter, Hasbrouck (2009) raises doubt on this premium for liquidity risk. He finds that during a long historical sample (1926 to 2006), there is only weak evidence that liquidity risk is a priced factor. We contribute to the existing literature by investigating a new dimension of liquidity risk: a security's EDL risk.

Third, we extend the literature on the application of extreme value theory and copulas in

[2]Gul (1992) suggests a utility function where individuals place a greater weight on losses relative to gains. He develops an axiomatic approach of disappointment aversion preferences.

[3]Barberis and Huang (2001), in one of their model variants, study equilibrium firm-level stock returns when investors are loss averse over the fluctuations of the individual stocks in their portfolio. They predict a large value premium in the cross-section. Other models with loss averse investors include Benartzi and Thaler (1995) and Barberis, Huang, and Santos (2001).

finance. Despite their long history in statistics, multivariate extreme value theory has been applied to the analysis of financial markets only very recently. Longin and Solnik (2001) use extreme value theory to model the bivariate return distributions between different international equity markets and Rodriguez (2007) applies copulas to measure contagion. Focusing on risk management applications, Ané and Kharoubi (2003) propose to model the dependence structure of international stock index returns via parametric copulas and derive their tail dependence behavior. Poon, Rockinger, and Tawn (2004) present a general framework for identifying joint-tail distributions based on multivariate extreme value theory. They argue that the use of traditional dependence measures could lead to inaccurate portfolio risk assessment. Finally, Ruenzi and Weigert (2011) investigate extreme dependence structures between individual stocks and the market and find that extreme dependence structures are priced factors in the cross-section of stock returns. Up to now, extreme value theory has been applied to describe dependence patterns across different markets, different assets as well as individual stock returns and the market return. However, to the best of our knowledge, ours is the first paper to investigate extreme dependence structures between (i) individual stock liquidity and market liquidity, (ii) individual stock returns and market liquidity, and (iii) individual stock liquidity and the market return.

The rest of this paper is organized as follows. Section 2 provides an overview of the liquidity measure, the estimation of EDL risk and the development of EDL risk over time. Section 3 demonstrates that stocks with high EDL risk have high future returns. Section 4 performs robustness checks and Section 5 concludes.

2 Liquidity and EDL Risk

2.1 Liquidity

Liquidity is a broad concept with many different dimensions. In this study we focus on measuring the price impact when trading large amounts of shares. Due to the large sample period from 1968-2009 and the limited availability of market microstrucutre data (in particular before 1990), we have to rely on a low-frequency liquidity proxy for liquidity.

We follow Amihud (2002), Acharya and Pedersen (2005) and Menkveld and Wang (2011) and use the Amihud Illiquidity Measure (illiq) as our measure of illiquidity.[4] Illiq of stock i

[4]Goyenko, Holden, and Trzcinka (2009) suggest using either the Amihud Illiquidity Measure (illiq) or one of the effective spread measures divided by volume if a researcher wants to capture price impact. Hasbrouck (2009) finds that illiq correlates highest with market microstructure price impact measures.

in week t is defined as

$$\text{illiq}_t^i = \frac{1}{\text{days}_t^i} \sum_{d=1}^{\text{days}_t^i} \frac{|r_{td}^i|}{V_{td}^i}, \tag{1}$$

where r_{td}^i and V_{td}^i are respectively the return and dollar volume (in millions) on day d in week t and days_t^i is the number of valid observations in week t for stock i.[5] We use illiq_t^i as the illiquidity of stock i in week t if it has at least three valid return and dollar volume observations in week t.

There are two known problems with using illiq as a proxy for illiquidity. First, illiq can reach unrealistically high values for stocks with very low trading volume. Second, illiq is not stationary over the time period from 1968-2009. To solve these problems, we follow Acharya and Pedersen (2005) and define a normalized measure of illiquidity, c_t^i, by

$$c_t^i = \min(0.25 + 0.30 \cdot \text{illiq}_t^i \cdot P_{t-1}^m, 30) \tag{2}$$

where P_{t-1}^m is the ratio of the capitalizations of the market portfolio at the end of week $t-1$ and of the market portfolio at the end of July 1962. The P_{t-1}^m adjustment removes problems with regard to stationarity of illiq. In addition, by capping the illiquidity at a maximum value of 30%, we ensure that our results are not driven by extreme outliers of illiq.

Finally, to simplify the estimation of EDL risk (as discussed in section 2.2), we convert the normalized *illiquidity* into normalized *liquidity* via

$$d_t^i = -c_t^i. \tag{3}$$

The normalized liquidity measure d_t^i is very persistent. The average autocorrelation of d_t^i is around 0.89 at a weekly frequency. Thus, we focus on the innovations of the normalized liquidity measure

$$u_t = d_t^i - E_{t-1}(d_t^i) \tag{4}$$

of a stock when computing its EDL risk at week t. To calculate the expected normalized liquidity $E_{t-1}(d_t^i)$ for each stock i and week t, we fit an AR(5) time series model over the whole liquidity series of stock i. Hence,

$$E_{t-1}(d_t^i) = \hat{a}_0 + \hat{a}_1 \cdot d_{t-1}^i + \hat{a}_2 \cdot d_{t-2}^i + \hat{a}_3 \cdot d_{t-3}^i + \hat{a}_4 \cdot d_{t-4}^i + \hat{a}_5 \cdot d_{t-5}^i. \tag{5}$$

We then use the innovations of the normalized liquidity measure $u_t = d_t^i - E_{t-1}(d_t^i)$ for the

[5]The intuition behind this illiquidity measure is as follows. A stock is illiquid - that is, it has a high value of illiq_t^i - if the stock's price moves a lot in response to little volume.

computation of the EDL risk components (EDL_1 risk, EDL_2 risk, and EDL_3 risk) for stock i at week t as described in section 2.2.

2.2 Measuring EDL Risk

We measure the EDL risk components (EDL_1 risk, EDL_2 risk, and EDL_3 risk) by lower tail dependence coefficients. Intuitively, the lower tail dependence coefficient between two variables reflects the probability that a realization of one random variable is in the extreme lower tail of its distribution conditional on the realization of the other random variable also being in the extreme lower tail of its distribution. Formally, lower tail dependence λ_L is defined as

$$\lambda_L := \lambda_L(X_1, X_2) = \lim_{u \to 0+} P(X_1 \leq F_1^{-1}(u) | X_2 \leq F_2^{-1}(u)), \tag{6}$$

where $u \in (0,1)$ is the argument of the distribution function, i.e. $\lim_{u \to 0+}$ indicates the limit if we approach the left-tail of the distribution from above. If λ_L is equal to zero, the two variables are asymptotically independent in the lower tail.[6]

The lower tail dependence coefficient between two variables can be expressed in terms of a copula function $C : [0.1]^2 \mapsto [0,1]$.[7] Thus, a simple expression for λ_L in terms of the copula C of the bivariate distribution can be derived based on

$$\lambda_L = \lim_{u \to 0+} \frac{C(u,u)}{u}, \tag{7}$$

if F_1 and F_2 are continuous (McNeil, Frey, and Embrechts (2005)). The coefficient of lower tail dependence has closed form solutions for many parametric copulas. To allow for a flexible structure in modelling the bivariate dependence structure for the EDL risk components, we choose the Rotated-Joe/F-G-M/Joe-copula

[6] Similarly, the coefficient of upper tail dependence λ_U can be defined as

$$\lambda_U := \lambda_U(X_1, X_2) = \lim_{u \to 1-} P(X_1 \geq F_1^{-1}(u) | X_2 \geq F_2^{-1}(u)).$$

[7] Copula functions allow to isolate the description of the dependence structure of the bivariate distribution from the univariate marginal distributions. Sklar (1959) shows that all bivariate distribution functions $F(x_1, x_2)$ can be completely described based on the univariate marginal distributions F_1 and F_2 and a copula function C.

$$
\begin{aligned}
C(u_1, u_2; \Theta) &= w_1 \cdot (u_1 + u_2 - (u_1^{\theta_1} + u_2^{\theta_1} - u_1^{\theta_1} \cdot u_2^{\theta_1})^{1/\theta_1}) \\
&+ w_2 \cdot (u_1 u_2 (1 + \theta_2 (1 - u_1)(\overline{u}_2))) \\
&+ (1 - w_1 - w_2) \cdot (1 - ((\overline{u}_1)^{\theta_3} + (\overline{u}_2)^{\theta_3} - (\overline{u}_1)^{\theta_3} \cdot (\overline{u}_2)^{\theta_3})^{1/\theta_3}),
\end{aligned}
\tag{8}
$$

where $\overline{u} = 1 - u$ and Θ denotes the set of the copula parameters θ_i, $i = 1, 2, 3$ and the weights w_1 and w_2. This copula not only allows for asymptotic dependence in the lower tail, but also for asymptotic independence or asymptotic dependence in the upper tail.

We select the Rotated-Joe/F-G-M/Joe-copula based on results of Ruenzi and Weigert (2011), who show that this copula is selected most often in a horserace of 64 copula functions when describing the bivariate distribution of individidual asset returns and the market return.[8]

Our estimation approach for the lower tail dependence coefficients follows a two-step procedure. First, for each stock i and each week t we estimate the set of copula parameters Θ in the bivariate distribution of (i) individual liquidity and market liquidity , (ii) individual stock return and market liquidity, and (iii) individual liquidity and market return based on a 3-year horizon of weekly data.[9] The copula parameters Θ are estimated via the canonical maximum likelihood procedure of Genest, Ghoudi, and Rivest (1995).

Second, we compute the tail dependence coefficient $\hat{\lambda}_l$ implied by the estimated parameters $\hat{\Theta}$. For the Rotated-Joe/F-G-M/Joe-copula, the lower tail dependence coefficient $\hat{\lambda}_L$ is given by

$$
\hat{\lambda}_L = \hat{w}_1 \cdot 2 - 2^{1/\hat{\theta}_1}. \tag{9}
$$

For each stock i and week t, we calculate the lower tail dependence of (i) individual liquidity and market liquidity, (ii) individual stock return and market liquidity, and (iii) individual liquidity and market return. We refer the lower tail dependence coefficient in the distribution of (i) as EDL_1 risk (EDLR^1), (ii) as EDL_2 risk (EDLR^2) , and (iii) as EDL_3 risk (EDLR^3). As this procedure is repeated for each stock i and week t, we end up with a panel of tail dependence coefficients EDLR^1_{it}, EDLR^2_{it} and EDLR^3_{it} at the firm-week level. For a more detailed description of the estimation method, we refer the reader to Ruenzi and Weigert (2011).

[8] In unreported tests, we also perform the estimation procedure with other copula functions. Our estimation results for tail dependence coefficients remain almost unchanged.

[9] In computing the market return and market liquidity we exclude stock i, so the market return and market liquidity is slightly different for each stock's time series regression. This removes potential endogeneity problems when calculating lower tail dependence coefficients for each stock.

2.3 The Evolution of Aggregate EDL

Our sample consists of all common stocks (CRSP share codes 10 and 11) trading on the NYSE/AMEX between January 1, 1968 through December 31, 2009. For each firm i and each week t we estimate the EDL risk components (EDLR^1_{it}, EDLR^2_{it} and EDLR^3_{it}) based on weekly return- and liquidity data over a rolling window of 3 years (see section 2.2). EDL risk for stock i in week t is then defined as the sum of the EDL risk components:

$$\text{EDLR}_{it} = \text{EDLR}^1_{it} + \text{EDLR}^2_{it} + \text{EDLR}^3_{it}. \tag{10}$$

Using a rolling horizon of 3 years trades off two concerns: First, we need a sufficiently large number of observations to get reliable estimates for our EDL risk coefficients. Second, we want to account for time-varying EDL risk. Thus, very long estimation intervals may cause the estimates of EDL risk to be noisy. Since very small stocks show unrealistically high illiquidity levels, we exclude data for all weeks on which the stock's price is smaller than \$2. We retain the EDL risk estimates of all stocks in week t that have more than $156/2 = 78$ valid weekly return and liquidity observations during the last 3 years. Overall, there are $3,360,373$ firm-week observations with valid EDL risk. The number of firms in each year over our sample period ranges from $1,203$ to $2,176$ with an average of $1,858$.

We first investigate the development of aggregate EDL risk over time. We define aggregate EDL risk, $\text{EDLR}_{m,t}$, as the weekly cross-sectional, value-weighted, average of $\text{EDLR}_{i,t}$ over all stocks i in our sample. Panel A of Figure 1 plots the time series of $\text{EDLR}_{m,t}$.

[Insert Figure 1 about here]

Aggregate EDL risk remains relatively stationary over time. The graph does exhibit occasional spikes in $\text{EDLR}_{m,t}$ that roughly correspond to worldwide financial crises. The highest values in $\text{EDLR}_{m,t}$ occur during 1987-1989, the time period after Black Monday in October 1987, with the largest one-day percentage decline in US stock market history. Another spikes in aggregate EDL risk correspond to the financial crises of 1978-1979 (Second US Oil Crisis), 1997-1998 (Asian Financial Crisis), and 2007-2009 (Lehman Crisis). This suggests that $\text{EDLR}_{m,t}$ - similar to return correlations (Ang and Chen (2002)) and lower tail dependence in returns (Ruenzi and Weigert (2011)) - increases in times of financial crises.

In Panel B of Figure 1 we plot the time series of the separate aggregate EDL risk components. All time series are highly correlated with an average correlation of around 0.55. Interestingly, the graph displays different patterns in the behaviour of the EDL risk components during financial crises. In the 1987 (Black Monday) stock market crash, the spike in aggregate EDL risk is caused by increasing aggregate EDL_2 risk. However, the main drivers of the aggregate EDL risk spike in 2007-2009 are aggregate EDL_1 risk and aggregate EDL_3 risk.

We report value-weighted averages, medians, and standard deviations of aggregate EDL risk (with its components) for the whole sample and for 3-year subsamples from 1968 to 2009 in Table 1.

[Insert Table 1 about here]

Over the whole sample period, $\text{EDLR}_{m,t}$ has an average value of 0.30, a median of 0.27 and a standard deviation of 0.16. The period with the lowest aggregate EDL risk is 1983-1985 with an average of 0.19, while the highest average of 0.49 is reached during the period 1989-1991. We also document that all EDL risk components display similar statistical properties resulting in average values of $0.09 - 0.10$, medians of $0.09 - 0.08$, and standard deviations of $0.08 - 0.09$ over the whole sample.

Correlations among EDL risk and other security characteristics are displayed in Table 2.[10]

[Insert Table 2 about here]

We find that EDL risk is positively related to LTD in returns with a correlation coefficient coefficient of 0.31, market beta with a correlation of 0.13 and size with a correlation of 0.08. In addition, we find negative relations to past returns (correlation of -0.05), the illiquidity level (correlation of -0.06) and idiosyncratic volatility (correlation of -0.05). Interestingly, EDL risk is only slightly correlated to linear liquidity risk β_L, which provides first evidence that EDL risk is a different dimension of liquidity risk.

The separate EDL risk components display positive relationships (with correlations of 0.07, 0.10 and 0.31) among each others. The correlations between the separate EDL risk components with the linear liquidity risk counterparts are also positive (correlation of 0.08 between EDLR_1 and β_{L1}, correlation of 0.12 between EDLR_2 and β_{L2}, and correlation of 0.08 between EDLR_3 and β_{L3}). In addition, we find that EDL risk components are all positively related to LTD in returns and size, but negatively related to illiquidity and idiosyncrativ volatiltiy. In our later analysis, we will carefully take into account the impact of these correlations.

3 EDL Risk and Expected Returns

In the main part of the empirical analysis in this section we relate the EDL risk estimates at week t to portfolio and individual excess returns over the week $t + 1$.[11] We start by

[10] The exact procedure for the calculation of risk- and firm characteristics is described in Section 3.

[11] This procedure implicitly assumes that future returns are a good proxy for expected returns.

investigating univariate portfolio sorts based on EDL risk in section 3.1. We then perform bivariate portfolio sorts based on linear liquidity risk and EDL risk in 3.2. Thus, we explicitly control for linear liquidity risk exposure when determining a premium for EDL risk. In section 3.3, we document that the premium for EDL risk is robust controlling for different factor models. Finally, in section 3.4, we show that EDL risk is a determinant of the cross-section of stock returns controlling for different stock characteristics using Fama and MacBeth (1973) regressions.

3.1 Univariate Portfolio Sorts

To detect a premium for stock with strong EDL risk exposure, we first investigate univariate portfolio sorts. Each week t we sort stocks into five quintiles based on their past EDL risk over the last three years. We then investigate the equally-weighted average excess return over the risk free rate for these quintile portfolios over the following week $t+1$. Panel A of Table 3 reports these weekly quintile portfolio returns in column 2. We also report differences in average excess returns between quintile portfolio 5 (strong EDL risk) and quintile portfolio 1 (weak LTD risk).

[Insert Table 3 about here]

We find that stocks with strong EDL risk have significantly higher average returns than stocks with weak EDL risk. Stocks in the quintile with the weakest (strongest) EDL risk earn a weekly average excess return of 0.110% (0.178%). Thus, the return spread between quintile portfolio 1 and 5 is 0.068% per week, which is statistically significant at the 1% level. The return spread between stocks with strong EDL risk and stocks with weak EDL risk translates into an annual spread of 3.60% p.a.

Columns 3 and 4 of Panel A report past EDL- and linear liquidity risk (β_L) exposures. Similar as EDL risk, β_L risk is defined as the sum of the linear liquidity risk components β_{L1}, β_{L2}, and β_{L3}.[12]

[12]Following Acharya and Pedersen (2005), the linear liquidity risk components are defined as

$$\beta_{L1}(d_t^i, d_t^m) = \frac{\text{Cov}(d_t^i - E_{t-1}(d_t^i), d_t^m - E_{t-1}(d_t^m))}{\text{Var}(r_t^m - E_{t-1}(r_t^m) + (d_t^m - E_{t-1}(d_t^m)))}, \quad (11)$$

$$\beta_{L2}(r_t^i, d_t^m) = \frac{\text{Cov}(r_t^i, d_t^m - E_{t-1}(d_t^m))}{\text{Var}(r_t^m - E_{t-1}(r_t^m) + (d_t^m - E_{t-1}(d_t^m)))}, \quad (12)$$

$$\beta_{L3}(d_t^i, r_t^m) = \frac{\text{Cov}(d_t^i - E_{t-1}(d_t^i), r_t^m - E_{t-1}(r_t^m))}{\text{Var}(r_t^m - E_{t-1}(r_t^m) + (d_t^m - E_{t-1}(d_t^m)))}, \quad (13)$$

where r_t^i and d_t^i denote security i's return and normalized liquidity at time t, and r_t^m and d_t^m denote the market return and normalized market liquidity at time t. The linear liquidity risk components are estimated based on weekly data over a rolling horizon of 3 years.

There is significant cross-sectional dispersion in EDL risk and β_L risk. Average EDL risk ($\beta_L \cdot 100$ risk) in the lowest quintile is 0.06 (1.30), while it rises to 0.51 (2.95) for the highest quintile. The results indicate that on the portfolio level there is a strong positive correlation between EDL risk and linear liquidity risk exposure. Thus, strong EDL risk stocks may earn high returns because they have high β_L risk.[13]

In the last two columns of Panel A, we report the results of the univariate portfolio sorts in the time period from 1968 to 1987 (column 4) and the time period from 1988 to 2009 (column 5). The return spread for stocks with strong EDL risk and stocks with weak EDL risk highly differs during those two time periods. In the time period 1968-1987, the weekly spread between quintile portfolio 1 and 5 is only 0.025% (1.31% p.a.), which is not statistically significant at the 10% level. However, in the period 1988-2009 the weekly return spread increases to 0.107% (5.72% p.a.), which is statistically significant at the 1% level.

In Panels B-D of Table 3 we disentangle the univariate premium for EDL risk into its three different risk components. Each week t we sort stocks into five quintiles based on past EDL_1 risk (Panel B), EDL_2 risk (Panel C), and EDL_3 risk (Panel D) over the last three years. We then investigate equally-weighted average excess return over the risk-free rate for these quintile portfolios over the following week $t + 1$.

Panel B shows the relationship between past EDL_1 risk and weekly average returns. We do not find an increasing relationship. The weekly return spread between quintile portfolios 1 and 5 is only 0.002% (0.10% p.a.), which is far away from statistical significance.

Panel C documents an increasing relationship between EDL_2 risk and weekly average returns. Stocks in the quintile with the weakest (strongest) EDL_2 risk earn an weekly average excess return of 0.127% (0.188%). On average, stocks in quintile portfolio 5 outperform stocks in quintile portfolio 1 by significant 0.061% per week, which translates into an annual return spread of 3.22% p.a. We also show that the return premium for EDL_2 risk is increasing over time. The univariate premium for EDL_2 risk rises from 0.038% per week (2.00% p.a.) during 1968-1987 to a premium of 0.083% per week (4.41% p.a.) during 1988-2009. The respective premiums are statistically significant at the 10% level in the period 1968-1987 and statistically significant at the 1% level in the period 1988-2009.

Finally, we report the results of portfolio sorts for EDL_3 risk and average returns in Panel D. Stocks in the quintile with the weakest (strongest) EDL_3 risk earn a weekly average excess return of 0.123% (0.178%), which documents an increasing relationship between EDL_3 risk and average returns. The return spread between quintile portfolio 5 and quintile portfolio 1 is 0.055% per week (2.90% p.a.), which is statistically significant at the 1% level. Columns 4

[13] We wil control for linear liquidity risk exposure in portfolio double-sorts in section 3.2 and in multivariate Fama and MacBeth (1973)-regressions in section 3.4.

and 5 in Panel D show that this spread can be attributed to the time period from 1988-2009. While there is no significant return spread between stocks with strong EDL_3 risk and stocks with weak EDL_3 risk in the time period from 1968 to 1987, the premium in the period during 1988 to 2009 is large. During 1988-2009 stocks in quintile portfolio 5 outperform stocks in quintile portfolio 1 by 0.110% per week (5.88% p.a.), which is statistically significant at the 1% level.

In summary, the results from Table 3 provide first evidence that EDL risk is a determinant of the cross-section of expected stock returns. Stocks with strong EDL risk earn higher future returns than stocks with weak EDL risk. We find that the main drivers of the EDL risk premium are the EDL_2- and EDL_3 risk components. While we only find weak evidence for a premium for EDL risk during 1968-1987, the spread between stocks with strong EDL risk exposure and stocks with weak EDL risk exposure is statistically and economically highly significant during 1988-2009.

3.2 Bivariate Portfolio Sorts

The results of section 3.1 indicating a premium for EDL risk in the cross-section of stock returns could be driven by linear liquidity (β_L) risk exposure. Surprisingly, Table 2 shows that on the stock-level, EDL risk and β_L risk are only weakly correlated with a correlation coefficient of 0.04. However, Table 3 documents that on the portfolio-level an increase in average EDL risk also increases the average β_L risk of the stock portfolios. Thus, it is not clear whether the documented return premium in Table 3 can be attributed to EDL risk or β_L risk.

To disentangle the return premium of EDL risk from β_L risk, we now conduct dependent portfolio double sorts based on these variables. Each week t we form quintile portfolios based on their past β_L risk (and their respective β_L risk components in Panel B-D). Then, within each β_L risk quintile, we sort stocks into five portfolios based on EDL risk (and their respective EDL risk components in Panel B-D). Similar as above, both EDL risk and β_L risk are computed over the same three-year horizon. We then investigate equally-weighted average excess returns over the risk free rate for these 25 $\beta_L \times$ EDL risk portfolios over the following week $t+1$. We also report differences in average excess returns between quintile portfolio 5 (strong EDL risk) and quintile portfolio 1 (weak LTD risk) for all β_L risk quintiles.

[Insert Table 4 about here]

Panel A of Table 4 shows the results of the 25 $\beta_L \times$ EDL risk portfolios. In line with the results of Acharya and Pedersen (2005), we find that in all EDL risk quintiles, high β_L risk stocks outperform low β_L risk stocks. More importantly for our investigation, we also show that in all β_L risk quintiles stocks with strong EDL risk have higher average returns than stocks with weak EDL risk. The return difference between the weakest LTD quintile and the strongest LTD quintile within all beta quintiles is economically large and at least statistically significant at the 10% level. It ranges from 0.038% per week (2.00% p.a.) in β_L-quintile 2 up to 0.098% per week (5.23% p.a.) in the highest β_L-quintile. The average spread in excess returns amounts to 0.059% per week (3.11% p.a.), which is statistically significant at the 5% level. Hence, regular linear liquidity risk is different from EDL risk and cannot account for the reward earned by holding stocks with strong EDL risk.

The last two columns of Panel A report average excess returns of EDL risk portfolios controlling for the β_L risk portfolios in the time period from 1968 to 1987 (column 8) and the time period from 1988 to 2009 (column 9). In the time period 1968-1987 the weekly average spread between quintile portfolio 1 and 5 is only 0.022% (1.15% p.a.), which is not statistically significant at the 10% level. However, in the period 1988-2009 the weekly return spread increases to 0.092% (4.90% p.a.), which is statistically significant at the 5% level. Hence, the increase in the return premium for EDL risk after 1987 (as documented in Table 3) remains when we control for linear liquidity risk exposure.

In Panels B-D of Table 4 we report the results of dependent portfolio double sorts based on separate β_L risk- and EDL risk components. Similar as above, in a first step we form quintile portfolios sorted on β_{L1} risk (Panel B), β_{L2} risk (Panel C), and β_{L3} risk (Panel D). Then, within each quintile, we sort stocks into five portfolios based on EDL$_1$ risk (Panel B), EDL$_2$ risk (Panel C), and EDL$_3$ risk (Panel D). We then investigate the equally-weighted average excess return over the risk free rate for these 25 portfolios over the following week $t + 1$.

The results of the double sorts in Panel B-D of Table 4 confirm the results of the univariate sorts. Panel B documents that there is no return premium associated with EDL$_1$ risk exposure controlling for β_{L1} risk. Panel C shows that there exists an increasing relationship between EDL$_2$ risk and future weekly average returns controlling for β_{L2} risk. On average, stocks in the quintile with the lowest (highest) EDL$_2$ risk earn a weekly excess return of 0.127% (0.192%). This return premium amounts to 0.065% per week (3.44% p.a.), which is statistically significant at the 5% level. Finally, in Panel D we document an increasing relationship between EDL$_3$ risk and future weekly average returns controlling for β_{L3} risk. On average, stocks in the EDL$_3$ risk quintile portfolio 5 outperform stocks in the EDL$_3$ risk quintile portfolio 1 by 0.049% per week (2.58% p.a.). This spread is significant at the 10% level.

To summarize, based on double sorts we provide strong evidence that EDL risk is different from linear liquidity risk. We confirm the univariate results that the premium for EDL risk is economically and statistically significant, especially after 1987. Double sorts offer the advantage that they also allow us to detect potential non-linearities. However, in double sorts we can only control for one stock characteristic at a time. Thus, we now turn to a multivariate approach that allows us to examine the joint impact of different return and other characteristics of the firm that might have an impact on the cross-section of expected stock returns.

3.3 Factor Models

In sections 3.1 and 3.2 we provide evidence of a premium for EDL risk in the cross-section of stock returns based on univariate and bivariate portfolio sorts. We now proceed to analyze whether this premium is different from other risk- and firm characteristics (apart from linear liquidity risk) that are known to determine the cross-section of stock returns.

First, we investigate whether the premium for EDL risk can be explained by systematic risk factors in multivariate factor models. To do so, we perform risk-adjusted univariate portfolio sorts. Each week t we sort stocks into five quintiles based on their past EDL risk. Then we investigate the equally-weighted average risk-adjusted return over the risk-free rate for these quintile portfolios over the following week $t+1$. To risk-adjust the portfolio returns, we run a one-factor model adjusting returns for their exposure to the market factor (as in Sharpe (1964)), a Fama and French (1993) three-factor model that additionally corrects for the exposure to the size as well as the book-to-market factor, and a Carhart (1997) four-factor model, that additionally controls for the momentum factor.[14] Table 5 reports average weekly risk-adjusted returns. We also report differences in average risk-adjusted returns between quintile portfolio 5 (strong EDL risk) and quintile portfolio 1 (weak LTD risk).

[Insert Table 5 about here]

We find that all alphas from different factor models are increasing in EDL risk. The return spread between quintile 1 and quintile 5 for risk-adjusted returns ranges from 0.040% per week (2.10% p.a.) for the Fama and French (1993) alpha to 0.061% per week (3.22% p.a.) for the Carhart (1997) alpha. The spread is statistically significant at the 1% level for the CAPM- and the Carhart (1997)-adjusted returns and statistically significant at the 5% level for the Fama and French (1993)-adjusted returns. Columns 5 and 6 report risk-adjusted returns according to Carhart (1997)'s four-factor model in the time periods 1968-1987 and

[14] Daily market-, size-, book-to-market-, and momentum-factors are obtained from Kenneth French's Homepage. Based on these daily factor returns we calculate weekly factor returns.

1988-2009. We show that the risk-adjusted premium for EDL risk is economically and statistically significant during 1988-2009 (with a risk-adjusted return spread of 0.095% per week (5.06% p.a.), while there is no significant premium before.

We also check whether exposures to systematic risk factors other than the market, the Fama and French (1993)- and the Carhart (1997)-factors drive our results. To do so, we regress the time series of the return difference between EDL risk portfolio 5 and EDL risk portfolio 1 on various factors, which are shown to determine the cross-section of expected stock returns. Since most factors are only available on a monthly basis, we transform our weekly returns to a monthly time series and investigate risk-adjusted returns according to these factors. Table 6 reports the results.

[Insert Table 6 about here]

In Regression (1) we regress the return difference between EDL risk portfolio 5 and EDL risk portfolio 1 on the monthly four-factor model by Carhart (1997). We find that the return difference between EDL risk portfolio 5 and EDL risk portfolio loads significantly positive on the market factor and the book-to-market factor, while it loads negative on the size factor and the momentum factor. Confirming the results of Table 5, the risk-adjusted monthly alpha is 0.334% (4.08% p.a.), which is significant at the 1% level. In Regression (2), we additionally control for the Pastor and Stambaugh (2003)'s traded liquidity risk factor. As expected, the EDL risk return difference loads positive on this factor; however, this liquidity risk factor cannot explain the premium for EDL risk. Our results show that the monthly alpha is economically large and statistically significant at the 1% level. Regression (3) accounts for the Baker and Wurgler (2006) sentiment index orthogonalized with respect to a set of macroeconomic factors. The EDL risk return difference does not load on the sentiment index and the monthly alpha remains stable at 0.334% (4.08% p.a.), which is significant at the 1% level. In Regression (4), we additionally control for Bollerslev, Tauchen, and Zhou (2009)'s variance risk premium factor. The variance risk premium defined as the difference between implied and realized variance (based on S&P500 index options) is not able to explain the premium for EDL risk. In contrast, controlling for variance risk, the monthly alpha of the EDL risk return difference increases to 0.445% (5.47% p.a.) and is significant at the 1% level. In Regression (5), we replace the momentum factor with the Fama-French short- and long-term reversal factors. We find that in this setting the monthly alpha reduces to 0.213% (2.58% p.a.), but remains different from zero at a significance level of 5%. In Regression (6), we use an alternative factor model proposed by Chen, Novy-Marx, and Zhang (2011), consisting of the market factor, an investment factor and a return-on-equity-factor, to risk-adjust the returns of the EDL risk return difference. Controlling for these alternative factors, we document a monthly alpha of 0.237% (2.88% p.a.), which is statistically significant at the 5% level. Finally, Regressions (7) and (8) control for factors proposed by Cremers, Petajisto, Zitzewitz (2010), which contain various combinations of return differences between the S&P 500 and Russell 2000 and 3000 subindexes as well as the momentum factor. In our specifications, we use either four (Regression (7)) or six factors (Regression (8)) out of the ten proposed factors by Cremers, Petajisto, Zitzewitz (2010). We find that neither in Regression (7) nor in Regression (8), these factors can explain the return premium associated with EDL risk. In both regressions the monthly alpha is economically large and significant at the 1% level.

These results suggest that the premium for EDL risk is robust controlling for a wide array of alternative factor specifications. However, one must be careful in determining the cross-section of stock returns with factor-sensitivies alone. Daniel and Titman (1997) show that the return premiums for size and book-to-market do not arise because of the comovements of these stocks with pervasive factors. Instead, it is the firm characteristics themselves and not the covariance structure of returns that explain the cross-sectional variation of stock returns. To account for specific firm characteristics, we now proceed to perform Fama and MacBeth (1973) regressions on the firm level.

3.4 Fama-MacBeth Regressions

We run Fama and MacBeth (1973) regressions of excess firm returns in week $t+1$ on firm characteristics measured at week t on the individual firm level in the period from 1968-2009.[15] Panel A of Table 7 presents the regression results of future excess returns on EDL risk, β_L risk, regular market (return) beta β_R, lower tail dependence in returns (LTD), and a firm's illiquidity level (illiq). LTD is defined as the lower tail dependence coefficient between an individual firm's return and the market return. Ruenzi and Weigert (2011) show that assets with strong LTD exposure have high average returns.

[Insert Table 7 about here]

In Regression (1), we look at the univariate influence of EDL risk on excess returns and confirm that it carries an economically and statistically positive coefficient. In Regressions (2)-(6), we add linear liquidity risk β_L, market beta β_R, and LTD as explanatory variables.

[15] We are aware that this econometric procedure has the disadvantage that risk factors are estimated less precisely in comparison to using portfolios as test assets. However, Ang, Liu and Schwarz (2010) show analytically and demonstrate empirically that the smaller standard errors of risk factor estimates from creating portfolios does not necessarily lead to smaller standard errors of cross-sectional coefficient estimates. Creating portfolios destroys information by shrinking the dispersion of risk factors and leads to larger standard errors.

We find that EDL risk remains significantly positive at the 1% level in each specification. We also show that linear liquidity risk is a significant determinant of the cross-section of stock returns, while market beta does not have any explanatory power. Finally, in Regression (7), we add the illiquidity level as an explanatory variable. Consistent with the results of Amihud (2002) and Ruenzi and Weigert (2011), we document that illiquid stocks and stocks with strong LTD exposure have high future returns. The inclusion of the illiquidity level and LTD only marginally reduces the significance of EDL risk as an explanatory variable, which remains statistically significant at the 1% level. In terms of economic significance, our regression results indicate that a one standard deviation (i.e. 0.175) increase in EDL risk leads to an increase in future returns of approximately 0.79% p.a. controlling for linear liquidity risk, market beta, LTD in returns, and the firm's illiquidity level.

Panel B of Table 7 disentangles the reward for EDL risk into its separate components EDL_1 risk, EDL_2 risk, and EDL_3 risk. In Regressions (1)-(3), we investigate the univariate relationship of these components to excess returns. As already indicated in the univariate and bivariate portfolio sorts in section 3.1 and 3.2, the premium for EDL risk can be attributed to EDL_2 risk and EDL_3 risk, but not to EDL_1 risk. Controlling for the separate components of linear liquidity risk, market beta, LTD, and illiquidity, we find that both EDL_2 risk and EDL_3 risk remain positively significant at least at the 5% level in all regressions. Based on Regression (7) we find that a one standard deviation (i.e. 0.090) increase in $EDLR_2$ leads to an increase in future returns of approximately 1.10% p.a. and a one standard deviation (i.e. 0.089) increase in $EDLR_3$ leads to an increase in future returns of approximately 0.42% p.a.

We now expand our multivariate regression model and add other firm characteristics including size, book-to-market, momentum, idiosyncratic volatility, and a stock's lottery features captured by the maximum daily return over the past month (Bali, Cakici, and Whitelaw (2011)) as described in more detail below. We calculate size as the log of market capitalization and the book-to-market ratio as the fraction of book value (obtained from Compustat) and market capitalization in the month before week t.[16] We capture momentum effects (Jegadeesh and Titman (1993)) by including the past 1-year excess return of the firm. Ang, Hodrick, Xing, and Zhang (2006) and Ang, Hodrick, Xing, and Zhang (2009) find that idiosyncratic volatility has a negative impact on returns. Idiosyncratic volatility is calculated as the standard deviation of CAPM-residuals of daily firm returns in the month before week t. Finally, some recent papers document that investors have a preference for lottery-like assets. In this context, Bali, Cakici, and Whitelaw (2011) examine the role of extreme positive

[16]Since book-to-market ratios can get very large if prices are low, we winsorize all realizations of our independent variables at the 1% and 99% levels in order to avoid outliers driving our results. In unreported tests we find that our results do not hinge on this winsorization.

daily returns in the cross-sectional pricing of stocks. They find that stocks with the highest maximum daily return over the past one month period have low future returns. Thus, we control for the past maximum daily returns over the past one month before week t, which we denote as max. Regression results with the full set of control variables are displayed in Table 8.

[Insert Table 8 about here]

Regression (1) in Panel A of Table 8 includes a standard set of explanatory variables. It shows that book-to-market and momentum are positively related to future returns, while size is negatively related. We do not find a significant effect of market beta on future returns. In Regression (2), we add EDL risk as an explanatory variable. We find that the premium for EDL risk is statistically significant at the 1% level and is robust to controlling for market beta, size, book-to-market, and momentum. In Regressions (3)-(5), we expand the set of independent variables by including linear liquidity (β_L) risk, LTD, and the illiquidity level. We find that LTD is positvely related to future returns, while (β_L) risk and illiquidity are insignificant (although showing the expected sign). The inclusion of those variables slightly reduces the coefficient on EDL risk; however, it remains statistically significant at the 1% level. In Regressions (6) and (7), we expand our set of independent variables with idiosyncratic volatility and max. Consistent with the results of Ang, Hodrick, Xing, and Zhang (2006) and Bali, Cakici, and Whitelaw (2011), we document that stocks with high idiosyncratic volatility have low future returns (Regression (6)). This effect is reduced when including max as an explanatory variable (Regression (7)); max is now negatively related to future returns with statistical significance at the 1% level. In all specifications, EDL risk remains a robust explanatory variable for the cross-section of expected stock returns.

Finally, Panel B of Table 8 disentangles the reward for EDL risk into its separate components controlling for market beta, size, book-to-market, linear liquidity risk components, LTD, illiquidity, idiosyncratic volatility, and max. In all Regressions (1)-(7), we find that EDL_2 risk and EDL_3 risk are the main drivers for the importance of EDL risk. Both EDL_2 risk and EDL_3 risk are positively related to future expected returns and are statistically significant at least at the 10% level. Again, we do not find evidence of a premium for EDL_1 risk.

In summary, we provide strong evidence that EDL risk is priced in the cross-section of expected stock returns. The premium for EDL risk is robust to portfolio double sorts with regard to linear liquidity risk, is robust to different asset pricing factor models, and is robust to a wide list of firm characteristics, such as market beta, size, book-to-market, linear liquidity risk, LTD, illiquidity, idiosyncratic volatility, and max.

4 Robustness Checks

4.1 Weighting Scheme

One potential concern about the previous analysis is that each stock is treated equally in the portfolio sorts and factor regressions.[17] Thus, even though we exclude penny stocks, our results could be influenced by overweighting the importance of small stocks. Placing greater weight on snall firms could generate noise, and although it measures the effect of a typical firm, it might not reflect the effect of an average dollar.

Therefore, we now examine the results of univariate and bivariate value-weighted portfolio sorts based on EDL risk as well as linear liquidity risk and EDL risk. Results are presented in Table 9.

[Insert Table 9 about here]

Univariate value-weighted results for EDL risk are presented in Panel A of Table 9. Consistent with our previous results, column 2 shows that stocks in the quintile with the weakest (strongest) EDL risk earn an weekly average excess return of 0.071% (0.135%). The spread in average excess returns between quintile portfolio 1 and 5 is 0.064% per week, which is statistically significant at the 1% level. This return spread translates into an annual spread of 3.38% p.a.

Columns 3-5 report the results of univariate portfolio sorts based on EDL_1 risk, EDL_2 risk, and EDL_3 risk. Column 3 reveals that there is no increasing relationship between EDL_1 risk and future weekly average returns. However, we do find increasing relationships between EDL_2 risk and future returns as well as EDL_3 risk and future returns. Univariate sorts based on EDL_2 risk reveal that the return spread between stocks with strong EDL_2 risk and stocks with weak EDL_2 risk is 0.037% per week (1.94% p.a.), which is significant at the 10% level. Column 5 documents similar results for univariate sorts based on EDL_3 risk. Stocks in the quintile with the strongest EDL_3 risk quintile outperform stocks in the quintile with the weakest EDL_3 risk by statistically significant 0.047% per week (2.47% p.a.).

In Panel B of Table 9 we show the results of value-weighted double-sorts based on β_L risk and EDL risk, β_{L1} risk and EDL_1 risk, β_{L2} risk and EDL_2 risk as well as β_{L3} risk and EDL_3. We only report the average return across the linear liquidity risk (linear liquidity risk component) portfolios for the five EDL risk (EDL risk component) portfolios as well as the difference portfolio. As in the equal-weighted bivariate portfolio sorts, we find that the return premium for EDL risk cannot be explained by linear liquidity risk. Stocks in the

[17]Similar concerns can also be raised with respect to the Fama and MacBeth (1973) regression results as each observations enters the regressions with the same weight.

quintile with the weakest (strongest) EDL risk earn a weekly average excess return over all β_L risk quintiles of 0.108% per week (0.151% per week). The return spread between stocks with strong EDL risk and stocks with weak EDL risk is 0.043% per week (2.26% p.a.), which is significant at the 10% level. We find similar patterns for the double sorts based on EDL_2- and β_{L2} risk (column 4) as well as double sorts based on EDL_3- and β_{L3} risk (column 5).

Overall, using value-weighted portfolios rather than equal weighting does not change our main finding of significantly higher returns for stocks with strong EDL risk. This shows that our results are not driven by extreme returns of a handful of very small firms.

4.2 Regression Methods

Our multivariate regression evidence in Section 3.4 relies on Fama and MacBeth (1973) regressions with winsorized variables. We now perform several variations of this basic regression approach on the full set of independent variables for the full time period from 1968 – 2009. Results are presented in Table 10.

[Insert Table 10 about here]

In Regressions (1) and (2) we perform pooled OLS-regressions with time-fixed effects and standard errors clustered by stock. In Regressions (3) and (4) we perform panel data regressions with firm fixed effects. Finally, in Regressions (5) and (6) we regress excess returns on the independent variables via random-effect panel data regressions.

In Regressions (1), (3), and (5), we document that EDL risk is a highly significant explanatory factor for the cross-section of expected stocks returns independent of the specific regression setup. The point estimate for the influence of EDL risk is between 0.00115 and 0.0013 and higher than that in the Fama and MacBeth (1973) regressions in Section 3.4. In Regressions (2), (4), and (6), our results reveal that EDL_2 risk and EDL_3 risk are the main drivers for the importance of EDL risk independent of the specific regression setup. We do not find evidence for a positive impact of EDL_1 on future returns in any of the different regressions.

Hence, our results are not driven by the specific regression technique or by a certain dependence structure of the error terms.

5 Conclusion

The cross-section of expected stock returns reflects a premium for EDL risk. Stocks that are characterized by strong EDL risk earn significantly higher future returns than stocks with weak EDL risk. A trading strategy that is long in a portfolio consisting of the 20% stocks with the strongest EDL risk delivers an excess return which is 3.60% p.a. higher than that of a portfolio consisting of the 20% stocks with the weakest EDL risk.

We find that the high future returns earned by stocks with strong EDL risk cannot be explained by linear liquidity risk nor various risk- and firm characteristics. Controlling for linear liquidity risk, the average spread between stocks with strong EDL risk and weak EDL risk is significant 3.11% p.a. The return premium for EDL risk is robust to different factor model specifications (among others, the market model by Sharpe (1964), the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and an alternative three-factor model by Chen, Novy-Marx, and Zhang (2011)) as well as a large number of firm characteristics. EDL risk remains a statistically and economically significant explanatory variable when we control for size, book-to-market, momentum, LTD in returns, linear liquidity risk, idiosyncratic volatility, and lottery characteristics of a stock. Our results indicate that EDL risk is an important determinant of the cross-section of expected stock returns and that asset pricing models that rely on linear liquidity risk alone might be misspecified.

We find that the main drivers of the premium for EDL risk are EDL_2 risk (lower tail dependence in the distribution of individual stock returns and market liquidity) as well as EDL_3 risk (lower tail dependence in the distribution of individual stock liquidity and market return). Both EDL_2 risk and EDL_3 risk separately show significant return premiums. Moreover, we document that the premium for EDL risk has increased over time. During 1988-2009, a portfolio consisting of the 20% stocks with the strongest EDL risk delivers an excess return which is 5.72% p.a. higher than that of a portfolio consisting of the 20% stocks with the weakest EDL risk.

The fact that investors earn a premium for bearing EDL risk can have serious implications: If financial institutions do not have to bear the expected costs of a severe market downturn (e.g. because they expect to be bailed out in a severe crises), they might be inclined to invest in exactly those securities that are characterized by EDL risk in order to earn the associated premium we document. Such incentives would make those institutions even more vulnerable.

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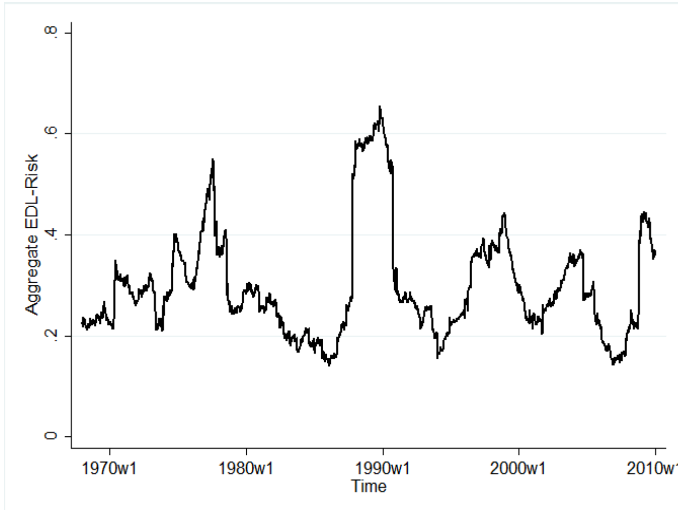
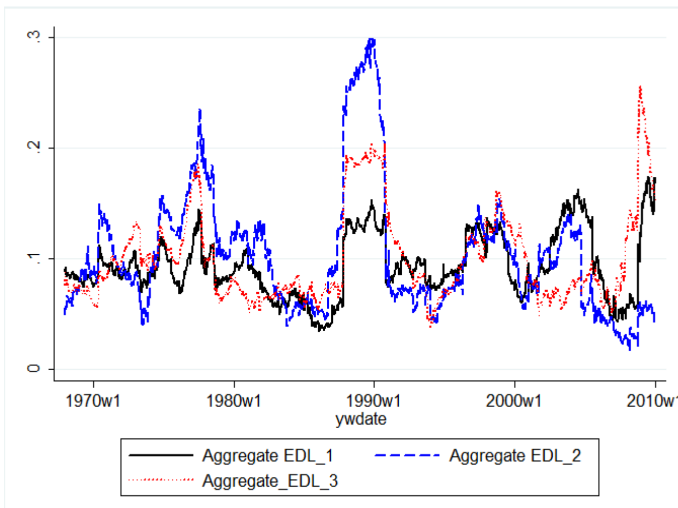
Figure 1: Aggregate EDL Risk Over Time (1968 - 2009)



(a) Panel A: Aggregate EDL risk over time



(b) Panel B: Components of aggregate EDL risk over time)

This figure displays the evolution of aggregate EDL risk with its different components over time. Aggregate EDL risk in week t is defined as the value-weighted average of EDL risk over all stocks i in our sample. Analogously, we define the aggregate EDL risk components (aggregate EDL_1 risk, aggregate EDL_2 risk, aggregate EDL_3 risk) in week t as the value-weighted average of the EDL risk components (EDL_1, EDL_2, EDL_3) over all stocks i in our sample. Panel A draws the evolution of aggregate EDL over time, Panel B shows the evolution of the different aggregate EDL-risk components. The sample period is from January 1968 to December 2009.

Table 1: Aggregate EDL Risk Over Time

Time Period	No. of Different Stocks	EDL Mean	EDL Median	EDL StDev	EDL_1 Mean	EDL_1 Median	EDL_1 StDev	EDL_2 Mean	EDL_2 Median	EDL_2 StDev	EDL_3 Mean	EDL_3 Median	EDL_3 StDev
1968 – 1970	1,558	0.25	0.23	0.18	0.09	0.08	0.10	0.09	0.09	0.09	0.07	0.07	0.09
1971 – 1973	2,056	0.28	0.29	0.17	0.09	0.09	0.09	0.08	0.09	0.07	0.11	0.10	0.09
1974 – 1976	2,105	0.34	0.34	0.18	0.09	0.09	0.10	0.13	0.13	0.08	0.11	0.11	10
1977 – 1979	2,034	0.35	0.36	0.17	0.10	0.09	0.08	0.15	0.16	0.10	0.11	0.10	0.08
1980 – 1982	2,064	0.26	0.27	0.16	0.08	0.09	0.08	0.11	0.12	0.10	0.07	0.07	0.07
1983 – 1985	2,033	0.19	0.19	0.14	0.06	0.06	0.08	0.06	0.06	0.07	0.07	0.07	0.07
1986 – 1988	1,922	0.35	0.26	0.16	0.08	0.06	0.08	0.15	0.13	0.08	0.12	0.08	0.09
1989 – 1991	1,775	0.47	0.54	0.19	0.11	0.13	0.09	0.19	0.22	0.08	0.16	0.19	0.10
1992 – 1994	1,781	0.23	0.23	0.13	0.09	0.09	0.08	0.06	0.07	0.06	0.07	0.08	0.08
1995 – 1997	2,039	0.30	0.30	0.16	0.11	0.10	0.08	0.10	0.10	0.08	0.10	0.10	0.08
1998 – 2000	2,200	0.33	0.35	0.17	0.10	0.11	0.08	0.11	0.11	0.09	0.13	0.13	0.09
2001 – 2003	1,794	0.28	0.27	0.15	0.11	0.10	0.09	0.10	0.10	0.08	0.07	0.07	0.07
2004 – 2006	1,711	0.26	0.27	0.14	0.11	0.13	0.08	0.07	0.05	0.07	0.08	0.08	0.08
2007 – 2009	1,670	0.28	0.23	0.14	0.09	0.06	0.08	0.04	0.03	0.05	0.15	0.14	0.10
1968 – 2009	5,461	0.30	0.27	0.16	0.09	0.09	0.09	0.10	0.09	0.08	0.10	0.08	0.08

This table reports value-weighted averages, medians and standard deviations of aggregate EDL risk and the components of aggregate EDL risk (aggregate EDL_1 risk, aggregate EDL_2 risk, aggregate EDL_3 risk) within 3-year subsamples and over the whole sample period from January 1968 to December 2009. We define aggregate EDL risk, $EDLR_{m,t}$, as the weekly cross-sectional, value-weighted, average of $EDLR_{i,t}$ over all stocks i in our sample. Analogously, we define aggregate EDL_1 risk, aggregate EDL_2 risk, and aggregate EDL_3 risk as the weekly cross-sectional, value-weighted, average of individual $EDLR^1_{it}$, $EDLR^2_{it}$, and $EDLR^3_{it}$ over all stocks i in our sample.

Table 2: Correlations

	EDLR	$EDLR_1$	$EDLR_2$	$EDLR_3$	β_L	β_{L1}	β_{L2}	β_{L3}	β_R	LTD	size	bm	mom	illiq	idio vola	max
EDLR	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
$EDLR_1$	0.70	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-	-
$EDLR_2$	0.60	0.10	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-
$EDLR_3$	0.69	0.31	0.07	1.00	-	-	-	-	-	-	-	-	-	-	-	-
β_L	0.04	0.03	-0.02	0.08	1.00	-	-	-	-	-	-	-	-	-	-	-
β_{L1}	0.02	0.08	-0.03	-0.02	0.45	1.00	-	-	-	-	-	-	-	-	-	-
β_{L2}	0.09	0.02	0.12	0.04	0.12	0.18	1.00	-	-	-	-	-	-	-	-	-
β_{L3}	0.04	0.03	-0.02	0.08	0.98	0.44	0.10	1.00	-	-	-	-	-	-	-	-
β_R	0.13	0.07	0.07	0.13	0.04	0.03	0.50	0.03	1.00	-	-	-	-	-	-	-
LTD	0.31	0.11	0.32	0.18	-0.07	-0.14	0.06	-0.07	0.40	1.00	-	-	-	-	-	-
size	0.08	0.04	0.02	0.11	-0.26	-0.44	-0.34	-0.25	-0.01	0.23	1.00	-	-	-	-	-
bm	0.03	0.04	-0.01	0.03	0.09	0.21	0.11	0.09	0.00	-0.08	-0.45	1.00	-	-	-	-
mom	-0.05	-0.05	0.02	-0.08	0.02	0.03	0.00	0.02	-0.03	-0.01	0.10	-0.31	1.00	-	-	-
illiq	-0.06	-0.03	-0.02	-0.08	0.24	0.42	0.28	0.24	-0.04	-0.20	-0.81	0.39	-0.15	1.00	-	-
idio vola	-0.05	-0.02	-0.03	-0.04	0.20	0.32	0.21	0.19	0.32	-0.12	-0.50	0.16	0.03	0.36	1.00	-
max	0.00	0.02	-0.03	0.03	0.12	0.20	0.11	0.11	0.23	-0.00	-0.28	0.14	-0.04	0.20	0.50	1.00

This table displays linear correlations between the independent variables used in this study. As independent variables we use EDL risk (EDLR), the components of EDL risk ($EDLR_1$, $EDLR_2$, $EDLR_3$)), linear liquidity risk (β_L), the components of linear liquidity risk (β_{L1}, β_{L2}, β_{L3}), market beta (β_R), lower tail dependence in returns (LTD), size (computed as the log of market capitalization), book-to-market value (bm), past yearly excess return (mom), illiquidity (illiq, computed as the capped Amihud ratio), idiosyncratic volatility (idio vola), and the maximum daily return over the past month (max). A detailed description of the computation of these variables is given in the main text. The sample period for all independent variables is from January 1968 to December 2009.

Table 3: Univariate Equal-weighted Portfolio Sorts: EDL Risk and Returns

Panel A: EDL risk

Portfolio	Return	EDLR	$Beta_L$ $(\cdot 100)$	Return (1968-1987)	Return (1988-2009)
1 Weak EDLR	0.110%	0.06	1.30	0.115%	0.105%
2	0.147%	0.17	2.03	0.127%	0.166%
3	0.184%	0.26	2.48	0.143%	0.222%
4	0.166%	0.35	2.68	0.124%	0.204%
5 Strong EDLR	0.178%	0.51	2.95	0.140%	0.212%
5 Strong - Weak	0.068%***	0.45***	1.65***	0.025%	0.107%***

Panel B: $EDLR_1$

Portfolio	Return	$EDLR_1$	$Beta_1$ $(\cdot 100)$	Return (1968-1987)	Return (1988-2009)
1 Weak $EDLR_1$	0.148%	0.00	0.01	0.130%	0.164%
2	0.159%	0.02	0.02	0.134%	0.183%
3	0.172%	0.08	0.02	0.137%	0.203%
4	0.161%	0.13	0.02	0.126%	0.193%
5 Strong $EDLR_1$	0.150%	0.22	0.03	0.126%	0.172%
5 Strong - Weak	0.002%	0.22***	0.02***	−0.004%	0.008%

Panel C: $EDLR_2$

Portfolio	Return	$EDLR_2$	$Beta_2$ $(\cdot 100)$	Return (1968-1987)	Return (1988-2009)
1 Weak $EDLR_2$	0.127%	0.01	0.13	0.106%	0.145%
2	0.171%	0.03	0.15	0.149%	0.192%
3	0.162%	0.08	0.16	0.141%	0.180%
4	0.171%	0.13	0.17	0.139%	0.200%
5 Strong $EDLR_2$	0.188%	0.21	0.18	0.144%	0.228%
5 Strong - Weak	0.061%**	0.20***	0.05***	0.038%*	0.083%***

Panel D: $EDLR_3$

Portfolio	Return	$EDLR_3$	$Beta_3$ $(\cdot 100)$	Return (1968-1987)	Return (1988-2009)
1 Weak $EDLR_3$	0.123%	0.00	0.76	0.121%	0.125%
2	0.149%	0.02	1.52	0.141%	0.157%
3	0.161%	0.07	2.33	0.125%	0.194%
4	0.182%	0.13	2.65	0.149%	0.211%
5 Strong $EDLR_3$	0.178%	0.21	3.33	0.115%	0.235%
5 Strong - Weak	0.055%***	0.21***	2.57***	−0.006%	0.110%***

This table reports equal-weighted average future returns, EDL risk- and $Beta_L$ risk characteristics of stocks sorted by past EDL risk (Panel A), $EDLR_1$ (Panel B), $EDLR_2$ (Panel C), and $EDLR_3$ (Panel D). Each week we rank stocks into quintiles (1-5) based on estimated EDL risk (or the respective EDL risk component) over the last three years and form equal-weighted portfolios at the beginning of each weekly period. The column labelled 'Return' reports the average return in excess of the one-month T-bill rate over the next week. The row labelled 'Strong - Weak' reports the difference between the returns of portfolio 5 and portfolio 1 with corresponding statistic significance level. The sample period is from January 1968 to December 2009. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 4: Dependent Equal-weighted Portfolio Sorts: Liquidity Beta Risk vs. EDL Risk

Panel A: β_L Risk and EDL Risk

Portfolio	1 Weak β_L	2	3	4	5 Strong β_L	Average	Avg. 68-87	Avg. 88-09
1 Weak EDLR	0.107%	0.088%	0.119%	0.137%	0.131%	0.117%	0.115%	0.118%
2	0.133%	0.120%	0.146%	0.178%	0.193%	0.154%	0.123%	0.181%
3	0.146%	0.147%	0.148%	0.175%	0.213%	0.166%	0.133%	0.196%
4	0.173%	0.144%	0.146%	0.195%	0.226%	0.177%	0.142%	0.209%
5 Strong EDLR	0.179%	0.126%	0.162%	0.181%	0.229%	0.175%	0.136%	0.211%
Strong-Weak	0.072%***	0.038%*	0.042%*	0.044%*	0.098%***	0.059%**	0.022%	0.092%**

Panel B: β_{L1} Risk and EDLR$_1$

Portfolio	1 Weak β_{L1}	2	3	4	5 Strong β_{L1}	Average	Avg. 68-87	Avg. 88-09
1 Weak EDLR$_1$	0.118%	0.135%	0.159%	0.193%	0.173%	0.156%	0.137%	0.173%
2	0.083%	0.131%	0.167%	0.193%	0.200%	0.155%	0.120%	0.186%
3	0.129%	0.139%	0.177%	0.157%	0.190%	0.159%	0.133%	0.182%
4	0.106%	0.143%	0.154%	0.209%	0.206%	0.163%	0.127%	0.196%
5 Strong EDLR$_1$	0.137%	0.133%	0.140%	0.149%	0.207%	0.153%	0.124%	0.180%
Strong-Weak	0.020%	−0.002%	−0.020%	−0.044%*	0.034%	−0.003%	−0.013%	0.007%

Panel C: β_{L2} Risk and EDLR$_2$

Portfolio	1 Weak β_{L2}	2	3	4	5 High β_{L2}	Average	Avg. 68-87	Avg. 88-09
1 Weak EDLR$_2$	0.139%	0.127%	0.145%	0.118%	0.105%	0.127%	0.106%	0.146%
2	0.179%	0.184%	0.174%	0.116%	0.132%	0.157%	0.142%	0.170%
3	0.137%	0.159%	0.189%	0.176%	0.179%	0.168%	0.144%	0.190%
4	0.137%	0.176%	0.166%	0.178%	0.191%	0.170%	0.132%	0.204%
5 Strong EDLR$_2$	0.191%	0.161%	0.188%	0.187%	0.232%	0.192%	0.144%	0.236%
Strong-Weak	0.052%**	0.033%	0.044%*	0.069%***	0.127%***	0.065%**	0.039%	0.090%**

Panel D: β_{L3} Risk and EDLR$_3$

Portfolio	1 Weak β_{L2}	2	3	4	5 Strong β_{L2}	Average	Avg. 68-87	Avg. 88-09
1 Weak EDLR$_3$	0.123%	0.103%	0.127%	0.123%	0.171%	0.129%	0.126%	0.133%
2	0.151%	0.119%	0.121%	0.191%	0.192%	0.155%	0.132%	0.175%
3	0.144%	0.148%	0.148%	0.170%	0.193%	0.161%	0.129%	0.190%
4	0.160%	0.146%	0.166%	0.186%	0.201%	0.172%	0.144%	0.198%
5 Strong EDLR$_3$	0.167%	0.134%	0.144%	0.193%	0.239%	0.178%	0.124%	0.227%
Strong-Weak	0.044%*	0.031%*	0.018%	0.070%***	0.068%**	0.049%*	−0.002%	0.094%***

This table reports equal-weighted average future returns of 25 portfolios sorted by past linear liquidity risk (and linear liquidity risk components) and past EDL risk (and EDL risk components), respectively. First, we form quintile portfolios sorted on linear liquidity risk. Then, within each linear liquidity risk quintile, we sort stocks into five equal-weighted portfolios based on EDL risk. Panel A displays the results of the 25 β_L risk - EDL risk sorts, Panel B shows the results of the 25 β_{L1} - EDLR$_1$ sorts, Panel C shows the results of the 25 β_{L2} - EDLR$_2$ sorts and Panel D shows the results of the 25 β_{L3} - EDLR$_3$ sorts. The row labelled 'Strong - Weak' reports the difference between the returns of portfolio 5 and portfolio 1 in each beta quintile with corresponding statistic significance level. The sample period is from January 1968 to December 2009. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 5: Univariate Equal-weighted Portfolio Sorts: EDL Risk and Alphas

Portfolio	CAPM-Alpha	FF-Alpha	CAR-Alpha	CAR-Alpha (68-87)	CAR-Alpha (88-09)
1 Weak EDLR	0.030%	−0.019%	−0.006%	0.035%	−0.029%
2	0.061%	0.007%	0.024%	0.039%	0.026%
3	0.095%	0.036%	0.059%	0.057%	0.076%
4	0.073%	0.012%	0.042%	0.041%	0.057%
5 Strong EDLR	0.081%	0.021%	0.055%	0.059%	0.066%
Strong-Weak	0.051%***	0.040%**	0.061%***	0.024%	0.095%***

This table reports equal-weighted average alphas of stocks sorted by past EDL Risk. Each year we rank stocks into quintiles (1-5) and form equal-weighted portfolios at the beginning of each annual period. The column labelled 'CAPM-Alpha' reports the average weekly future alpha with regard to Sharpe (1964)'s capital asset pricing model. The column labelled 'FF-Alpha' reports average weekly future alpha with regard to Fama and French (1993)'s three factor model. In the column labelled 'CAR-Alpha', we report the average weekly future alpha with regard to Carhart (1997)'s four factor model. In the last two columns, we report the average weekly future Carhart (1997) alpha in the time period from 1968-1987 and 1988-2009. The row labelled 'Strong - Weak' reports the difference between the alphas of portfolio 5 (Strong LTD) and portfolio 1 (Weak LTD) with corresponding statistic significance level. The sample period is from January 1968 to December 2009. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 6: EDL Risk and Returns: Factor Models

	(1) ret-diff	(2) ret-diff	(3) ret-diff	(4) ret-diff	(5) ret-diff	(6) ret-diff	(7) ret-diff	(8) ret-diff
Marketrf	0.124***	0.102***	0.124***	0.0970***	0.151***	0.114***		
	(6.52)	(5.32)	(6.51)	(3.26)	(7.49)	(5.66)		
SMB	-0.101***	-0.108***	-0.101***	-0.192***	-0.0965***			
	(-3.87)	(-4.26)	(-3.86)	(-5.49)	(-3.22)			
HML	0.0479*	0.000377	0.0478*	-0.0167	0.0929***			
	(1.66)	(0.01)	(1.65)	(-0.40)	(2.75)			
MOM	-0.128***	-0.0993***	-0.128***	-0.0683***			-0.0757***	-0.140***
	(-7.03)	(-5.20)	(-7.03)	(-2.74)			(-3.91)	(-5.97)
PS Liqui		0.0816***						
		(3.49)						
Sent Index			0.0000655					
			(0.08)					
Var Risk				-0.000191				
				(-0.03)				
Rev Short					-0.000618			
					(-0.02)			
Rev Long					0.00346			
					(0.09)			
Inv						0.0866*		
						(1.66)		
Roe						-0.0138		
						(-0.53)		
s5rf							0.135***	
							(6.30)	
r2s5							-0.143***	
							(-5.25)	
r3vr3g							0.0496	
							(1.44)	
rms5								0.0126
								(0.17)
r2rm								-0.274***
								(-4.49)
s5vs5g								0.00149
								(0.02)
rmvrmg								-0.0991
								(-1.27)
r2vr2g								0.0875
								(1.07)
constant	0.00334***	0.00299***	0.00334***	0.00445***	0.00213**	0.00237**	0.00371***	0.00500***
	(4.04)	(3.64)	(4.02)	(2.97)	(2.49)	(2.53)	(4.11)	(4.44)
N	504	492	504	228	504	456	372	287
R^2	0.196	0.159	0.196	0.201	0.116	0.073	0.210	0.202

This table lists OLS-regression results of a trading strategy based on the difference of past strong EDL (quintile 5) and past weak EDL (quintile 1) on different factor models. As factors we include Marketrf, SMB, HML, and MOM of the four-factor model by Carhart (1997), the Pastor and Stambaugh (2003)'s traded liquidity risk factor (PS Liqui), the Baker and Wurgler (2006) sentiment index (Sent Index), the variance risk factor of Bollerslev, Tauchen, and Zhou (2009) (Var Risk), a short- and long-term reversal factor (Rev Short and Rev Long), an investment factor (Inv) and a return-on-equity factor (Roe) proposed by Chen, Novy-Marx, and Zhang (2011), and seven factors of Cremers, Petajisto, Zitzewitz (2010) which contain various combinations of return differences between the S&P 500 and Russell 2000 and 3000 subindexes (s5rf, r2s5, r3vr3g, rms5, r2rm, s5vs5g, rmvrmg, and r2vr2g). Portfolios are rebalanced weekly. The sample period is from January 1968 to December 2009. t statistics are in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 7: Fama MacBeth Regressions - Basic Model

Panel A: EDL risk

	(1) return	(2) return	(3) return	(4) return	(5) return	(6) return	(7) return
EDLR	0.00122*** (2.98)	0.00118*** (2.92)	0.00113*** (3.46)	0.00098*** (2.85)	0.0011*** (3.36)	0.00082*** (2.69)	0.00086*** (2.90)
β_L		0.00135* (1.82)			0.00176** (2.53)	0.00194*** (2.83)	0.0019*** (2.67)
β_R			-0.00014 (-0.36)		-0.00015 (-0.38)	-0.00028 (-0.69)	-0.00032 (-0.77)
LTD				0.00094 (1.15)		0.00138** (2.47)	0.00183*** (3.60)
Illiq							0.00213** (2.12)
constant	0.00120*** (2.45)	0.00118 ** (23.53)	0.00137*** (4.59)	0.00094** (2.26)	0.00136*** (4.55)	0.00121*** (3.84)	0.00080** (2.42)
R^2	0.003	0.005	0.02	0.008	0.02	0.03	0.03

Panel B: EDL Risk Components

	(1) return	(2) return	(3) return	(4) return	(5) return	(6) return	(7) return
$EDLR_1$	-0.0000 (-0.04)			-0.00050 (-0.91)	-0.00067 (-1.29)	-0.00069 (-1.46)	-0.00045 (-0.97)
$EDLR_2$		0.00266*** (3.57)		0.00261*** (3.53)	0.00276*** (3.76)	0.00240 *** (3.78)	0.00232*** (3.58)
$EDLR_3$			0.00189** (2.56)	0.0016 ** (2.36)	0.00150 ** (2.41)	0.00112** (2.14)	0.00091** (1.80)
β_{L1}					0.42021 * (1.66)	0.43069* (1.80)	0.32116 (1.28)
β_{L2}					0.29289 (1.24)	0.25580* (1.82)	0.24088 ** (1.72)
β_{L3}					0.00093 (1.48)	0.00115 (1.87)	0.00126 ** (1.72)
β_R						-0.00030 (-0.79)	-0.0003 (-0.90)
LTD						0.00145*** (2.79)	0.00168*** (3.38)
Illiq							0.00136 (1.37)
constant	0.00156*** (3.03)	0.001279** (2.42)	0.00135*** (2.70)	0.00113** (2.32)	0.00125 *** (3.08)	0.00110 *** (3.60)	0.00086*** (2.63)
R^2	0.001	0.002	0.002	0.005	0.02	0.03	0.04

Table 7: continued

This table displays the results of Fama and MacBeth (1973) regressions of weekly excess returns over the risk free rate on EDL risk, β_L, market beta (β_R), LTD in returns and illiq (Panel A). Panel B displays the results of Fama and MacBeth (1973) regressions of weekly excess returns over the risk free rate on EDLR_1, EDLR_2, EDLR_3, β_{L1}, β_{L2}, β_{L3}, β_R, LTD in returns and illiq. The independent variables are winsorized at the 1% level and at the 99% level. The sample period is from January 1968 to December 2009. t statistics are in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 8: Fama MacBeth Regressions - Full Model

Panel A: EDL risk

	(1) return	(2) return	(3) return	(4) return	(5) return	(6) return	(7) return
β_R	-0.0000 (-0.24)	-0.0001 (-0.36)	-0.00015 (-0.39)	-0.00029 (-0.75)	-0.00034 (-0.87)	-0.00007 (-0.21)	-0.00002 (-0.08)
Size	-0.00011 (-1.59)	-0.00013* (-1.83)	-0.00013* (-1.85)	-0.00016** (-2.26)	-0.00009 (-1.12)	-0.00019*** (-2.65)	-0.00020*** (-2.86)
BM	0.00062*** (4.58)	0.00061*** (4.53)	0.00060 *** (4.46)	0.00060*** (4.46)	0.00064*** (4.60)	0.0005*** (4.16)	0.00059*** (4.39)
Mom	0.00188*** (5.20)	0.00192*** (5.37)	0.00191*** (5.34)	0.00192*** (5.38)	0.00198*** (5.51)	0.00204*** (5.79)	0.0020*** (5.89)
EDLR		0.00097*** (3.81)	0.00097*** (3.78)	0.00084*** (3.27)	0.00074*** (2.88)	0.00063** (2.48)	0.00063** (2.45)
β_L			0.00056 (0.85)	0.00062 (0.94)	0.00120 (1.61)	0.00125* (1.68)	0.00133 * (1.78)
LTD				0.00141*** (3.13)	0.00151*** (3.32)	0.00128*** (2.85)	0.00130*** (2.90)
Illiq					0.00056 (0.59)	0.00042 (0.45)	0.00040 (0.43)
Idio Vola						-0.01645** (-2.28)	-0.00249 (-0.36)
Max							-0.0151*** (-8.12)
constant	0.00299** (2.01)	0.00312** (2.10)	0.00318** (2.13)	0.00357** (2.42)	0.00210 (1.19)	0.0046*** (2.94)	0.00492*** (3.12)
R^2	0.04	0.04	0.05	0.05	0.05	0.06	0.06

Table 8: Continued

Panel B: EDL Risk Components

	(1) return	(2) return	(3) return	(4) return	(5) return	(6) return	(7) return
β_R	-0.0000 (-0.24)	-0.00015 (-0.39)	-0.00012 (-0.31)	-0.00017 (-0.45)	-0.00014 (-0.39)	-0.00033 (-0.88)	0.00002 (0.08)
Size	-0.00010 (-1.53)	-0.00012* (-1.78)	-0.00012* (-1.75)	-0.00013* (-1.85)	-0.0001* (-1.74)	-0.00008 (-1.09)	-0.00020*** (-2.82)
BM	0.00061*** (4.52)	0.00063*** (4.67)	0.00061*** (4.50)	0.00061*** (4.55)	0.00060*** (4.50)	0.00064*** (4.63)	0.00059*** (4.40)
Mom	0.0018*** (5.25)	0.00188*** (5.20)	0.00191*** (5.32)	0.00192*** (5.36)	0.00195*** (5.50)	0.00202*** (5.66)	0.00210*** (6.00)
EDLR_1	-0.00011 (-0.26)			-0.00030 (-0.71)	-0.00034 (-0.79)	-0.00037 (-0.84)	-0.00044 (-0.98)
EDLR_2		0.00255*** (4.27)		0.00254*** (4.25)	0.00254*** (4.10)	0.00208*** (3.28)	0.00197*** (3.18)
EDLR_3			0.00130*** (2.97)	0.00120*** (2.72)	0.00115*** (2.64)	0.00101** (2.26)	0.00077* (1.75)
β_{L1}					0.05391 (0.24)	0.32581 (1.32)	0.46344* (1.89)
β_{L2}					0.1555 (1.20)	0.15470 (1.21)	0.10172 (0.83)
β_{L3}					0.00044 (0.65)	0.00075 (0.96)	0.00070 (0.90)
LTD						0.00131*** (2.88)	0.0010** (2.41)
Illiq						0.00025 (0.27)	0.00009 (0.10)
Idio Vola							-0.00357 (-0.52)
Max							-0.01561*** (-8.38)
constant	0.00292** (1.96)	0.00306** (2.06)	0.003144** (2.12)	0.00312** (2.10)	0.00297** (2.01)	0.00204 (1.17	0.00487*** (3.12)
R^2	0.04	0.04	0.04	0.05	0.05	0.06	0.06

Table 8: continued

This table displays the results of Fama and MacBeth (1973) regressions of weekly excess returns over the risk free rate on market beta (β_R), Size (log of market capitalization), book-to-market ratio (BM), the past 12-month excess returns (Mom), EDL risk, β_L, LTD in returns, illiq, idiosyncratic volatility and the maximum daily return over the past one year (max) (Panel A). Panel B displays the results of Fama and MacBeth (1973) regressions of weekly excess returns over the risk free rate on market beta (β_R), Size (log of market capitalization), book-to-market ratio (BM), the past 12-month excess returns (Mom), EDLR_1, EDLR_2, EDLR_3, β_{L1}, β_{L2}, β_{L3}, β_R, LTD in returns, illiq, idiosyncratic volatility, and the maximum daily return over the past one year (max). The independent variables are winsorized at the 1% level and at the 99% level. The sample period is from January 1968 to December 2009. t statistics are in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 9: Value-weighted Portfolio Sorts: EDL Risk and Returns

Panel A: Univariate Portfolio Sorts

Portfolio	Return EDLR	Return $EDLR_1$	Return $EDLR_2$	Return $EDLR_3$
1 Weak	0.071%	0.125%	0.078%	0.073%
2	0.091%	0.093%	0.125%	0.074%
3	0.129%	0.120%	0.105%	0.121%
4	0.109%	0.121%	0.112%	0.125%
5 Strong	0.135%	0.108%	0.115%	0.120%
5 Strong - Weak	0.064%***	−0.017%	0.037%*	0.047%**

Panel B: Bivariate Portfolio Sorts

Portfolio	Return EDLR	Return $EDLR_1$	Return $EDLR_2$	Return $EDLR_3$
1 Weak	0.108%	0.156%	0.086%	0.102%
2	0.135%	0.136%	0.125%	0.125%
3	0.138%	0.139%	0.112%	0.142%
4	0.153%	0.163%	0.133%	0.157%
5 Strong	0.151%	0.131%	0.136%	0.161%
5 Strong - Weak	0.043%*	−0.025%	0.050%*	0.059%**

This table reports value-weighted univariate (Panel A) and bivariate portfolio sorts (Panel B). In Panel A we rank stocks into quintiles (1-5) based on estimated past EDL risk (or the respective EDL risk component) over the last three years and form value-weighted portfolios at the beginning of each weekly period. In Panel B of Table 9 we show the results of value-weighted double-sorts on β_L risk and EDL risk, β_{L1} risk and EDL_1 risk, β_{L2} risk and EDL_2 risk as well as β_{L3} risk and EDL_3. We only report the average across the linear liquidity risk (linear liquidity risk component) portfolios for the five EDL risk (EDL risk component) portfolios as well as the difference portfolio. The row labelled 'Strong - Weak' reports the difference between the returns of portfolio 5 and portfolio 1 with corresponding statistic significance level. The sample period is from January 1968 to December 2009. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 10: Different Regression Methods

Regression	(1)	(2)	(3)	(4)	(5)	(6)
EDLR	0.00115***		0.00119***		0.00133***	
	(6.17)		(5.27)		(5.89)	
$EDLR_1$		-0.00081**		-0.00006		-0.00005
		(-2.32)		(-1.21)		(-1.12)
$EDLR_2$		0.00239***		0.00312***		0.00317***
		(6.20)		(6.97)		(7.14)
$EDLR_3$		0.00231***		0.00191***		0.00201***
		(6.20)		(6.32)		(6.12)
Controls	yes	yes	yes	yes	yes	yes
Method	ols	ols	panel	panel	panel	panel
Windsorized	yes	yes	yes	yes	yes	yes
Year Effects	yes	yes	yes	yes	yes	yes
Firm Effects	no	no	fixed	fixed	random	random
Clustered SE	firm	firm	no	no	no	no
R^2	0.183	0.183	0.227	0.227		

This table reports regressions results of excess returns on firm- and risk characteristics from using various regression techniques. The independent variables are the same as in Regression (7) of Table 8. We only display the results for the coefficient estimates for the impact of EDL risk and EDL risk components. All other variables are included in the regression but suppressed in the table. In Regressions (1) and (2), we perform pooled OLS-regressions with time-fixed effects and standard errors clustered by stock. In Regressions (3) (4), we perform panel data regressions with firm fixed effects. Finally, in Regressions (5) and (6), we regress excess returns on the independent variables via a random-effect panel data regression. The sample period is from January 1968 to December 2009. t-statistics are in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.