

Extreme Downside Liquidity Risk

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Abstract

We merge the literature on downside return risk with that on systematic liquidity risk and introduce the concept of extreme downside liquidity (EDL) risk. We show that the cross-section of expected stock returns reflects a premium for EDL risk. Strong EDL risk stocks deliver a risk premium of more than 4% p.a. as compared to weak EDL risk stocks. The effect is more pronounced after the market crash of 1987. It is not driven by linear liquidity risk, downside liquidity risk or extreme downside return risk, and it cannot be explained by other firm characteristics or other systematic risk factors.

Keywords: Asset Pricing, Crash Aversion, Downside Risk, Liquidity Risk, Tail Risk

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1 Introduction

The recent empirical asset pricing literature documents that investors care about the systematic downside- and crash-exposure of stock returns and shows that stocks with such exposures earn a significant risk-premium (e.g., Ang et al., 2006; Kelly and Jiang, 2014; and Chabi-Yo et al., 2017). At the same time, the theoretical literature shows that investors should care about the systematic component of liquidity risk and there are successful attempts to show empirically that systematic liquidity risk also bears a premium in the cross-section of returns (e.g., Pastor and Stambaugh, 2003, and Acharya and Pedersen, 2005). The aim of our paper is to merge these two important strands of the literature for the first time.

The starting point of our paper is the conjecture that investors are less concerned about systematic liquidity risk during normal market conditions than during periods of market stress like return crashes or periods of extreme illiquidity. For example, investors probably care less about how a specific stock's liquidity co-moves with the liquidity of other stocks when markets are relatively calm and when they face no urgent trading needs. However, stocks that suddenly become very illiquid exactly during market crises (e.g., during the liquidity crisis of September 2008) are very unattractive, while assets that still remain relatively liquid in times of market stress are very attractive assets to hold. This is particularly true for institutional investors that might be subject to asset fire sale problems or might strongly depend on funding liquidity conditions. As shown in the theoretical model by Brunnermeier and Pedersen (2009), liquidity tends to be fragile and is characterized by sudden systemic droughts of extreme magnitude. The anticipation of such events should lead investors to demand a premium for holding stocks whose liquidity is particularly sensitive to them.

In this paper, we introduce the concept of extreme downside liquidity (EDL) risk and show that stocks with high levels of EDL risk bear an economically large and statistically significant risk premium of roughly 4% per year which is neither subsumed by extreme downside return (EDR) risk (as in Kelly and Jiang, 2014, or Chabi-Yo et al., 2017) nor by linear systematic liquidity risk (as in Pastor and Stambaugh, 2003, or Acharya and Pedersen,

2005). Our empirical approach is closely related to 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 (scaled) correlation of an asset's liquidity to market liquidity, (ii) the (scaled) correlation of an asset's return to market liquidity, and (iii) the (scaled) correlation of an asset's liquidity to the market return. However, we want to focus on times of market stress and when focusing on extreme events (e.g. in liquidity and returns), linear correlations fail to measure increased dependence in the tails of the distribution (see Embrechts et al., 2002). Hence, the liquidity-adjusted CAPM cannot account for a stock's EDL risk and, as a result, might be misspecified if investors care especially about extreme joint realizations in liquidity and returns, as hypothesized in this paper. Thus, we use the method to capture EDR risk based on lower tail dependencies between stock and market returns introduced in Chabi-Yo et al. (2017) and Weigert (2016) and apply it to liquidity to capture EDL risk.¹ Like Acharya and Pedersen (2005) for linear liquidity risk, in doing so we distinguish three components of extreme downside liquidity risk (EDL risk₁, EDL risk₂, and EDL risk₃):

- (i) Clustering in the lower left tail of the bivariate distribution between individual stock liquidity and market liquidity (EDL risk₁): During extreme market liquidity downturns, funding liquidity is often reduced as well (e.g., margin requirements may increase; see Brunnermeier and Pedersen, 2009). During those times, investors are often forced to liquidate assets and realize additional liquidity costs. Hence, strong exposure to EDL risk₁ increases liquidity costs at a time when it is likely that an investor's wealth has decreased.
- (ii) Clustering in the lower left tail of the bivariate distribution between the individual stock return and market liquidity (EDL risk₂): 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 risk₂, such liquidations will occur in

¹For a theoretical motivation of using lower tail dependence coefficients in asset pricing, see Chabi-Yo et al. (2017).

times of extreme market liquidity downturns. Liquidation in those times also 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 risk₃): In times of market return crashes, institutional investors (such as mutual fund managers) are often forced to sell because their investors withdraw funds (Coval and Stafford, 2007) or financial intermediaries withdraw from providing liquidity (Brunnermeier and Pedersen, 2009). If a selling investor holds securities with strong EDL risk₃, she will suffer from high transaction costs at the precise moment when her wealth has already dropped and additional losses are particularly painful.

We capture the three distinct EDL risk components based on bivariate extreme value theory and copulas, using 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. Furthermore, closely following Acharya and Pedersen (2005), 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, liquidity-crash-averse investors, who are particularly interested in insuring against such extreme events, will require a premium for holding those stocks.

As our main liquidity proxy we use the Amihud (2002) Illiquidity Ratio.² Using weekly data from 1963 to 2012 we estimate lower tail dependence coefficients for (i) individual stock liquidity and market liquidity (EDL risk₁), (ii) individual stock return and market liquidity

²We also employ several other low-frequency and high-frequency liquidity measures in robustness checks. Our results remain stable across the different proxies; see Section 4.1.

(EDL risk₂), and (iii) individual stock liquidity and the market return (EDL risk₃) for each stock i and week t in our sample. Aggregate EDL risk (defined as the value-weighted average of EDL risk over all stocks in the sample) peaks during times of financial crises, such as around 1978-1979 (Second U.S. Oil Crisis), after 1987 (Black Monday Stock Market Crash), between 1997 and 1998 (Asian Financial Crisis), as well as in the years of the U.S. subprime crisis starting in 2007.

We then relate stocks' EDL risk (and the EDL risk components) to future returns. Our asset pricing tests—based on portfolio sorts, factor regressions, and Fama and MacBeth (1973) regressions on the individual firm level—are completely out-of-sample and focus on the relationship between past EDL risk exposure and future excess returns. We document that there exists a positive impact of EDL risk on the cross-section of average future returns. From 1969 to 2012, a portfolio that is long in stocks with strong EDL risk and short in stocks with weak EDL risk yields a significant average excess return of 4.00% p.a. We confirm that the premium for EDL risk is not explained by other risk- and firm characteristics. Hence, our results suggest that EDL risk is an important determinant of the cross-section of expected stock returns. Supporting the crash risk-based nature of the premium, we find that the impact of EDL risk is more pronounced when we interact the probability of the joint outcome with a proxy for the magnitude of the outcome, i.e., when we take into account the severity of the worst return and liquidity shocks.

When investigating the variation of the EDL risk premium over time, we find that the premium has increased in the second half of our sample period. During 1988-2012, a portfolio consisting of the 20% stocks with the strongest EDL risk exposure delivers a raw return which is 5.91% p.a. higher than that of a portfolio consisting of the 20% stocks with the weakest EDL risk exposure, whereas the return difference in the earlier sample period (1969-1987) is 1.49% p.a. These results suggest that investors have become more concerned about a stock's EDL risk during the second half of our sample. This finding is consistent with results from the empirical option pricing literature. Rubinstein (1994) and Bates (2008) find that

deep out-of-the-money index puts (i.e., financial derivatives that offer protection against strong market downturns) became more expensive after the stock market crash in 1987. These results are also consistent with the argument recently put forward by Gennaioli et al. (2015) that investors fear a future crash more when there is a recent crash they still vividly remember. Also consistent with increased crash-aversion after market crises, Chabi-Yo et al. (2017) show that the premium for a stock’s crash sensitivity increases substantially after severe market downturns.

The stability of our results is confirmed in a battery of additional robustness tests. These tests include using low-frequency and high-frequency liquidity proxies other than the Amihud (2002) Illiquidity Ratio, using a different weighting scheme in the portfolio sorts, and altering the estimation procedure for the lower tail dependence coefficients.

Our study contributes to three strands of the literature. First, we contribute to the literature on the impact of liquidity and liquidity risk on the cross-section of stock returns. Amihud and Mendelson (1986) show theoretically and empirically that stocks with low levels of liquidity deliver higher average returns. More recently, Menkveld and Wang (2012) find that stocks with higher probabilities of realizing extremely low liquidity levels (called “liquileak probability”) command a premium. Thus, while they focus on the impact of individual extreme illiquidity levels, we focus on the joint likelihood that an individual stock is extremely illiquid (has an extremely low return) when market liquidity (the market return) is extremely low, i.e., we focus on a systematic risk component.

There are also numerous studies investigating 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. Acharya and Pedersen (2005) derive an equilibrium model for returns that includes the liquidity level and a stock’s return and liquidity covariation with market liquidity and the market return. They provide some evidence that liquidity risk is a priced factor in the cross-section of stock returns. This result is confirmed in an international setting by Lee (2011) and Martinez et al. (2005). However,

Hasbrouck (2009) raises doubts on the existence of a premium for liquidity risk. He documents that in a long historical sample (U.S. data from 1926 to 2006), there is only weak evidence that liquidity risk is a priced factor. Some of the studies on systematic liquidity risk specifically analyze time-variation across crises and 'normal times', which further motivates our focus on the extreme downside. Watanabe and Watanabe (2008) find that liquidity risk and the pricing of liquidity risk vary over time, with higher liquidity risk during times of high volatility. Acharya et al. (2013) analyze the relation between liquidity in corporate bonds, stocks, and treasury bonds. They also find evidence for time-varying systematic risk in crises vs. 'normal times'. We contribute to the existing literature by investigating a new dimension of liquidity risk: a security's EDL risk. Thus, we provide new evidence that systematic liquidity components are actually priced.

Closely related to our analysis are concurrent papers by Wu (2015) and Anthonisz and Putnins (2016). Wu (2015) documents that stocks with strong sensitivities to a liquidity tail risk factor earn high expected returns. Anthonisz and Putnins (2016) find that stocks with strong downside liquidity risk (i.e., stocks whose illiquidity is highly correlated to negative market returns) earn an economically meaningful return premium. In our empirical analysis, we explicitly control for the Wu (2015) liquidity tail risk sensitivity and the Anthonisz and Putnins (2016) LPM liquidity risk beta. We show that the premium for EDLR risk is not subsumed by liquidity tail risk nor by LPM liquidity risk and hence, EDLR captures a distinct and important determinant for the cross-section of expected stock returns. It is not surprising that the return premium of EDL risk is distinct from the return premium of the LPM liquidity risk beta by Anthonisz and Putnins (2016). EDL risk is conceptually different from the LPM liquidity risk beta, as the latter places no particular emphasis on tail events. In comparison, EDL risk is concerned with the worst return and worst liquidity realizations of stocks.

Second, our paper relates to the empirical asset pricing literature on rare disaster and downside crash risk. Ang et al. (2006a) find that stocks with high downside return betas

earn high average returns. Kelly and Jiang (2014), Chabi-Yo et al. (2017), and Cholette and Lu (2011) investigate the impact of a stock’s return crash risk and return tail risk on the cross-section of expected stock returns. They find that investors demand additional compensation for holding stocks that are crash-prone, i.e., stocks that have particularly bad returns exactly when the market crashes. In an international setting, Berkman et al. (2011) show that rare disaster risk premia increase after crises. We complement their findings by showing that EDL risk premia also increase after the 1987 crash.

Third, we extend the literature on the application of extreme value theory and copulas in the cross-sectional pricing of stocks. Copulas are mainly used to model bivariate return distributions between different international equity markets (see Longin and Solnik, 2001, and Ané and Kharoubi, 2003) and to measure contagion (see Rodriguez, 2007).³ Chabi-Yo et al. (2017) investigate extreme dependence structures between individual stocks and the market and find that extreme dependencies are priced factors in the cross-section of stock returns. Until now, extreme value theory has been applied to describe dependence patterns across different markets and 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 individual level and market level liquidity and returns, respectively.

2 Methodology and Data

Section 2.1 defines our main measure of liquidity and outlines the calculation of liquidity shocks. In Section 2.2 we introduce our estimation method for EDL risk. Section 2.3 describes our stock market data and the development of aggregate EDL risk over time and provides summary statistics.

³Further applications include the use of copulas in dynamic asset allocation (Patton, 2004). Poon et al. (2004) suggest a general framework to identify tail distributions based on multivariate extreme value theory.

2.1 Measuring Liquidity

Liquidity is a broad, multi-dimensional concept, which makes it hard to find a single theoretically satisfying measure for it. Like Acharya and Pedersen (2005), we assume that the liquidity proxies used in this study should measure the 'ease of trading securities', without focusing on one particular dimension of liquidity. The limited availability of intradaily data (particularly before the 1990s) forces us to rely on a *low*-frequency liquidity proxy as the main measure of liquidity for our main tests.⁴ Fortunately, many low-frequency proxies are highly correlated with benchmark measures based on high-frequency data (Goyenko et al., 2009; Hasbrouck, 2009).

We follow Amihud (2002), Acharya and Pedersen (2005) and Menkveld and Wang (2012) and use the Amihud Illiquidity Ratio (illiq) as our main measure of illiquidity. Hasbrouck (2009) finds that illiq correlates most highly with market microstructure price impact measures. Illiq of stock i in week t is defined as

$$illiq_t^i = \frac{1}{days_t^i} \sum_{d=1}^{days_t^i} \frac{|r_{td}^i|}{V_{td}^i}, \quad (1)$$

where r_{td}^i and V_{td}^i denote, 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 . We use $illiq_t^i$ as the illiquidity of stock i in week t if it has at least three valid return and non-zero dollar-volume observations in week t .

There are two caveats when using illiq as a proxy for illiquidity. First, illiq can reach extremely high values for stocks with very low trading volume. Second, inflation of dollar-volume (the denominator) makes illiq non-stationary. To solve these problems, we follow

⁴We verify the stability of our results with various other low-frequency (for 1963-2012) and high-frequency (for 1996-2010) liquidity proxies in Section 4.1. A detailed description of all liquidity measures used in this study is given in the Appendix A.

Acharya and Pedersen (2005) and define a normalized measure of illiquidity, c_t^i , by

$$c_t^i = \min(0.25 + 0.30 \cdot illiq_t^i \cdot P_{t-1}^m, 30) \quad (2)$$

where P_{t-1}^m is the ratio of the capitalizations of the market portfolio (NYSE and AMEX) at the end of week $t - 1$ relative to that at the end of July 1962. The adjustment by P_{t-1}^m alleviates problems due to inflation. Additionally, a linear transformation is performed to make c_t^i interpretable as effective half-spread. Finally, by capping the illiquidity proxy at a maximum value of 30%, we ensure that our results are not driven by unrealistically extreme outliers of illiq.⁵

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

$$d_t^i = -c_t^i. \quad (3)$$

The normalized liquidity measure d_t^i is very persistent: Ljung-Box tests reject the null-hypothesis of 'no autocorrelation at the first lag' at a 10% significance level for 92% of stocks. Thus, we will focus on the innovations of the normalized liquidity measure

$$l_t^i = d_t^i - E_{t-1}(d_t^i) \quad (4)$$

of a stock when computing our EDL risk measures. To calculate the expected normalized liquidity $E_{t-1}(d_t^i)$ for each stock i and week t , we fit an AR(4) time series model over the liquidity time series of stock i .⁶ Hence,

⁵We check that this winsorization procedure for illiq from Acharya and Pedersen (2005) does not drive our results by excluding the 1% to 6% of stocks, for which EDL risk estimates rely on one or more winsorized illiqs. Economic and statistical significance remain unchanged.

⁶The number of lags is set at 4 since the partial autocorrelation function of d_t^i becomes insignificant before the fifth lag for most stocks in the sample. In order to consider possible time-variation of the illiquidity process (such as increased mean liquidity or faster mean-reversion) and to keep the innovation estimates fully out-of-sample, the AR(4)-parameters are estimated using a three year moving window of data up to week $t - 1$ of the liquidity series of stock i . We verify the robustness of our results to using simple liquidity-differences

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

We then use l_t^i for the computation of the EDL risk components for stock i at week t as described in the following section. For a more detailed description of the computation of the liquidity innovations, see Appendix A.

2.2 Measuring EDL Risk

We estimate lower tail dependence coefficients to capture (i) EDL risk₁ between individual stock liquidity and market liquidity, (ii) EDL risk₂ between individual stock return and market liquidity, and (iii) EDL risk₃ between individual stock liquidity and market return. Intuitively, the lower tail dependence coefficient between two random variables reflects the likelihood 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. Given two random variables X_1 and X_2 , lower tail dependence λ_L is formally defined as

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

where $u \in (0, 1)$ denotes the value of the distribution function, i.e., $\lim_{u \rightarrow 0+}$ indicates the limit if we approach the left tail of the distribution from above.⁷ If λ_L is equal to zero (as is the case for joint normal distributions), the two variables are asymptotically independent in the lower tail.

The lower tail dependence coefficient between two variables can be expressed in terms of

instead of estimated liquidity-shocks in Section 4.2.

⁷Similarly, the coefficient of upper tail dependence λ_U can be defined as

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

a copula function $C : [0,1]^2 \mapsto [0,1]$.⁸ McNeil et al. (2005) show that a simple expression for λ_L in terms of the copula C of the bivariate distribution can be derived based on

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

if F_1 and F_2 are continuous. Equation (7) has analytical solutions for many parametric copulas. In this study we use 12 different basic copula functions. A detailed overview of these basic copulas and the corresponding lower tail dependencies (and upper tail dependencies) is provided in Table B.1 of Appendix B. As in Chabi-Yo et al. (2017) and Weigert (2016), we form 64 convex combinations of the basic copulas consisting of one copula (out of four) that allows for asymptotic dependence in the lower tail, C_{λ_L} , one copula (out of four) that is asymptotically independent, C_{λ_I} , and one copula (out of four) that allows for asymptotic dependence in the upper tail, C_{λ_U} :

$$\begin{aligned} C(u_1, u_2, \Theta) = & w_1 \cdot C_{\lambda_L}(u_1, u_2; \theta_1) + w_2 \cdot C_{\lambda_I}(u_1, u_2; \theta_2) \\ & + (1 - w_1 - w_2) \cdot C_{\lambda_U}(u_1, u_2; \theta_3), \end{aligned} \quad (8)$$

where Θ denotes the set of the basic copula parameters θ_i , $i = 1, 2, 3$ and the convex weights w_1 and w_2 .

To determine which convex copula combinations deliver the best fit for the data, we use 3-year rolling windows of weekly data. We fit all 64 convex copula combinations to the bivariate distribution of each stock's (i) liquidity and market liquidity, (ii) return and market liquidity, and (iii) liquidity and market return in the rolling window. We select a specific copula combination for each stock and EDL risk component based on the estimated log-

⁸Copula functions 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 . For a detailed introduction to the theory of copulas, see Nelsen (2006).

likelihood value among the 64 different copulas.⁹ We then use the copula with the best fit for the respective stock and EDL risk component over the previous three years in the estimation of tail dependence coefficients using Equation (7). As this procedure is repeated for each stock i and week t , we end up with a panel of tail dependence coefficients EDL risk $_{it}^1$, EDL risk $_{it}^2$ and EDL risk $_{it}^3$ at the stock-week level.

Joint EDL risk for stock i in week t is subsequently defined as the sum of the EDL risk components:

$$\text{EDL risk}_{it} = \text{EDL risk}_{it}^1 + \text{EDL risk}_{it}^2 + \text{EDL risk}_{it}^3. \quad (9)$$

For a more detailed description of the estimation method, we refer to Appendix B.

2.3 Data and the Evolution of Aggregate EDL Risk

We obtain data for all common stocks (CRSP share codes 10 and 11) traded on the NYSE/AMEX between January 1, 1963 and December 31, 2012. The period from 1963 through 1965 is used for the calculation of first illiquidity innovations and the period from 1966-1968 is used to fit the first copulas and estimate EDL risk (as explained in Section 2.2 and Appendix B). Asset pricing tests are performed in the time period from 1969-2012.

To keep our liquidity measure consistent across stocks, we exclude common stocks traded on NASDAQ since NASDAQ volume data includes interdealer trades and thus is not directly comparable to NYSE/AMEX volume data. For each firm i and each week t we estimate the EDL risk components (EDL risk $_{it}^1$, EDL risk $_{it}^2$ and EDL risk $_{it}^3$) based on weekly return- and liquidity data over a rolling 3-year window. We use the weekly value-weighted CRSP market return and the AR(4)-innovations of the value-weighted average of liquidity over all stocks in the sample as market return and market liquidity, respectively. Using a 3-year rolling

⁹Table B.2 in the Appendix reports the results of this selection method. Over all stock-week observations, copula (1-D-IV) of Table B.1 is the most frequently selected copula for the EDL risk $_1$ distribution, copula (1-A-IV) is the most frequently selected copula for the EDL risk $_2$ distribution, and copula (1-A-IV) is the most frequently selected copula for the EDL risk $_3$ distribution. Copula (1-D-IV) relates to the Clayton-FGM-Rotated Clayton-copula and copula (1-A-IV) relates to the Clayton-Gauss-Rotated Clayton-copula. We verify the robustness of our results to using worse-fitting and likelihood-weighted copulas in Section 4.2.

horizon of weekly data offsets two potential concerns: First, to obtain reliable estimates for the EDL risk coefficients, we need a sufficiently large number of observations. Second, we try to avoid very long estimation intervals as EDL risk is likely to be time-varying.¹⁰ Similarly, we use a weekly frequency for our return and liquidity observations to trade off the low number of observations (and thus power) in monthly data with the noisiness of our liquidity proxies at higher frequencies.¹¹ We then define EDL risk for stock i in week t is then defined as in Equation (9) calculated as the sum of the separate EDL risk components.

To avoid microstructure issues, we exclude data for all weeks t in which the stock's price at the end of week $t - 1$ is less 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, we obtain 3,670,214 firm-week observations after applying these filters. The number of firms in each year over our sample period ranges from 1,290 to 2,036 with an average of 1,693. Table 2 provides summary statistics.

[Insert Table 2 about here]

In the first five columns we report the mean, the 25%, the 50%, the 75% quantile and the standard deviation for EDL risk, the weekly excess return over the risk-free rate, and other key variables in this study. The mean (median) for EDL risk is 0.188 (0.157) with a standard deviation of 0.147. Joint EDL risk can be decomposed into its risk components with average values of 0.066 (EDL risk₁), 0.066 (EDL risk₂), and 0.056 (EDL risk₃).¹² The mean weekly excess return across all stocks is 0.15%. We present the weekly excess return in week $t + 2$ as we will relate returns in this week to EDL risk measures determined in week t in our

¹⁰Our results are stable if we use rolling horizons of 1-year, 2-years, or 5-years, respectively (see Section 4.2).

¹¹For comparison, Ang et al. (2006a) use daily data to estimate downside betas arguing that such a high frequency is necessary to estimate downside risk precisely while Acharya and Pedersen (2005) use monthly Amihud illiquidity ratios to estimate liquidity shocks.

¹²We also compute the corresponding extreme upside liquidity (EUL) risk coefficients with upper tail dependence coefficients. The mean (median) for EUL risk is much smaller than for EDL risk with a value of 0.139 (0.105). In unreported tests, we do not find an impact of EUL Risk on average future stock returns. Our results on the impact of EDL risk on average future stock returns are unaffected when controlling for EUL Risk.

later asset pricing tests (Section 3). Summary statistics of additional firm characteristics and return patterns (that we later use in our empirical analysis mainly as control variables) are displayed in the rest of the table. For detailed descriptions of all variables, see Appendix C.

The last three columns of Table 2 show average characteristics of stocks that are classified as above or below, respectively, the median EDL risk stock according to their EDL risk value in the respective week, as well as the difference between the two. Average future weekly returns for above median EDL risk stocks are 0.17% (8.84% p.a.), whereas they are only 0.12% (6.24% p.a.) for below median EDL risk stocks. The difference amounts to 0.05% per week (2.60% p.a.) and is statistically significant at the 1%-level.

Table 2 also shows that (somewhat surprisingly) above median EDL risk stocks tend to have lower linear liquidity risk as measured by the Acharya and Pedersen (2005) liquidity beta. However (as expected) they tend to have higher downside return and downside liquidity betas (defined following the logic of downside return betas from Ang et al., 2006a) as the sum of the three Acharya and Pedersen (2005) linear liquidity betas conditional on the market return and market liquidity, respectively, being below their respective means). Above median EDL risk stocks also tend to have higher return betas and higher extreme downside return risk (EDR). The two groups also differ with respect to other firm characteristics like size, book-to-market, and liquidity. These patterns mandate that we control for the influence of these variables in our later asset pricing exercise.

We report cross-correlations between the key variables used in this study in Table 3.

[Insert Table 3 about here]

Our results reveal that the magnitude of correlations between EDL risk and other independent variables is moderate.¹³ EDL risk is positively correlated with EDR risk (correlation of 0.26), downside linear return risk β_R^- (correlation of 0.12), and negatively correlated with

¹³By construction, EDL risk is highly correlated with the separate EDL components. The separate EDL risk components display positive relationships (with correlations of 0.12, 0.24 and 0.08) among each other.

return coskewness (correlation of -0.18). Interestingly, EDL risk is hardly correlated with (downside) linear liquidity risks β_L and β_L^- (correlations of -0.02 and 0.05); this provides the first evidence that EDL risk measures a dimension of liquidity risk which is different from linear liquidity risk as analyzed in Acharya and Pedersen (2005). EDL risk is negatively correlated with illiquidity and positively correlated with firm size (with correlations of -0.11 and 0.11). These associations might be caused by the greater systemic risk of large and usually more liquid firms. EDL risk measures a conditional probability, which does not automatically increase with the volatility of returns and liquidity shocks. In contrast, the liquidity betas from Acharya and Pedersen (2005) are mechanically linked to the volatility of liquidity shocks, which itself is strongly related to illiquidity and firm size (e.g. β_L exhibits a correlation of 0.50 with illiquidity and -0.50 with firm size).

To better understand the temporal variation of EDL risk, we investigate the development of aggregate EDL risk over time. Aggregate EDL risk, $\text{EDL risk}_{m,t}$, is defined as the weekly cross-sectional, value-weighted, average of $\text{EDL risk}_{i,t}$ over all stocks i in our sample. Panel A of Figure 1 plots the time series of $\text{EDL risk}_{m,t}$.

[Insert Figure 1 about here]

Aggregate EDL risk appears relatively stationary over time. The graph exhibits occasional persistent spikes in $\text{EDL risk}_{m,t}$ that seem to coincide with worldwide market crises. A large peak in $\text{EDL risk}_{m,t}$ occurs during 1987-1990, the time period after Black Monday in October 1987, the largest one-day percentage decline in U.S. stock market history. Other spikes in aggregate EDL risk correspond to the crises of 1978-1979 (Second U.S. Oil Crisis), 1997-1998 (Asian Financial Crisis), and 2008-2011 (Global Financial Crisis). We also plot the development of aggregate EDR (extreme downside return) risk over time in Panel A.¹⁴ Aggregate EDL risk and aggregate EDR risk are highly correlated with a value of 0.74,

¹⁴In the same way as the EDL risk components, EDR risk is computed as the lower tail dependence coefficient in the bivariate distribution between individual stock return and the market return. Subsequently, aggregate EDR risk, $\text{EDR risk}_{m,t}$ is defined as the weekly cross-sectional, value-weighted, average of $\text{EDR risk}_{i,t}$ over all stocks i in our sample.

suggesting that both time series are affected by similar sources of economic risk. The general tendency for stronger asymptotic return dependence in the left tail in down markets is well-documented in Ang and Chen (2002) and Chabi-Yo et al. (2017).

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 value of around 0.59. 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 mainly caused by increasing aggregate EDL risk₁ and EDL risk₂. In contrast, all three components of EDL risk drive the aggregate EDL risk peak during 2008-2011.

Finally, we check whether future EDL risk can be predicted by investors using realized EDL risk. To do so, we analyze the persistence of EDL risk in Fama and MacBeth (1973) regressions on the firm level and display the results in Table A.2 in the Appendix. We find that realized EDL risk significantly predicts future EDL risk, estimated from non-overlapping 156-week windows.

3 EDL Risk and Future Returns

In the main part of the empirical analysis we relate EDL risk estimates at week t to portfolio and individual stock excess returns over week $t + 2$. We skip week $t + 1$ when investigating the relationship between EDL risk and future returns to avoid spurious correlations due to short-term reversals or bid-ask bounce. Note that we only use data observable to the investor at the end of week t in order to predict stock returns in week $t + 2$. Strictly separating the estimation window for EDL risk and the subsequent return prediction window alleviates concerns related to overfitting. The use of weekly return horizons is natural since we estimate EDL risk and other risk measures based on weekly data. However, our results are robust if we relate EDL risk estimates at week t to excess returns over week $t + 1$ or if we evaluate monthly return frequencies (see Section 4.3). To properly account for the impact

of autocorrelation and heteroscedasticity on statistical significance in portfolio sorts, factor models, and multivariate regressions, we use Newey and West (1987) standard errors.

3.1 Univariate Portfolio Sorts

We start our empirical analysis with univariate portfolio sorts. For each week t we sort stocks into five quintiles based on their EDL risk estimated over the past three years as described in Section 2.2. We then investigate the equally-weighted average excess return over the risk-free rate as well as CAPM- and Carhart (1997) alphas for these quintile portfolios as well as differences in average returns and alphas between quintile portfolio 5 (strong EDL risk) and quintile portfolio 1 (weak EDL risk) over week $t + 2$.¹⁵

[Insert Table 4 about here]

Column (1) of Panel A reports average EDL risk coefficients of the stocks in the quintile portfolios. There is considerable cross-sectional variation in EDL risk; average EDL risk ranges from 0.04 in the bottom quintile portfolio to 0.39 in the top quintile portfolio. More importantly, in column (2) we find that stocks with strong EDL risk earn significantly higher average future returns than stocks with weak EDL risk. Stocks in the quintile with the weakest (strongest) EDL risk earn an annual average excess return of 5.77% (9.77%). The return spread between quintile portfolio 1 and 5 is 4.00% p.a., which is statistically significant at the 1% level (t-statistic of 3.66).¹⁶ The results also show that the returns are monotonically increasing from the weakest to the strongest EDL risk quintile. This pattern is also confirmed based on the Patton and Timmermann (2010) monotonicity test, which clearly rejects the null hypothesis of a flat or decreasing pattern over the five EDLR portfolio returns at a

¹⁵To compute average weekly CAPM- and Carhart (1997) alphas, we regress the weekly $t + 2$ return of the EDL risk portfolios on the corresponding weekly US excess market factor as well as on the weekly US excess market, SMB, HLM, and UMD factors. These weekly asset pricing risk factors are computed based on daily risk factors which are provided on Kenneth French's homepage.

¹⁶As we are sorting stocks by their sensitivity to extreme market states, one might argue that high non-normality of strong-weak returns could be a problem for the standard measurement of statistical significance in a finite sample. This is not the case: Bootstrapped 99% confidence intervals (unreported) for the EDLR difference portfolio remain comfortably above zero.

p-value of 0.2%. Columns (3) and (4) provide results when we look at average CAPM- and Carhart (1997) alphas instead of raw returns. We find that the spread between quintile portfolio 1 and 5 is still 2.85% p.a. (3.03% p.a.) when adjusting returns for exposures to the CAPM (Carhart (1997)) model. The spreads are statistically significant at the 1% level with t-statistics of 2.80 and 2.90, respectively.

In Panels B through D of Table 4, we disentangle the premium for EDL risk into its three risk components. Panel B shows the relationship between EDL risk₁ as well as annualized average future excess returns and alphas. The yearly return spread between quintile portfolios 1 and 5 is only 0.33% p.a. and is not statistically significant. Panel C documents an increasing relationship between EDL risk₂ as well as annualized average future returns and alphas. Stocks in the quintile with the weakest (strongest) EDL risk₂ earn an annualized average excess return of 5.73% (9.80%). Thus, on average, stocks in quintile portfolio 5 outperform stocks in quintile portfolio 1 by 4.08% p.a., which is statistically significant at the 1% level (t-statistic of 4.74). Results based on CAPM- and Carhart (1997) alphas show an outperformance of 3.32% and 3.09% and are also statistically significant at the 1% level (t-statistics of 4.10 and 3.69). Finally, we report the results of portfolio sorts for EDL risk₃ as well as average future excess returns and alphas in Panel D. We find that stocks in the quintile with the weakest (strongest) EDL risk₃ earn an average excess return of 6.38% (9.97%) p.a. The return spread between quintile portfolio 5 and quintile portfolio 1 is 3.59% p.a., which is also statistically significant at the 1% level (t-statistic of 3.87). Results based on CAPM- and Carhart (1997) alphas are again slightly reduced, but still positive and statistically significant at the 1% level.

In summary, the results from Table 4 provide evidence that EDL risk has an impact on the cross-section of expected stock returns. Stocks with strong EDL risk exposure earn higher average future returns as well as CAPM- and Carhart (1997) alphas than stocks with weak EDL risk exposure. The main drivers of the EDL risk premium are the EDL risk₂ and EDL risk₃ components. The finding that EDL risk₁ (commonality in liquidity) is not

priced is analogous to results by Acharya and Pedersen (2005) for linear liquidity risk. In the following sections, we mostly present the results of the impact of joint EDL risk on future returns. However, our results remain stable if we concentrate on the sole impact of EDL risk₂ and EDL risk₃ and are typically insignificant for EDL risk₁.¹⁷

3.2 Bivariate Portfolio Sorts

The correlations in Table 3 document that EDL risk is correlated with other related (liquidity and return) risk measures and firm characteristics. For example, an increase in EDL risk tends to go along with an increase in linear downside liquidity (β_L^-) risk and extreme downside return (EDR) risk. Hence, the higher average future returns and alphas for strong EDL risk portfolios could be driven by differences in these other variables. To isolate the return premium of EDL risk from the impact of other related characteristics, we now conduct dependent equal-weighted portfolio double sorts.¹⁸

[Insert Table 5 about here]

In Panel A of Table 5, we analyze whether the EDL risk premium is explained by linear liquidity risk, β_L (see Appendix C), which measures systematic variation in liquidity unconditional on market conditions. We first form five portfolios sorted by β_L . Then, within each β_L quintile, we sort stocks into five portfolios based on EDL risk.¹⁹ We report the annualized average weekly $t + 2$ portfolio returns in excess of the risk-free rate for the 25 $\beta_L \times$ EDL risk portfolios.

As in Acharya and Pedersen (2005), we find that average future returns of strong β_L stocks are higher than those of weak β_L stocks within the two top EDL risk quintiles, while there is no notable impact of β_L in the lower EDL risk quintiles. More importantly, we find that

¹⁷We report robustness tests for the component-wise return premiums — controlling for important determinants of stock returns — in Table 11.

¹⁸As in Section 3.1, EDL risk as well as β_L , β_L^- , EDR risk, LPM liquidity risk, and liquidity tail risk in week t are estimated over a three-year horizon. We then investigate equally-weighted average excess returns over week $t + 2$.

¹⁹Our results (not reported) are stable if we reverse the sorting order or conduct independent sorts.

strong EDL risk stocks clearly outperform weak EDL risk stocks in all β_L quintiles. The return difference between the weakest EDL risk quintile and the strongest EDL risk quintile ranges from 2.60% p.a. in the second-lowest β_L quintile up to 6.10% p.a. in the highest β_L quintile. The return difference is on average 3.68% p.a., which is statistically significant at the 1%-level. Similar results are obtained when we adjust raw returns by exposures to the CAPM- and Carhart (1997) model. Differences in alphas are on average 2.89% p.a. and 2.83% p.a., respectively, and are both statistically significant at the 1%-level. Hence, regular linear liquidity risk as analyzed in Acharya and Pedersen (2005) cannot account for the reward earned by holding stocks with strong EDL risk.

In Panel B of Table 5, we analyze whether the EDL risk premium is explained by linear downside liquidity risk, β_L^- (see Appendix C), which — like EDL risk — focuses on systematic downside liquidity risk. However, the conceptional difference between EDL risk and β_L^- risk is that the latter focuses on systematic risk to market returns (liquidity) below the mean, while the former explicitly focuses on extreme events. As above, in a first step we form five portfolios sorting by β_L^- . Then, within each β_L^- quintile, we sort stocks into five portfolios based on EDL risk and report annualized average excess portfolio returns. We again find that in all β_L^- quintiles strong EDL risk stocks outperform weak EDL risk stocks significantly. Across all β_L^- quintiles stocks in the weak EDL risk portfolios earn average excess returns of 5.75% p.a., whereas stocks in the strong EDL risk portfolios earn average excess returns of 9.68% p.a. and the difference is highly significant overall as well within each individual β_L^- quintile. Average CAPM- as well as Carhart (1997) alphas are also significantly larger for strong EDLR stocks compared to weak EDLR stocks within each individual β_L^- quintile. Thus, linear downside liquidity risk cannot account for the EDL risk premium either.

In Panel C of Table 5, we investigate whether EDL risk is different from extreme downside return risk, EDR risk (see Appendix C), which captures systematic crash risk in returns. Again, to explicitly control for variation in EDR risk, we first form quintile portfolios sorted on EDR risk. Then, within each EDR risk quintile, we sort stocks into five portfolios based

on EDL risk and report annualized average excess portfolio returns. As in Chabi-Yo et al. (2017), we find that strong EDR risk stocks outperform weak EDR risk stocks within all EDL risk quintiles. Furthermore, the return difference between the weak EDL risk quintile and the strong EDL risk quintile is again positive in all EDR risk quintiles and statistically significant in four of the five quintiles. On average, the return spread (spread in CAPM alphas, spread in Carhart (1997) alphas) amounts to 3.25% p.a. (2.28% p.a., 2.26% p.a.), which is statistically significant at the 1% level (5% level, 5% level). Therefore, the impact of EDL risk on future stock returns is also clearly different from the impact of EDR risk.

Finally, in Panel D and Panel E, we analyze whether the EDL risk premium can be explained by a stock's exposure to lower-partial moment (LPM) liquidity risk (as in Anthonisz and Putnins, 2016) and liquidity tail risk (as in Wu, 2015). As Anthonisz and Putnins (2016) and Wu (2015), we find that average future returns of stocks with strong LPM liquidity risk (liquidity tail risk) are higher than those of stocks with weak LPM liquidity risk (liquidity tail risk). More importantly, we find that the average EDL risk premium controlling for LPM liquidity risk (liquidity tail risk) is 3.86% (3.87%) annually and statistically significant at the one percent level in each case. Similar results are again obtained when considering alphas instead of raw returns.

To summarize, dependent portfolio double sorts provide strong evidence that EDL risk is not explained by β_L , β_L^- , EDR risk nor by LPM liquidity risk (as in Anthonisz and Putnins, 2016) and liquidity tail risk (as in Wu, 2015). So far, our analysis relies on return differences and we only control for the impact of systematic risk factors indirectly by double-sorting portfolios based on EDL risk and other risk characteristics of the stock. To control for the exposure to other systematic risk factors, we now investigate whether the EDL risk premium can be explained by alternative multivariate factor models suggested in the literature.

3.3 Factor Models

We regress the weekly $t + 2$ return of the EDL risk quintile difference portfolio on various factors that have been shown to determine the cross-section of average stock returns.²⁰ Since most factors are only available on a monthly basis, we build portfolios, which are rebalanced monthly based on past EDL risk, again leaving a minimum of a one-week gap between calculation of EDL risk and portfolio formation. We then investigate risk-adjusted monthly returns according to these factors. Table 6 reports the results.

[Insert Table 6 about here]

Results for our main specifications are reported in Panel A of Table 6. In regressions (1) and (2) we adjust the EDL risk quintile difference portfolio for its exposure to the market factor, and the Carhart (1997) four-factor model. We find that the EDL risk portfolio loads significantly positively on the market factor and significantly negatively on the momentum factor. The risk-adjusted annualized alpha is significantly positive at the 1%-level and amounts to 2.70% for the market-model and 3.52% for the Carhart (1997) 4-factor alpha.

In regression (3), we include the Pastor and Stambaugh (2003) traded liquidity factor. Surprisingly, we find that the EDL risk portfolio does not load significantly on the Pastor and Stambaugh (2003) factor and the return premium for EDL risk is not reduced. The risk-adjusted alpha of the EDL risk portfolio is 3.52% p.a.²¹

Regressions (4) through (7) additionally control for the EDR risk factor of Chabi-Yo et al. (2017), the Bali et al. (2011) factor for lottery-type stocks, the Kelly and Jiang (2014) tail risk factor, and the U.S. equity betting-against-beta factor from Frazzini and Pedersen (2014). Again, the annual alpha of the EDL risk portfolio remains statistically significant at least at the 5% level in each case and ranges from 2.51% to 4.10%.

²⁰The formal definitions of all factors used are provided in Appendix C.

²¹In unreported tests, we find that the EDL risk portfolio loads significantly positively on the Pastor and Stambaugh (2003) factor in the period from 1969 through 2000, the time span that is analyzed in their paper. However, the yearly alpha of the EDL risk portfolio is also not reduced by the Pastor and Stambaugh (2003) liquidity factor during this sub-period. We obtain similar results when we adjust the EDL risk quintile difference portfolio for its exposure to the Sadka (2006) liquidity factor (which is based on the permanent-variable component of the price impact function) in our model.

Panel B of Table 6 reports annualized alphas for additional alternative factor models. We regress the EDL risk quintile difference portfolio on the factors from the Fama and French (2015) five-factor model, the Hou et al. (2015) and Novy-Marx (2013) four-factor models, as well as the Carhart (1997) four-factor model extended by the Fama and French short- and long-term reversal factors, the leverage factor from Adrian et al. (2014), the quality-minus-junk factor from Asnes et al. (2014), the undervalued-minus-overvalued factor from Hirshleifer and Jiang (2010), the Anthonisz and Putnins (2016) LPM liquidity risk factor, and the Wu (2015) liquidity tail risk factor. The alpha of our strong minus weak EDL risk return ranges from 2.80% p.a. to 4.04% p.a. and is always statistically significant at the 1%-level.

The results reveal that the premium for EDL risk is robust to controlling for a wide array of alternative factor specifications. However, Daniel and Titman (1997) advocate considering not just factor sensitivities in the analysis of determinants of cross-sectional stock returns. Thus, to also account for firm specific characteristics in our asset pricing tests, we now proceed to run Fama and MacBeth (1973) regressions on the firm level.

3.4 Fama-MacBeth Regressions

We perform individual Fama and MacBeth (1973) regressions of excess stock returns over the risk-free rate in week $t + 2$ on risk and firm characteristics measured at week t in the period from 1969 to 2012.²² Table 7 presents the regression results of future weekly excess returns on EDL risk and various combinations of control variables.

[Insert Table 7 about here]

In regression (1), we include EDL risk as the only explanatory variable. Consistent with our results from portfolio sorts and multivariate factor models, it shows a highly statistically

²²Running Fama and MacBeth (1973) regressions on the individual firm level has the disadvantage that risk factors are estimated less precisely in comparison to using portfolios as test assets. However, Ang et al. (2010) show that forming portfolios does not necessarily lead to smaller standard errors of cross-sectional coefficient estimates. Creating portfolios degrades information by shrinking the dispersion of risk factors and leads to larger standard errors.

as well as economically positive impact. For example, stocks with top quintile EDL risk earn higher future returns of around 3.35% p.a. as compared to bottom quintile EDL risk stocks.²³

In regression (2), we add a stock’s market return beta (β_R), size, book-to-market ratio, and its past yearly return to our model. EDL risk remains statistically significant at the 1% level when including these additional variables.

Regression (3) expands our model and includes a stock’s linear liquidity risk (β_L) from Acharya and Pedersen (2005), extreme downside return (EDR) risk (Chabi-Yo et al., 2017), the illiquidity level (Amihud, 2002), exposure to tail risk (β_{Tail}) from Kelly and Jiang (2014), idiosyncratic volatility (Ang et al., 2006b), and a stock’s coskewness with the market (Harvey and Siddique, 2000). We find that the inclusion of these additional variables only slightly reduces the impact of EDL risk on future returns, which is still statistically significant at the 1% level.

In regression (4), we replace β_R by β_R^- and β_R^+ as well as β_L by β_L^- and β_L^+ . None of these variables shows any significant impact on returns. In contrast, our main result regarding the impact of EDL risk on future returns remains unchanged — EDL risk is statistically significant at the 1% level and has an economically significant positive impact. Top quintile EDL risk stocks earn higher future returns by about 2.64% p.a. than bottom quintile EDL risk stocks, controlling for the full set of additional variables.

The coefficient estimates for the impact of the control variables broadly confirm findings from the existing literature: Firm size (book-to-market) is shown to have a negative (positive) impact on expected returns (e.g., Banz, 1981; Basu, 1983; and Fama and French, 1993), while stocks that realize the best (worst) returns over the past 3 to 12 months are found to continue to perform well (poorly) over the subsequent 3 to 12 months (e.g., Jegadeesh and Titman, 1993). EDR risk and β_{Kelly} are positively related to future average returns (Kelly and Jiang, 2014, and Chabi-Yo et al., 2017), whereas *idio vola* shows a negative impact (e.g., Ang et

²³Top (bottom) quintile EDL risk stocks have an average EDL risk exposure of 0.39 (0.04). Hence, our regressions results indicate an annual return spread of $0.00184 \cdot 0.35 \cdot 52 = 3.35\%$.

al., 2006b). However, when adding the full set of explanatory variables, we do not find a statistically significant impact for β_L , illiq or coskew, possibly due to the sometimes high correlations across variables (see Table 3).

Finally, in regressions (5) and (6), we add a stock’s LPM return and LPM liquidity risk beta (see Anthonisz and Putnins, 2016) as well as its liquidity tail risk sensitivity (see Wu, 2015) to our model. Although these variables seem to be similar to the concept of EDLR, we empirically find that inclusion of these variables only marginally diminishes the impact of EDLR on future average stock returns. EDLR remains statistically significant at the 1% level and economically meaningful in size, confirming that EDLR measures a different dimension of extreme liquidity risk than these measures,

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 regards to β_L , β_L^- , EDR Risk, LPM liquidity risk, and liquidity tail risk. It is robust to various asset pricing factor models, and remains significant when controlling for a wide list of firm characteristics.

3.5 Does the Magnitude of the Extreme Downside Matter?

Our asset pricing tests examine the impact of EDL risk, defined as the sum of three lower tail dependence coefficients (see Equation (6)). A lower tail dependence coefficient is defined as 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. Thus, EDL risk tells us how *likely* it is that a stock realizes (i) its worst liquidity at the time when the market realizes its worst liquidity, (ii) its worst return when the market realizes its worst liquidity, and (iii) its worst liquidity when the market realizes its worst return. However, EDL risk does not take into account the *severity* of the worst return or liquidity shock, i.e., its magnitude.

This feature of tail dependence might actually be an advantage relative to other measures

of risk used in finance. A trained financial economist—used to correlations and betas—might think that tail dependence is complicated or even a 'black box'. We disagree: It is simply a conditional probability, the answer to the question 'How likely is X given Y?' For someone *without* a background in econometrics and theoretical portfolio theory, such probabilities are arguably easier to understand than correlations or betas. However, one could also argue that the magnitude of the worst return or liquidity shock we condition on should matter. We now check whether the impact of EDL risk is stronger if we can expect the worst outcome for a stock to be particularly bad, i.e., if we interact the probability of the joint outcome with a proxy for the magnitude of the outcome.

As proxies for the magnitude of a bad outcome, we use four ex-ante proxies based on the dispersion of returns (liquidity shocks): a stock's return (liquidity shock) standard deviation during the past three years, its idiosyncratic return (liquidity shock) volatility (controlling for value-weighted market returns and liquidity shocks) during the past three years, its Value-at-Risk (VaR, defined as the 5% quantile of the weekly returns (liquidity shocks) of the stock during the past three years), and its conditional Value-at-Risk (CoVaR, defined as the conditional mean of all weekly returns (liquidity shocks) below the 5% quantile). The worst outcomes with respect to returns and liquidity shocks tend to be particularly bad for stocks with a high standard deviation (a high idiosyncratic volatility, a low VaR and a low CoVaR) regarding the respective variable.

To examine whether dispersion of returns and liquidity shocks indeed increases the impact of EDL risk, we sort stocks into two categories: Low dispersion stocks which display a standard deviation or idiosyncratic volatility (VaR or CoVar) of returns *and* liquidity shocks below (above) the respective median measure and high dispersion stocks which display a standard deviation or idiosyncratic volatility (VaR or CoVar) of returns *and* liquidity shocks above (below) the respective median measure. Panel A of Table 8 reports the annualized excess returns of the top (bottom) EDL risk quintile portfolio and differences in returns as well as alphas for the low and the high dispersion samples.

[Insert Table 8 about here]

As expected, our results reveal that the impact of EDL risk on future returns is stronger for the high dispersion stocks, irrespective of which ex-ante proxy for dispersion we use. In the high dispersion sample, top quintile EDL risk stocks outperform bottom quintile EDL risk stocks by an average of 4.95% p.a. (3.97% p.a. based on the CAPM alpha, 3.54% p.a. based on the Carhart (1997) alpha). Top quintile EDL risk stocks also clearly outperform bottom quintile EDL risk stocks in the low dispersion sample. However, in contrast to the high dispersion sample, the outperformance is significantly reduced to 3.33% p.a. (2.06% p.a. based on the CAPM alpha, 2.16% p.a. based on the Carhart (1997) alpha).

To investigate whether these results are driven by correlations of the dispersion measures with other independent variables, we repeat regression (5) of Table 7 for the high and the low dispersion sample separately.²⁴ Results for the impact of EDL risk are shown in Panel B of Table 8. The impact of EDL risk is 50% to 100% stronger for firms where bad outcomes are particularly severe, i.e., for firms with a high dispersion (high standard deviation, high idiosyncratic volatility, low VaR, and low CoVar) of returns and liquidity shocks. Hence, greater dispersion of returns and liquidity shocks indeed increases the impact of EDL risk on future average stock returns.

3.6 Temporal Differences in the EDL Risk Premium

We now investigate whether the premium for EDL risk is stable over time. We first reproduce the results of the univariate portfolio sorts for the time period from January 1969 through December 1987 and from January 1988 through December 2012. As a cutoff for our sample, we select 1987, the year of Black Monday, when the U.S. stock market had its largest one-day percentage decline in history. Focusing on this event is motivated by studies from the empirical option pricing literature (e.g., Rubinstein, 1994, and Bates, 2008)

²⁴We include all other explanatory variables from regression (5) of Table 7, but suppress them in the Panel.

which document that premiums for deep-out-of-the-money put options strongly increased after 1987, possibly due to investors becoming more crash-averse. Thus, our conjecture is that this increased crash aversion might also have led to a higher premium for EDL risk in the cross-section of stock returns after 1987. Panel A of Table 9 reports the annualized excess portfolio returns and alphas of portfolios sorted by EDL risk. We also report differences in average excess returns between quintile portfolio 5 (strong EDL risk) and quintile portfolio 1 (weak EDL risk).

[Insert Table 9 about here]

The EDL risk premium between the two subperiods varies considerably. In the first subsample from 1969 through 1987, we only find weak evidence of a positive EDL risk premium. The return spread between the strong EDL risk and the weak EDL risk portfolio is 1.49% p.a. and not statistically significant at conventional levels. The results for the CAPM-alpha and the Carhart (1997) four-factor model are similar. The only statistically significant EDL risk premium is found for the Carhart (1997) specification, where the annualized return spread between the strong and the weak EDL risk portfolio amounts to 2.32% p.a. and is statistically significant at the 10%-level.

In the post-crash period from 1988 through 2012, the premium for EDL risk strongly increases. Stocks in the quintile with the weakest (strongest) EDL risk earn an annual average excess return of 6.69% (12.60%). The return spread between quintile portfolios 1 and 5 is 5.91% p.a., which is statistically significant at the 1% level. We also find that this premium remains when we adjust raw returns for exposures to systematic risk factors using the standard factor models. The return spread with regard to the Carhart (1997) factor alpha is 3.99% p.a. and strongly significant at the 1% level.

Panel B of Table 9 reports the results from regressions (1) and (5) of Table 7 separately for the two subperiods. The results are similar to the above results from portfolio sorts. In the earlier time period prior to the 1987 crash, we do not find evidence of a significant EDL

risk premium. In contrast, the EDL risk premium in the time period from 1988 through 2012 is statistically significant at the 1% level and economically large.

Figure 2 shows the temporal variation of the (cumulative) yearly Carhart (1997) factor alpha of the top EDL risk minus bottom EDL risk portfolio during the whole sample from January 1969 through December 2012.²⁵

[Insert Figure 2 about here]

The graph reveals that the highest profits of the trading strategy can be attributed to the years 1990 and 2009. These years are subsequent to two severe market and liquidity crises: namely, the Black Friday stock market crash in 1987 and the financial crisis in 2008. We conjecture that these market crashes have strongly increased the crash aversion of investors, which subsequently has increased the premium (discount) for strong (weak) EDL risk stocks, which is in line with the findings of the empirical option literature mentioned above, which indicate increasing prices (and low expected returns) for securities that offer protection against strong market downturns after 1987.

4 Robustness Checks

4.1 Liquidity Proxies

The empirical analysis in Section 3 is performed using EDL risk estimates of liquidity innovations based on the Amihud (2002) Illiquidity Ratio, analogous to Acharya and Pedersen (2005). One potential concern is that our main findings are driven by the measurement error component of our proxy for liquidity. Attenuation bias caused by this measurement error would lead to an underestimation of the return premium for EDL risk. Nevertheless, to assure the stability of our findings, we now test whether our results regarding the impact of EDL risk on future returns are robust to using different (low-frequency and high-frequency)

²⁵When computing the yearly and cumulative alphas for the top EDL risk - bottom EDL risk portfolio, no trading costs are taken into account.

proxies of liquidity. As additional low-frequency liquidity proxies we use the Corwin and Schultz (2012) measure (*Corwin*), the Lesmond et al. (1999) measure (*Zeros*), and the Fong et al. (2017) measure (*FHT*).²⁶ As high-frequency liquidity proxies we select the effective spread (*EffSpr*), the relative spread (*RelSpr*), the intraday Amihud measure (*IntAmi*), and the 5-minute price impact measure (*PriImp*). The high-frequency liquidity proxies are calculated for common stocks traded on the NYSE/AMEX using the TAQ dataset in the period between January 1, 1996 and December 31, 2010. The big advantage of these proxies is their much lower measurement error. We perform asset pricing tests for the high-frequency proxies in the time period from 2002 to 2010.²⁷

In the same way as for the Amihud (2002) Illiquidity Ratio, we estimate liquidity shocks, and subsequently the EDL risk, for each firm i in each week t based on weekly returns and liquidity shocks over 3-year rolling windows. Correlations between EDL risk based on different liquidity proxies are shown in Panel B of Table A.1 in the Appendix. We find that all correlations between EDL risk measures based on low-frequency proxies and those based on high-frequency proxies are positive. EDL risk based on *Corwin* has the highest positive correlations to the high-frequency measures ranging from 0.48 to 0.57.²⁸

To investigate whether EDL risk is a priced factor in the cross-section of expected stock returns if measured based on other liquidity proxies, we perform portfolio sorts, factor regressions and multivariate Fama and MacBeth (1973) regressions similar to the ones from the previous section. Table 10 reports the results.

[Insert Table 10 about here]

Consistent with our previous results, Panel A shows that EDL risk is priced across all low-frequency measures in our study. The annualized return spread between quintile portfolios 1

²⁶Detailed definitions of these variables, as well as data requirements, are given in Appendix A.

²⁷We compute illiquidity shocks for each stock based on a 3-year time horizon starting in January 1996. We then use the time period from 1999 to 2001 to estimate the first EDL risk values for each stock. Thus, our asset pricing tests using high frequency proxies only start in January 2002.

²⁸For additional information about summary statistics and temporal variation of the different liquidity measures, see Appendix A.

and 5 ranges from 1.47% p.a. for the *Zeros* measure to 4.00% p.a. for the *illiq* measure. We also find that return spreads, risk-adjusted by standard factor models (i.e., the Sharpe (1964) CAPM model and the Carhart (1997) four-factor model) remain positive for all liquidity measures and statistically significant for most of them. Moreover, we find supportive evidence for the pricing of EDL risk when investigating portfolio sorts for the high-frequency liquidity measures. All EDL raw and risk-adjusted return spreads are positive and economically significant. In addition, we find statistically significant impact of EDL risk on future returns for *EffSpr*, *IntAmi*, and *PriImp*. This is a remarkable result given that our sample period for our asset pricing tests is only 9 years in this case, which generally makes it very hard to detect any significant asset pricing patterns.

To confirm that our results are not driven by correlations of EDL risk with other explanatory variables, we repeat regression (5) of Table 7 for the EDL risk based on the alternative liquidity proxies. Our findings indicate that the impact of EDL risk is stable across the different liquidity proxies and not driven by measurement error. All EDL risk coefficients are positive. Except for the *Zeros* and *RelSpr* measures, coefficients are also statistically and economically significant, indicating a robust impact of EDL risk on future returns.

4.2 Estimation Procedures and Weighting Scheme

The estimation procedure of EDL risk in Section 3 is performed using an estimation horizon of 3 years of weekly returns and AR(4) liquidity-shocks, and a copula function that shows the best fit for each combination of firm, week and EDL risk component in the estimation window. Furthermore, portfolio sorts are conducted on an equally weighted basis. Thus, one concern might be that our results are specific to the details of our procedure.

To address concerns of overfitting, we now demonstrate the robustness of our results to several changes in the estimation procedure: First, we apply different estimation horizons of 1 year (EDL risk_{1y}), 2 years (EDL risk_{2y}), and 5 years (EDL risk_{5y}) for the estimation of EDL risk. Second, we use simple differences in stock liquidity instead of shocks from an AR(4)

model. This robustness test alleviates concerns, that noise added through the estimation of AR(4)-parameters drives results. Third, we use different copula functions in the estimation procedure of the EDL risk components. In particular, we test the robustness of our results with copulas that performed best (EDL risk_{C1}), second-best (EDL risk_{C2}), second-worst (EDL risk_{C63}) and worst (EDL risk_{C64}) for this stock-week, as well as a copula that is a likelihood-weighted average of all 64 copulas we consider (EDL risk_{Cw}). The robustness of our results to these variations should show that they are not caused by estimation error and overfitting through selecting particular estimation horizons, liquidity-shock estimates, and copula functions. Finally, we check the stability of our results when considering the three different risk components EDL risk₁, EDL risk₂, and EDL risk₃ in asset pricing tests separately.

To examine whether EDL risk is priced when the estimation procedure is varied, we again perform portfolio sorts, factor model regressions and multivariate Fama and MacBeth (1973) regressions. Results are reported in Table 11.

[Insert Table 11 about here]

Panel A shows that, in univariate equal-weighted portfolio sorts and based on standard factor models, EDL risk is significantly priced across specifications with alternative estimation horizons, different copulas, and when we use simple differences in stock liquidity instead of shocks from an AR(4) model. The annual EDL risk spread in average excess returns between quintile portfolios 1 and 5 ranges from 2.91% p.a. for EDL risk_{1y} to 5.66% p.a. for the specification with liquidity differences instead of AR(4) shocks. We also find that risk-adjusted return spreads remain positive and are statistically significant at least at the 5%-level across different estimation procedures. In line with our results from Section 3.1, we confirm that the premium for EDL risk is driven by the EDL risk₂ and EDL risk₃ components if we control standard factor models.

Finally, in Panel B, we repeat regression (5) of Table 7 of future returns on EDL risk (estimated using different horizons, liquidity differences and different copula functions) and

other explanatory variables. Our results reveal that the positive, statistically significant impact of EDL risk on future returns is stable across different estimation procedures even when controlling for a wide array of firm and risk characteristics. Remarkably, we find a significant impact of both EDL risk₂ and EDL risk₃ when performing a joint regression of future stock returns on all EDL risk components at the same time. Overall, our robustness tests show that our main findings are not driven by overfitting or estimation errors.

Our previous portfolio sorts in Section 3 were performed based on equal-weighted portfolios. Thus, even though we exclude < \$2- and NASDAQ-stocks, our results could be influenced by overweighting the importance of very small stocks. We now examine the results of value-weighted portfolio sorts. First, we form five portfolios sorted on firm size. Then, within each size quintile, we sort stocks into value-weighted portfolios based on EDL risk. Results are presented in Table 12.

[Insert Table 12 about here]

Consistent with our previous results, Panel A documents that the value-weighted EDL risk premium is positive and economically meaningful within each individual size quintile, ranging from 2.17% p.a. to 5.22% p.a. and typically significant at least at the 5%-level. It is smallest and not statistically significant at conventional levels in the highest size quintile, which is consistent with the weakest return premium for EDL risk in the top size quintile from Panel D in Table 5. The average value-weighted EDL risk premium across all size quintiles is 3.71% and is statistically significant at the one percent level. Similar results are obtained when looking at CAPM alphas and Carhart (1997) alphas instead of raw returns.

Panel B repeats the factor model regressions of Table 6 for the average across size quintiles of value-weighted strong-minus-weak EDL risk portfolios. In short, the results are very similar to the results based on equal-weighted portfolios from Table 6. Exposures (suppressed in Table 12) are qualitatively the same and all 7 specifications result in statistically significant annualized alphas ranging from 2.35% to 3.56%. Overall the results for value-weighted

portfolios confirm that the EDL risk premium is not just driven by a large number of tiny firms.

4.3 Regression Methods and Adjusted Returns

Our multivariate regression results in Section 3.4 rely on Fama and MacBeth (1973) regressions with winsorized variables. We now vary the regression approach, using the full set of independent variables for the complete sample period from 1969 to 2012. Results are presented in Panel A of Table 13.

[Insert Table 13 about here]

Regression (1) varies the baseline regression (5) from Table 7 by not using Newey-West standard errors in the second stage of the Fama and MacBeth (1973) regressions to determine statistical significance. Regression (2) uses the standard Fama and MacBeth (1973) approach without winsorizing the independent variables. In regression (3) we conduct a pooled OLS regression with time-fixed effects and standard errors clustered by stock. Regression (4) is a variation of (3), where we cluster standard errors by industry using the SIC-2-digits classification.²⁹ Regressions (5) and (6) use panel data regressions with firm-fixed effects. In regression (6) standard errors are additionally clustered by firm. Finally, in regression (7) we regress excess returns on the independent variables in a random-effect panel regression. In all regression modifications, we document that EDL risk is a highly significant explanatory factor for the cross-section of expected stocks returns. The point estimate for the impact of EDL risk is always above 0.00117 and statistically significant at the 1% level.

So far, we have used weekly excess returns over week $t + 2$ as our dependent variable in the asset pricing exercises. We now test the robustness of our results if we use different return lags, namely weekly returns in $t + 1$, $t + 3$, and $t + 4$ as our dependent variable. Furthermore, we also investigate the impact of EDL risk on future monthly returns in month $t + 1$. Results

²⁹Results are virtually unchanged whether we cluster by Fama-French 48 or SIC industries.

in Panel B of Table 13 document a stable and statistically significant impact of EDL risk on future returns across the different lags and return horizons.

Next, we adjust the return of each stock by subtracting the return of its corresponding Daniel et al. (1997) characteristic-based benchmark (DGTW).³⁰ Again, our main result of a significant EDL risk premium remains unaffected.

Finally, some extreme market downturns might be driven by specific industries thus causing our findings to be potentially biased by industry effects. To investigate whether this is the case, we repeat our multivariate regressions with the full set of controls (i.e., regression (5) from Table 7), using industry-adjusted returns instead of raw returns as the dependent variable. To identify and cluster by industries, we use the SIC-2, SIC-3, the SIC-4 digit industry classification (with weekly returns), as well as the Fama-French 12 (FF12) and 48 (FF48) industry classifications (with monthly returns). For all classifications, the EDL risk coefficient remains positive and statistically significant.

5 Conclusion

This study investigates whether investors receive compensation for holding stocks with strong extreme downside liquidity (EDL) risk: Strong EDL risk stocks realize their lowest return and liquidity in periods of market return and market liquidity crises. We hypothesize that such stocks are unattractive assets to hold for crash-averse investors leading them to demand a premium for holding strong EDL risk stocks.

Our empirical analysis provides clear evidence to support this hypothesis: 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 a raw return that is 4.00% p.a. higher than that of a portfolio consisting

³⁰This test is performed using monthly data. Monthly DGTW benchmark returns are available via <http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm>.

of the 20% stocks with the weakest EDL risk. The high future returns earned by stocks with strong EDL risk can be explained neither by linear liquidity risk (as in Acharya and Pedersen, 2005) nor by different factor model specifications and are not due to differences in firm characteristics. Our results are stable across different liquidity measures and alternative estimation procedures of EDL risk.

Overall our results have important implications for portfolio performance management and financial stability: There is evidence that certain investor groups seek (and can identify) stocks with strong tail risk exposure. For example, Agarwal et al. (2016) show that hedge fund managers actively invest in such stocks and are able to earn the associated premium. If financial institutions do not suffer the (unmitigated) consequences of a market crash or liquidity crisis (e.g., because they expect to be bailed out), they are incentivized to buy strong EDL risk assets in order to earn the premium documented in our study. Such behavior would make those institutions, and consequently financial markets, more fragile.

A Appendix: Liquidity Measures

Appendix A provides the definitions of the eight liquidity proxies used in this study, along with data requirements, details about the computation of liquidity shocks and a short analysis of how well EDL risk estimates based on low-frequency proxies correlate with high-frequency benchmark values.

A.1 Liquidity Proxy Definitions and Data Requirements

The low-frequency data for proxies (1)-(4) comes from CRSP. The high-frequency proxies (5)-(8) use data from the NYSE TAQ database.

- (1) The Amihud (2002) Illiquidity Ratio (*illiq*) is defined as in Acharya and Pedersen (2005):

$$c_t^i = \min(0.25 + 0.30 \cdot illiq_t^i \cdot P_{t-1}^m, 30)\% \quad (10)$$

with

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

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 (available return and non-zero dollar-volume) observations in week t for stock i . c_t^i can be interpreted as the effective half-spread of stock i .

- (2) The Corwin and Schultz (2012) illiquidity measure (*Corwin*) is defined as follows:

$$c_t^i = \frac{1}{\text{days}_t^i - 1} \sum_{d=2}^{\text{days}_t^i} \max \left(\frac{2 \cdot (e^{\alpha_{td}^i} - 1)}{e^{\alpha_{td}^i} + 1}, 0 \right) \quad (11)$$

with

$$\begin{aligned} \alpha_{td}^i &= \frac{\sqrt{2 \cdot \beta_{td}^i} - \sqrt{\beta_{td}^i}}{3 - 2 \cdot \sqrt{2}} - \sqrt{\frac{\gamma_{td}^i}{3 - 2 \cdot \sqrt{2}}} \\ \beta_{td}^i &= \left(\log \left(\frac{hi_{t,d-1}^i}{lo_{t,d-1}^i} \right) \right)^2 + \left(\log \left(\frac{hi_{t,d}^i}{lo_{t,d}^i} \right) \right)^2 \\ \gamma_{td}^i &= \left(\log \left(\frac{tdhi_{t,d}^i}{tdlo_{t,d}^i} \right) \right)^2 \end{aligned}$$

where $hi_{t,d}^i$ and $lo_{t,d}^i$ stand for high- and low-prices on day d in week t for stock i , $tdhi_{t,d}^i$ and $tdlo_{t,d}^i$ stand for 2-day high- and low-prices on days $d - 1$ and d in week t for stock i and $days_t^i$ is the number of days for which high-, low- and closing prices are available. We use the same adjustments for strong overnight price changes and thinly traded stocks as Corwin and Schultz (2012). c_t^i can be interpreted as the spread of stock i .

- (3) The Lesmond et al. (1999) illiquidity measure (*Zeros*) is defined as:

$$c_t^i = \frac{x_{td}^i}{days_t^i} \quad (12)$$

where x_{td}^i is the number of zero-return days and $days_t^i$ is the number of available daily returns in week t for stock i .

- (4) The Fong et al. (2017) illiquidity measure (*FHT*) is defined as follows:

$$c_t^i = 2 \cdot \sigma_t^i \cdot N^{-1} \left(\frac{1 + Zeros2}{2} \right) \quad (13)$$

with

$$Zeros2 = \frac{x_t^i}{7}$$

where x_t^i is the number of zero-return days for week t , σ_t^i is the standard-deviation of daily returns in week t , and $N^{-1}(\cdot)$ is the inverse of the standard normal cdf. c_t^i can be interpreted as the spread of stock i .

- (5) The relative spread (*RelSpr*) is defined as:

$$c_t^i = \frac{1}{days_t^i} \sum_{d=1}^{days_t^i} \frac{1}{N_{td}^i} \sum_{n=1}^{N_{td}^i} RS_{tdn}^i \quad (14)$$

with

$$RS_{tdn}^i = \frac{A_{tdn}^i - B_{tdn}^i}{Q_{tdn}^i}$$

where A_{tdn}^i , B_{tdn}^i and $Q_{tdn}^i = \frac{A_{tdn}^i + B_{tdn}^i}{2}$ are prevailing ask quote, prevailing bid quote and quote midpoint price in transaction n of day d in week t . $days_t^i$ is the number of days with available transactions of stock i in week t and N_{td}^i is the number of transactions of stock i on day d in week t . The prevailing bid- and ask-quotes are the latest available quotes up to at least one second before the trade.

(6) The effective spread (*EffSpr*) is defined as follows:

$$c_t^i = \frac{1}{\text{days}_t^i} \sum_{d=1}^{\text{days}_t^i} \frac{1}{N_{td}^i} \sum_{n=1}^{N_{td}^i} ES_{tdn}^i \quad (15)$$

with

$$ES_{tdn}^i = \frac{2 \cdot |P_{tdn}^i - Q_{tdn}^i|}{Q_{tdn}^i}$$

where all variables are defined as above and P_{tdn}^i is the transaction price of transaction n of day d in week t .

(7) The 5-minute price impact (*PriImp*) is defined as follows:

$$c_t^i = \frac{1}{\text{days}_t^i} \sum_{d=1}^{\text{days}_t^i} \frac{1}{N_{td}^i} \sum_{n=1}^{N_{td}^i} PI_{tdn}^i \quad (16)$$

with

$$PI_{tdn}^i = \frac{2 \cdot |Q_{tdn5}^i - Q_{tdn}^i|}{Q_{tdn}^i}$$

where all variables are defined as above and Q_{tdn5}^i is the quote midpoint 300 seconds after transaction n of day d in week t .

(8) The intraday Amihud measure (*IntAmi*) is defined as follows:

$$c_t^i = \frac{1}{\text{days}_t^i} \sum_{d=1}^{\text{days}_t^i} \frac{1}{N_{td}^i} \sum_{n=1}^{N_{td}^i} IA_{tdn}^i \quad (17)$$

with

$$IA_{tdn}^i = \frac{2 \cdot |Q_{tdn5}^i - Q_{tdn}^i|}{Q_{tdn}^i \cdot w_{tdn}^i}$$

where all variables are defined as above and w_{tdn}^i is the transaction volume (in shares) of transaction n of day d in week t .

For all liquidity proxies, a missing value is recorded if there are less than three daily observations for week t and stock i , i.e., $\text{days}_t^i < 3$.³¹

³¹We make an exception for the week of September 11th 2001, when just one trading day occurred on NYSE/AMEX. For this week the minimum number of observations is lowered to 1.

A.2 Computation of Illiquidity Shocks and Analysis of EDL Risk Estimates For Different Proxies

As explained in the main text, we use $d_t^i = -c_t^i$, i.e., liquidity(-shocks) instead of illiquidity(-shocks) for the estimation of EDL risk (see Appendix B) in order to facilitate the interpretation of extreme downside *liquidity* risk. As d_t^i is highly persistent for most of the stocks in our sample, we estimate liquidity shocks based on the difference between the normalized realized liquidity value d_t^i and the expected normalized liquidity $E_{t-1}(d_t^i)$ for each stock i and week t . Expected normalized liquidity $E_{t-1}(d_t^i)$ is computed via an AR - time series model.

In order to deal with possible time-variation of parameters and to keep estimates fully out-of-sample, the estimation is run on a 3-year rolling window basis. The choice of a persistent but mean-reverting process seems natural for liquidity. Statistical tests – based on non-overlapping 3-year periods between 1963 and 2011³² – generally support this choice. First, the null-hypothesis of 'no autocorrelation at the first lag' is rejected by Ljung-Box tests at a 10% significance level for most stocks (e.g., 92% of stocks for the Amihud Illiquidity Ratio). Second, Augmented Dickey-Fuller tests – with four lagged difference terms, with drift and without time-trend – reject the null-hypothesis of 'unit root present' at a 10% significance level for most stocks (e.g., 78% of stocks for the Amihud Illiquidity Ratio). Additionally, the partial autocorrelation function becomes insignificant at the fourth lag or less for most stocks (e.g., 86% of stocks for the Amihud Illiquidity Ratio). These results generalize to most proxies. Thus, it seems reasonable to use an AR(4)-model to estimate $E_{t-1}(d_t^i)$, as given in Equation (5).

In order to assess the quality of our EDL risk estimates for different liquidity proxies, we perform a comparison between our weekly low-frequency proxies (*illiq*, *Corwin*, *Zeros* and *FHT*) and high-frequency benchmarks (*EffSpr*, *RelSpr*, *IntAmi*, and *PriImp*) from 1996 to 2010, when both are available. Panel A of Table A.1 displays average time-series correlations between proxy-levels for the sample period from 1996 to 2010. As expected, all low-frequency proxies are positively correlated with high-frequency benchmarks. *illiq* and *Corwin* show the highest correlations with the high-frequency proxies. In Panel B of Table A.1 we report average time-series correlations between proxy-EDL risk estimates. We again find that EDL risk estimates of the *illiq* and the *Corwin* measure are more highly correlated with the high-frequency proxies than risk estimates of the *Zeros* and the *FHT* measure. The positive correlations between low-frequency proxy EDL risks and high-frequency proxy EDL risks

³²The results are qualitatively the same, if the model-selection is done for just 1963-1968, so that the EDL risk-estimates can still be interpreted as fully out-of-sample.

suggest, that – in spite of all the noise in weekly low-frequency liquidity shocks – our method captures lower tail dependence in actual liquidity. Additionally, the magnitude of correlations suggests that *Corwin* and *illiq* lead to more precise EDL risk estimates than *FHT* and *Zeros*. The same ranking emerges in unreported tests, when average cross-sectional correlations on the stock-level, time-series correlations for the value-weighted market shocks, and Spearman, i.e., rank correlations between liquidity-shocks, are analyzed.

To investigate the temporal variation of the different EDL risk proxy measures, we plot the development of aggregate EDL risks over time. As before, we define aggregate EDL risk as the weekly cross-sectional, value-weighted average of EDL risk $_{i,t}$ over all stocks i in our sample. Figure A.1 plots the time series of EDL risk $_{m,t}$ for the different low-frequency and high-frequency measures. It reveals that EDL risk $_{m,t}$ based on low-frequency proxies experiences the largest spikes during the time period after Black Monday in October 1987 and the financial crisis starting in 2007. The same spike in 2007 emerges for the EDL risk measures based on high-frequency proxies, which are only available after 2001. We attribute the difference in EDL risk levels across proxies to the noisiness of liquidity measures. Noise (without tail dependence) could cause lower EDL risk estimates. This would explain why our noisier proxies (*FHT* and *Zeros*, see Table A.1) are at lower absolute EDL risk levels than EDL risk estimates based on *Corwin* and *illiq*.

Table A.1: Average Time-Series Correlations between Liquidity Proxy Levels and EDL Risk Estimates

Panel A: Average Time-Series Correlations between Proxy Levels

	High-Frequency Proxies				Low-Frequency Proxies			
	<i>EffSpr</i>	<i>RelSpr</i>	<i>IntAmi</i>	<i>PriImp</i>	<i>illiq</i>	<i>Corwin</i>	<i>Zeros</i>	<i>FHT</i>
<i>EffSpr</i>	1.00							
<i>RelSpr</i>	0.41	1.00						
<i>IntAmi</i>	0.58	0.35	1.00					
<i>PriImp</i>	0.75	0.33	0.79	1.00				
<i>illiq</i>	0.25	0.41	0.29	0.19	1.00			
<i>Corwin</i>	0.12	0.20	0.19	0.11	0.16	1.00		
<i>Zeros</i>	0.04	0.06	0.02	0.01	-0.03	-0.03	1.00	
<i>FHT</i>	0.11	0.14	0.09	0.07	0.09	0.07	0.70	1.00

Panel B: Average Time-Series Correlations between EDL Risk Estimates

	High-Frequency Proxies				Low-Frequency Proxies			
	<i>EffSpr</i>	<i>RelSpr</i>	<i>IntAmi</i>	<i>PriImp</i>	<i>illiq</i>	<i>Corwin</i>	<i>Zeros</i>	<i>FHT</i>
<i>EffSpr</i>	1.00							
<i>RelSpr</i>	0.48	1.00						
<i>IntAmi</i>	0.62	0.47	1.00					
<i>PriImp</i>	0.73	0.48	0.75	1.00				
<i>illiq</i>	0.39	0.36	0.35	0.38	1.00			
<i>Corwin</i>	0.49	0.48	0.57	0.53	0.36	1.00		
<i>Zeros</i>	0.04	0.02	0.03	0.04	0.02	0.01	1.00	
<i>FHT</i>	0.13	0.10	0.11	0.13	0.10	0.13	0.23	1.00

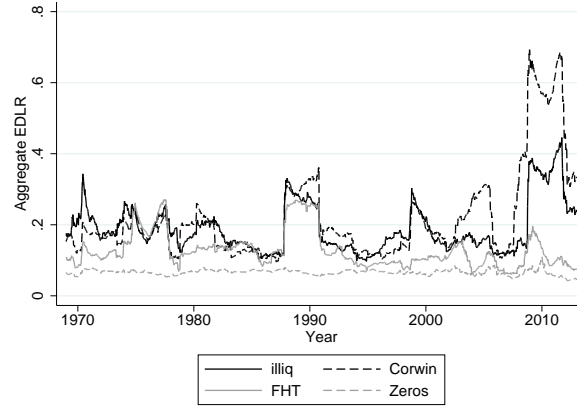
This table displays correlations between liquidity levels (Panel A) and EDL risk coefficients (Panel B) based on the different liquidity proxies used in this study. A detailed description of the computation of the proxy-levels and shocks is given above in Appendix A. The calculation of EDL risk coefficients is explained in Appendix B. The sample covers all U.S. common stocks traded on the NYSE / AMEX. The sample period for proxy levels (EDL risk estimates) is from January 1996 to December 2010 (January 2000 to December 2010).

Table A.2: Persistence of EDLR

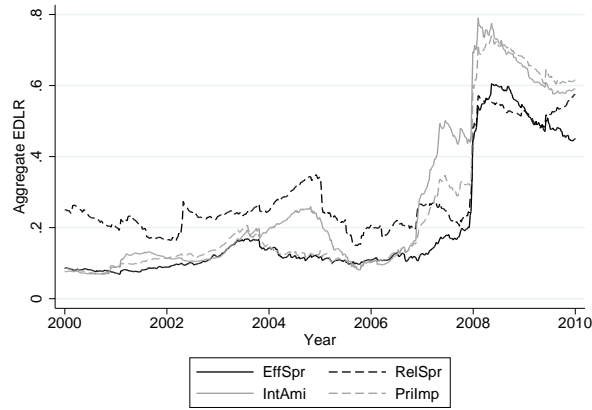
	(1) EDLR _{<i>t</i>+156}	(2) EDLR _{<i>t</i>+156}
EDL risk	0.0507*** (5.41)	0.0206*** (4.62)
β_R		0.0191*** (4.53)
size		0.0074*** (2.61)
btm		0.0076*** (4.97)
past return		0.0042 (0.63)
β_L		0.0314 (0.58)
EDR risk		0.0020 (0.29)
illiq		-0.0141*** (-4.94)
β_{Tail}		0.0097 (0.23)
idio vola		-0.0179 (-0.17)
coskew		-0.0038 (-0.50)
const	0.1793*** (13.17)	-0.0605 (-1.21)
Avg. R ²	0.0043	0.0741

This table displays the results of multivariate Fama and MacBeth (1973) regressions. We report the results of regressions of weekly EDL risk estimated based on weeks $t + 1$ to $t + 156$ on EDL risk estimated based on weeks $t - 155$ to t , β_R , the log of market capitalization (size), the book-to-market ratio (btm), the past 12-month excess returns (past year return), β_L , EDR risk, illiquidity (illiq), β_{Tail} from Kelly and Jiang (2014), idiosyncratic volatility (idio vola), and coskewness (*coskew*). All risk and firm characteristics are calculated using data available at (the end of) week t . A detailed description of the computation of these variables is given in the main text and in Appendix C. The sample covers all U.S. common stocks traded on the NYSE / AMEX and the sample period is from January 1969 to December 2012. t-statistics are in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively. We use Newey-West (1987) standard errors with 156 lags.

Figure A.1: Aggregate EDL Risk Over Time for Different Liquidity Measures



(a) Panel A: Low-Frequency Measures (1969 - 2012)



(b) Panel B: High-Frequency Measures (2002-2010)

This figure displays the evolution of aggregate EDL risk for different low-frequency and high-frequency liquidity measures. A detailed description of the computation of these variables is given in Appendix A. Panel A draws the evolution of aggregate EDL risk of the low-frequency measures, Panel B shows the evolution for the high-frequency measures. The sample covers all U.S. common stocks traded on the NYSE / AMEX and the sample period for low- (high-)frequency proxies is from 1969 (2000) to 2012 (2010).

B Appendix: Estimating Tail Dependence Coefficients

Appendix B provides the technical details of the copula estimation and selection procedure and the calculation of the respective tail dependence coefficients. The estimation procedure follows the approach of Chabi-Yo et al. (2017).

B.1 The Estimation Procedure

Bivariate extreme value distributions (such as in this paper) cannot be characterized by a fully parametric model in general, which leads to more complicated estimation techniques (see Frahm et al., 2005). Our estimation approach relies on the entire set of weekly returns r_t and liquidity innovations l_t of a firm i and the market in a 3-year period.

Coefficients of tail dependence have closed-form solutions for several basic parametric copulas (see Table B.1), but these basic copulas do not allow us to model upper and lower tail dependence simultaneously. However, Tawn (1988) shows that every convex combination of existing copula functions is again a copula. Thus, if $C_1(u_1, u_2)$, $C_2(u_1, u_2)$, \dots , $C_n(u_1, u_2)$ are bivariate copula functions, then

$$C(u_1, u_2) = w_1 \cdot C_1(u_1, u_2) + w_2 \cdot C_2(u_1, u_2) + \dots + w_n \cdot C_n(u_1, u_2)$$

is again a copula for $w_i \geq 0$ and $\sum_{i=1}^n w_i = 1$.

To allow for the maximum possible flexibility, we consider 64 possible convex combinations of the afore mentioned basic copulas from Table B.1. Each combination consists of one copula that allows for asymptotic dependence in the lower tail, C_{LTD} , one copula that is asymptotically independent, C_{NTD} , and one copula that allows for asymptotic dependence in the upper tail, C_{UTD} :

$$\begin{aligned} C(u_1, u_2, \Theta) = & w_1 \cdot C_{\text{LTD}}(u_1, u_2; \theta_1) \\ & + w_2 \cdot C_{\text{NTD}}(u_1, u_2; \theta_2) + (1 - w_1 - w_2) \cdot C_{\text{UTD}}(u_1, u_2; \theta_3), \end{aligned}$$

where Θ denotes the set of the basic copula parameters θ_i , $i = 1, 2, 3$ and the weights w_1 and w_2 .

For the sake of convenience, we only outline the estimation approach of lower tail dependence in the distribution of a stock's liquidity and market liquidity (EDL risk₁). The estimation of the other EDL risk components, namely EDL risk₂ (stock return and market liquidity) as well as EDL risk₃ (stock liquidity and market return) follows analogously.

Starting with 1966-1968, we determine the copula convex combination that shows the

best fit for the bivariate distribution of liquidity shocks for each stock and 3-year window. First, based on weekly liquidity innovations, we estimate a set of copula parameters Θ_j for $j = 1, \dots, 64$ different copulas $C_j(\cdot, \cdot; \Theta_j)$ between individual stock liquidity l_t^i and market liquidity l_t^m for each stock i based on a 3-year rolling window. Each of these convex combinations requires the estimation of five parameters: one parameter θ_i ($i = 1, 2, 3$) for each of the three basic copulas and two parameters for the weights w_1 and w_2 . The copula parameters Θ_j are estimated via the canonical maximum likelihood procedure of Genest et al. (1995). The details of this step are described in Section B.2.

Second, for each stock i and week t we compare the estimated log-likelihood values of all 64 copulas C_j and select the parametric copula $C_i^*(\cdot, \cdot; \Theta^*)$ that has the highest log-likelihood value. The result of this step is summarized in Table B.2 where we present the percentage frequency by which each of the possible 64 combinations is chosen. Most frequently, copula (1-D-IV) of Table B.1 is the best fit for the distribution for EDL risk₁ and copula (1-A-IV) is the best fit for the distributions for EDL risk₂ as well as EDL risk₃. Copula (1-D-IV) relates to the Clayton-FGM-Rotated Clayton-copula and copula (1-A-IV) relates to the Clayton-Gauss-Rotated Clayton-copula.

Third, for each stock i and week t , we compute the tail dependence coefficients λ_L implied by the estimated parameters Θ^* of the selected copula $C^*(\cdot, \cdot; \Theta^*)$. The computation of λ_L is straightforward if the copula in question has a closed form, as all the basic copulas used in this study do. Column (3) of Table B.1 displays the closed-form solutions to determine λ_L for the respective copula. The lower tail dependence coefficient of the convex combination is calculated using $\lambda_L^* = w_1^* \cdot \lambda_L(\theta_1^*)$. As this procedure is repeated for each stock and week, we end up with a panel of tail dependence coefficients at the stock-week level.

B.2 Estimation of the Copula Parameters

The estimation of the set of copula parameters Θ for a copula $C(\cdot, \cdot; \Theta)$ is performed as follows (see also Chabi-Yo et al., 2017):

Let $\{l_{i,k}, l_{m,k}\}_{k=1}^n$ be a random sample from the bivariate distribution

$$F(l_i, l_m) = C(F_i(l_i), F_m(l_m))$$

between individual stock liquidity l_i and market liquidity l_m , where n denotes the number of weekly return observations in a 3-year period. The marginal distributions F_i and F_m of individual stock liquidity l_i and market liquidity l_m are estimated non-parametrically by their scaled empirical distribution functions

$$\hat{F}_i(x) = \frac{1}{n+1} \sum_{k=1}^n \mathbb{1}_{l_{i,k} \leq x} \quad \text{and} \quad \hat{F}_m(x) = \frac{1}{n+1} \sum_{k=1}^n \mathbb{1}_{l_{m,k} \leq x}. \quad (18)$$

This non-parametric estimation approach avoids an incorrect specification of the marginal distributions. We then estimate the set of copula parameters Θ parametrically. The parameters Θ are estimated via the maximum likelihood estimator

$$\hat{\Theta} = \operatorname{argmax}_{\Theta} L(\Theta) \quad \text{with} \quad L(\Theta) = \sum_{k=1}^n \log(c(\hat{F}_{i,l_{i,k}}, \hat{F}_{m,l_{m,k}}; \Theta_j)), \quad (19)$$

where $L(\Theta)$ denotes the log-likelihood function and $c(\cdot, \cdot; \Theta)$ the copula density. $\hat{\Theta}$ is a consistent and asymptotic normal estimate of the set of copula parameters Θ under standard regularity conditions (e.g., Genest et al., 2005), assuming that $\{l_{i,k}, l_{m,k}\}_{k=1}^n$ is an i.i.d. random sample.

Table B.1: Bivariate Copula Functions with Tail Dependence Coefficients

Copula	Parametric Form	λ_L	λ_U
Clayton (1)	$C_{\text{Cla}}(u_1, u_2; \theta) = (u_1^{-\theta} + u_2^{-\theta} - 1)^{-1/\theta}$	$2^{-1/\theta}$	—
Rotated-Gumbel (2)	$C_{\text{RGum}}(u_1, u_2) = u_1 + u_2 - 1 + \exp(-(-\log(\bar{u}_1))^\theta + (-\log(\bar{u}_2))^\theta)^{1/\theta}$	$2 - 2^{1/\theta}$	—
Rotated-Joe (3)	$C_{\text{RJoe}}(u_1, u_2) = u_1 + u_2 - (u_1^\theta + u_2^\theta - u_1^\theta \cdot u_2^\theta)^{1/\theta}$	$2 - 2^{1/\theta}$	—
Rotated-Galambos (4)	$C_{\text{RGal}}(u_1, u_2) = u_1 + u_2 - 1 + (\bar{u}_1) \cdot (\bar{u}_2) \cdot \exp(((-\log(\bar{u}_1))^{-\theta} + (-\log(\bar{u}_2))^{-\theta})^{-1/\theta})$	$2^{-1/\theta}$	—
Gauss (A)	$C_{\text{Gau}}(u_1, u_2; \theta) = \Phi_\theta(\Phi^{-1}(u_1), \Phi^{-1}(u_2))$	—	—
Frank (B)	$C_{\text{Fra}}(u_1, u_2; \theta) = -\theta^{-1} \log\left(\frac{1 - \exp(-\theta) - (1 - \exp(-\theta u_1))(1 - \exp(-\theta u_2))}{1 - \exp(-\theta)}\right)$	—	—
Plackett (C)	$C_{\text{Pla}}(u_1, u_2; \theta) = \frac{1}{2}(\theta - 1)^{-1} \{1 + (\theta - 1)(u_1 + u_2) - [(1 + (\theta - 1)(u_1 + u_2))^2 - 4\theta u_1 u_2]^{1/2}\}$	—	—
F-G-M (D)	$C_{\text{Fgm}}(u_1, u_2; \theta) = u_1 u_2 (1 + \theta(1 - u_1)(\bar{u}_2))$	—	—
Joe (I)	$C_{\text{Joe}}(u_1, u_2; \theta) = 1 - ((\bar{u}_1)^\theta + (\bar{u}_2)^\theta - (\bar{u}_1)^\theta \cdot (\bar{u}_2)^\theta)^{1/\theta}$	—	$2 - 2^{1/\theta}$
Gumbel (II)	$C_{\text{Gum}}(u_1, u_2; \theta) = \exp(-(-\log(u_1))^\theta + (-\log(u_2))^\theta)^{1/\theta}$	—	$2 - 2^{1/\theta}$
Galambos (III)	$C_{\text{Gal}}(u_1, u_2; \theta) = u_1 \cdot u_2 \cdot \exp(((-\log(u_1))^{-\theta} + (-\log(u_2))^{-\theta})^{-1/\theta})$	—	$2^{-1/\theta}$
Rotated-Clayton (IV)	$C_{\text{RCla}}(u_1, u_2) = u_1 + u_2 - 1 + ((\bar{u}_1)^{-\theta} + (\bar{u}_2)^{-\theta} - 1)^{-1/\theta}$	—	$2^{-1/\theta}$

This table reports the parametric forms of bivariate copula functions considered in this study in the second column and the corresponding lower and upper tail dependence coefficients, λ_L and λ_U , in the last two columns. The Clayton-, the Rotated Joe-, the Rotated Gumbel-, and the Rotated Galambos-copula exhibit lower tail dependence. The Gauss-, the Frank-, the Plackett-, and the FGM-copula are asymptotically independent in both tails. The Joe-, the Gumbel-, the Galambos-, and the Rotated Clayton-copula exhibit upper tail dependence. In brackets we assign a label to each basic copula. We define $\bar{u}_1 = 1 - u_1$ and $\bar{u}_2 = 1 - u_2$. Φ denotes the standard normal $N(0, 1)$ distribution function, Φ^{-1} the functional inverse of Φ and Φ_θ is the bivariate standard normal distribution function with correlation θ .

Table B.2: Relative Percentage of Copula Selection

Full Sample: 1969-2012					
Distribution (l_i, l_m)		Distribution (r_i, l_m)		Distribution (l_i, r_m)	
Copula	Perc	Copula	Perc	Copula	Perc
(1-D-IV)	7.60%	(1-A-IV)	6.77%	(1-A-IV)	9.97%
(1-A-IV)	7.50%	(1-A-III)	6.70%	(1-D-IV)	6.05%
(1-A-III)	6.63%	(4-A-IV)	6.00%	(1-A-III)	5.51%
(3-B-IV)	0.00%	...		(3-B-II)	0.00%
(3-B-II)	0.00%	(2-D-II)	0.00%	(2-B-II)	0.00%
(3-B-I)	0.00%	(2-B-I)	0.00%	(2-B-I)	0.00%
		(2-B-II)	0.00%		
Total	100.00%	Total	100.00%	Total	100.00%

This table reports the percentage frequency of the selected parametric copula combinations in the period from 1969-2012 for the three EDL risk distributions: the distribution between (i) a stock's liquidity and market liquidity (l_i, l_m), (ii) a stock's return and market liquidity (r_i, l_m), and (iii) a stock's liquidity and the market return (l_i, r_m). We select the appropriate dependence structure for each stock-week and each bivariate distribution by comparing log-likelihood values for all 64 possible copula combinations. We indicate the label of the respective copula combination based on the basic copula labels from Table B.1. The copulas that are most often selected are: (1-D-IV) - the Clayton-FGM-Rotated-Clayton-copula for the distribution (l_i, l_m), (1-A-IV) - the Clayton-Gauss-Rotated-Clayton-copula for the distribution (r_i, l_m), and (1-A-IV) - the Clayton-Gauss-Rotated-Clayton-copula for the distribution (l_i, r_m).

C Appendix: Brief Definitions and Data Sources of Main Variables

The following table briefly defines the main variables used in our empirical analysis. Abbreviations for the data sources are:

- (i) CRSP: CRSP's Stocks Database
- (ii) KF: Kenneth French's Data Library
- (iii) CS: Compustat
- (iv) OP: The homepages of authors of the respective original papers

EST indicates that the variable is estimated or computed based on original variables from the respective data sources. Note that the eight liquidity proxies we use are defined separately in Appendix A.

Panel A: Return- and Liquidity-Based Variables

Variable Name	Description	Source
Return_t	Raw excess return of a portfolio (stock) over the risk-free rate in week t . As risk-free rate we use the 1-month T-Bill rate.	CRSP, KF, EST
EDL risk ₁	Extreme Downside Liquidity Risk 1 of a stock. Lower tail dependence between stock liquidity-shocks and (value-weighted) market liquidity-shocks, estimated based on weekly data from a 3-year rolling window, as detailed in Appendix B.	CRSP, EST
EDL risk ₂	Extreme Downside Liquidity Risk 2 of a stock. Lower tail dependence between stock returns and (value-weighted) market liquidity-shocks, estimated based on weekly data from a 3-year rolling window, as detailed in Appendix B.	CRSP, EST
EDL risk ₃	Extreme Downside Liquidity Risk 3 of a stock. Lower tail dependence between stock liquidity-shocks and (value-weighted) market returns, estimated based on weekly data from a 3-year rolling window, as detailed in Appendix B.	CRSP, EST
EDR (EUR) risk	Extreme Downside (Upside) Return Risk of a stock. Lower (Upper) tail dependence between stock returns and (value-weighted) market returns, estimated based on weekly data from a 3-year rolling window, as detailed in Appendix B.	CRSP, EST
EDL risk	Joint Extreme Downside Liquidity Risk of a stock. $\text{EDL risk} = \text{EDL risk}_1 + \text{EDL risk}_2 + \text{EDL risk}_3$, as detailed in the main text.	CRSP, EST
Aggregate EDL risk	Aggregate Extreme Downside Liquidity Risk. Value-weighted average of EDL risk (EDL risk_i) for each week over all stocks in the sample, as detailed in the main text.	CRSP, EST
Aggregate EDR risk	Aggregate Extreme Downside Return Risk. Value-weighted average of EDR risk for each week over all stocks in the sample, as detailed in the main text.	CRSP, EST
EDL risk _{xy}	As EDL risk, but based on an x -year rolling window, as detailed in the main text.	CRSP, EST
EDL risk _{Cx}	As EDL risk, but based on copula function Cx , as detailed in the main text and Appendix B.	CRSP, EST

Variable Name	Description	Source
β_R	Factor loading on the market factor from a CAPM one-factor regression estimated based on a 3-year rolling window of weekly data: $\beta_R = \frac{\text{COV}(r_i, r_m)}{\text{VAR}(r_m)}$.	CRSP, EST
β_R^-	Downside beta estimated based on a 3-year rolling window of weekly data, as defined in Ang et al. (2006a): $\beta_R^- = \frac{\text{COV}(r_i, r_m r_m < \mu_m)}{\text{VAR}(r_m r_m < \mu_m)}$, where μ_m is the mean market return.	CRSP, EST
β_R^+	Upside beta. As β_R^- , but with inverted signs within the conditional (co)variance.	CRSP, EST
β_{L1}	Liquidity beta 1 as defined in Acharya and Pedersen (2005), estimated based on a 3-year rolling window of weekly data: $\beta_{L1} = \frac{\text{COV}(l_i, l_m)}{\text{VAR}(r_m - l_m)}$, where l_i and l_m are the stock- and market-liquidity innovations, as described in the main text and Appendix B.	CRSP, EST
β_{L2}	Liquidity beta 2 as defined in Acharya and Pedersen (2005), estimated based on a 3-year rolling window of weekly data: $\beta_{L2} = \frac{\text{COV}(r_i, l_m)}{\text{VAR}(r_m - l_m)}$.	CRSP, EST
β_{L3}	Liquidity beta 3 as defined in Acharya and Pedersen (2005), estimated based on a 3-year rolling window of weekly data: $\beta_{L3} = \frac{\text{COV}(l_i, r_m)}{\text{VAR}(r_m - l_m)}$.	CRSP, EST
β_L	Joint linear liquidity risk. $\beta_L = \beta_1 + \beta_2 + \beta_3$.	CRSP, EST
β_{L1}^-	Downside liquidity beta 1, estimated based on a 3-year rolling window of weekly data: $\beta_{L1}^- = \frac{\text{COV}(l_i, l_m l_m < \mu_{l_m})}{\text{VAR}(r_m - l_m l_m < \mu_{l_m})}$, where μ_{l_m} is the mean weekly market liquidity innovation.	CRSP, EST
β_{L2}^-	Downside liquidity beta 2, estimated based on a 3-year rolling window of weekly data: $\beta_{L2}^- = \frac{\text{COV}(r_i, l_m l_m < \mu_{l_m})}{\text{VAR}(r_m - l_m l_m < \mu_{l_m})}$.	CRSP, EST
β_{L3}^-	Downside liquidity beta 3, estimated based on a 3-year rolling window of weekly data: $\beta_{L3}^- = \frac{\text{COV}(l_i, r_m r_m < \mu_{r_m})}{\text{VAR}(r_m - l_m r_m < \mu_{r_m})}$, where μ_{r_m} is the mean weekly market return.	CRSP, EST
β_L^-	Joint linear downside liquidity risk. $\beta_L^- = \beta_{L1}^- + \beta_{L2}^- + \beta_{L3}^-$.	CRSP, EST
β_L^+	Joint linear upside liquidity risk. As β_L^- , but with inverted signs within the (co)variances.	CRSP, EST
β_{Tail}	Exposure to tail risk, as measured in Kelly and Jiang (2014), , based on a 3-year rolling window of weekly data.	CRSP, EST

Variable Name	Description	Source
CAPM-Alpha, FF-Alpha, CAR-Alpha	Sharpe (1964)-based alpha, Fama and French (1993) three-factor alpha, and Carhart (1997) four-factor alpha of a portfolio. We use monthly portfolio returns to estimate the alphas.	CRSP, KF, EST
idio vola	A stock's idiosyncratic volatility, defined as the 3-year rolling window standard deviation of the CAPM-residuals of its weekly returns.	CRSP, EST
coskew	The coskewness of a stock's 3-year rolling window weekly returns with the market: $coskew = \frac{E[(r_i - \mu_i)(r_m - \mu_m)^2]}{\sqrt{VAR(r_i)VAR(r_m)}}.$	CRSP, EST
LPM return	Lower partial co-moment between a stock return and the market as computed in Anthonisz and Putnins (2016), estimated based on a 3-year rolling window of weekly data.	CRSP, EST
LPM liquidity risk	Sum of the the lower partial co-moments between a stock's liquidity and market liquidity, stock's return and market liquidity, and a stock's liquidity and the market return as computed in Anthonisz and Putnins (2016), estimated based on a 3-year rolling window of weekly data.	CRSP, EST
liquidity tail risk	Exposure to liquidity tail risk, as measured in Wu (2015), based on a 3-year rolling window of weekly data.	CRSP, EST
Marketrfr	Value-weighted CRSP market-return in excess of the risk-free rate.	KF
SMB	Small-Minus-Big factor portfolio return, available for each month.	KF
HML	High-Minus-Low factor portfolio return, available for each month.	KF
Mom	Winner-Minus-Loser (momentum) factor portfolio return, available for each month.	KF
past return	Last year's return for a given stock.	CRSP, EST
PS Liqui	Pastor and Stambaugh (2003)'s traded liquidity risk factor.	OP
Sadka Liqui	Sadka (2006)'s liquidity factor.	OP
EDRR	Chabi-Yo et al. (2017)'s equally-weighted EDR risk factor portfolio return.	OP

Variable Name	Description	Source
illiq	Amihud (2002) illiquidity ratio (average over last year).	CRSP, EST
Tail	Kelly and Jiang (2014)'s equal-weighted tail risk factor portfolio return.	CRSP, EST
BAB	Frazzini and Pedersen (2014)'s U.S. equity betting-against-beta return.	OP
Max	Bali et al. (2011)'s equally-weighted lottery factor.	OP
Standard- Deviation	Standard-deviation of the past 3 years' weekly returns or liquidity shocks.	CRSP, EST
VaR	Value at Risk. 5% quantile of the past 3 years' weekly returns or liquidity shocks.	CRSP, EST
CoVaR	Conditional Value at Risk. Conditional mean of the past 3 years' weekly returns or liquidity shocks below the 5% quantile.	CRSP, EST

Panel B: Other Firm Characteristics

Variable Name	Description	Source
size	The natural logarithm of a firm's equity market capitalization in million USD.	CS
btm	A firm's book-to-market ratio computed as the ratio of CS book value of equity per share (i.e., book value of common equity less liquidation value (CEQL) divided by common share outstanding (CSHO)) to share price (i.e., market value of equity per share).	CS
SIC 2, 3, 4	2-, 3- and 4-digit Standard Industrial Classification.	CRSP
FF 12, 48	Fama and French's 12 and 48 industry classifications.	KF
DGTW	Daniel et al. (1997)'s characteristic-based benchmark, available via Russ Wermer's homepage.	OP

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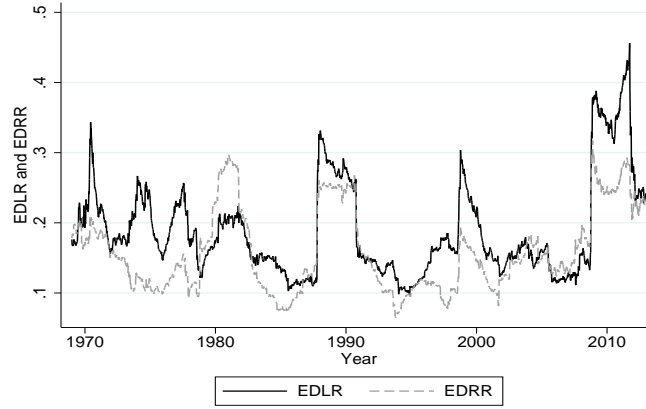
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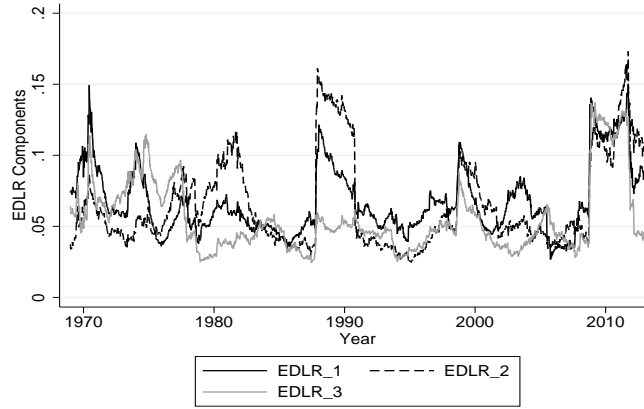
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Figure 1: Aggregate EDL Risk over Time (1969 - 2012)



(a) Panel A: Aggregate EDL Risk and EDR Risk over Time



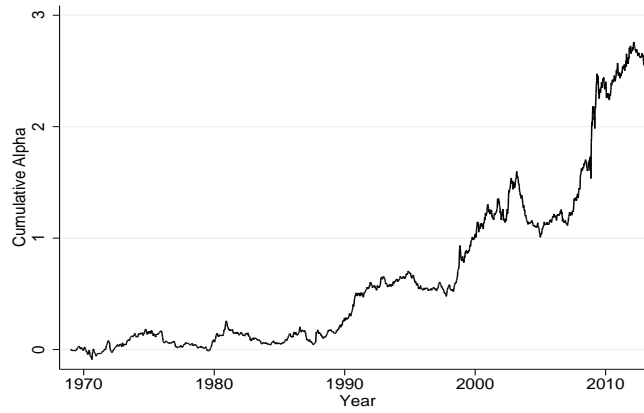
(b) Panel B: Components of Aggregate EDL Risk

This figure displays the evolution of aggregate EDL risk and EDR risk as well as the different components of EDL risk over time. Aggregate EDL risk (EDR risk) in week t is defined as the value-weighted average of EDL risk (EDR risk) over all stocks i in our sample. Analogously, we define the aggregate EDL risk components (aggregate EDL risk₁, aggregate EDL risk₂, aggregate EDL risk₃) in week t as the value-weighted average of the EDL risk components (EDL risk₁, EDL risk₂, EDL risk₃) over all stocks i in our sample. Panel A draws the evolution of aggregate EDL risk (EDR risk) over time. Panel B shows the evolution of the different aggregate EDL risk components. The sample covers all U.S. common stocks traded on the NYSE / AMEX and the sample period is from January 1969 to December 2012.

Figure 2: Yearly Alpha and Cumulative Alpha of EDL Risk Strategy



(a) Panel A: Yearly Alpha of EDL Risk Strategy



(b) Panel B: Cumulative Alpha of EDL Risk Strategy

This figure displays the evolution of the annualized 1-year Carhart-alpha and the cumulative Carhart-alpha of a trading strategy consisting of buying strong EDL risk stocks and selling weak EDL risk stocks with weekly rebalancing (no trading costs are taken into account). The sample covers all U.S. common stocks traded on the NYSE / AMEX and the sample period is from January 1969 to December 2012.

Table 2: Summary Statistics

	Mean	25%- Quantile	50%- Median	75%- Quantile	Std. Dev.	Above EDLR Median	Below EDLR Median	Above - Below
Return _{t+2}	0.15%	-2.73%	-0.11%	2.64%	6.00%	0.17%	0.12%	0.05%***
EDL risk	0.188	0.075	0.157	0.266	0.147	0.290	0.086	0.203
EDL risk ₁	0.066	0.000	0.038	0.107	0.079	0.107	0.026	0.081
EDL risk ₂	0.066	0.000	0.041	0.107	0.074	0.096	0.036	0.061
EDL risk ₃	0.056	0.000	0.030	0.086	0.070	0.087	0.025	0.062
$\beta_L(\cdot 100)$	1.525	0.033	0.245	1.500	2.819	1.477	1.573	-0.096***
$\beta_L^-(\cdot 100)$	2.344	-0.018	0.164	2.127	5.456	2.571	2.116	0.455***
EDRR	0.163	0.052	0.143	0.252	0.132	0.177	0.150	0.027***
β_R	1.008	0.652	0.966	1.312	0.508	1.056	0.960	0.096***
β_R^-	1.105	0.640	1.042	1.508	0.720	1.152	1.058	0.094***
size	19.620	18.037	19.600	21.099	2.117	19.814	19.416	0.398***
btm	0.835	0.397	0.659	1.057	0.665	0.816	0.855	-0.039***
illiq	1.075%	0.263%	0.340%	0.851%	1.671%	0.913%	1.241%	-0.328%***
past return	14.544%	-13.369%	8.954%	34.077%	44.843%	14.933%	14.143%	0.800%***
idio vola	4.891%	3.380%	4.515%	6.075%	1.909%	4.810%	4.973%	-0.163%***
coskew	-0.135	-0.278	-0.113	0.044	0.274	-0.143	-0.129	-0.012***

This table displays summary statistics for the main variables used in this study. The first five columns show the mean, the 25%-quantile, the 50%-quantile (median), the 75%-quantile, and the standard deviation of each variable. The last three columns display mean values of the variables conditional on EDL risk being above (below) its 50%-quantile as well as the difference with corresponding statistical significance level. We present results for future weekly excess stock returns over the 1-month T-Bill rate (Return_{t+2}), EDL risk, EDL risk₁, EDL risk₂, EDL risk₃, linear liquidity risk ($\beta_L \cdot 100$), linear downside liquidity risk ($\beta_L^- \cdot 100$), extreme downside return risk (EDRR), return beta (β_R), downside return beta (β_R^-), the log of market capitalization (size), book-to-market value (btm), illiquidity (illiq), idiosyncratic volatility (idio vola), the past yearly excess return (past return), and coskewness (coskew). A detailed description of these variables is given in the main text and in Appendix C. The sample covers all U.S. common stocks traded on the NYSE / AMEX and the sample period is from January 1969 to December 2012. t-statistics are in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 3: Correlations

	EDLR	EDLR ₁	EDLR ₂	EDLR ₃	β_L	β_L^-	EDRR	β_R	β_R^-	size	btm	illiq	past ret	idio vola	coskew	Return _{t+2}
EDL risk	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
EDL risk ₁	0.72	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-	-
EDL risk ₂	0.61	0.12	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-
EDL risk ₃	0.64	0.24	0.08	1.00	-	-	-	-	-	-	-	-	-	-	-	-
β_L	-0.02	-0.01	-0.05	0.03	1.00	-	-	-	-	-	-	-	-	-	-	-
β_L^-	0.05	0.02	-0.04	0.13	0.55	1.00	-	-	-	-	-	-	-	-	-	-
EDRR	0.26	0.14	0.27	0.10	-0.09	-0.07	1.00	-	-	-	-	-	-	-	-	-
β_R	0.18	0.09	0.11	0.15	0.03	0.00	0.27	1.00	-	-	-	-	-	-	-	-
β_R^-	0.12	0.06	0.11	0.07	0.08	0.08	0.42	0.68	1.00	-	-	-	-	-	-	-
size	0.11	0.10	0.06	0.05	-0.50	-0.42	0.11	-0.02	-0.13	1.00	-	-	-	-	-	-
btm	0.01	-0.02	0.00	0.04	0.19	0.17	-0.06	-0.01	-0.01	-0.45	1.00	-	-	-	-	-
illiq	-0.11	-0.08	-0.07	-0.06	0.50	0.42	-0.17	-0.14	-0.05	-0.60	0.33	1.00	-	-	-	-
past return	-0.05	-0.05	-0.01	-0.04	0.01	0.01	0.00	-0.01	0.00	0.10	-0.29	-0.04	1.00	-	-	-
idio vola	0.00	-0.02	-0.01	0.04	0.36	0.31	-0.02	0.33	0.32	-0.51	0.19	0.44	0.04	1.00	-	-
coskew	-0.18	-0.13	-0.24	0.03	0.05	0.05	-0.51	-0.03	-0.29	-0.06	0.06	0.03	0.04	0.04	1.00	-
Return _{t+2}	0.01	0.00	0.01	0.01	0.00	0.00	0.01	-0.00	-0.00	-0.00	0.02	0.00	0.01	0.00	0.01	1.00

This table displays linear correlations between the independent variables used in this study. As independent variables we use EDL risk, EDL risk₁, EDL risk₂, EDL risk₃, linear liquidity risk (β_L), linear downside liquidity risk (β_L^-), extreme downside return risk (EDRR), return beta (β_R), downside return beta (β_R^-), the log of market capitalization (size), book-to-market value (btm), illiquidity (illiq), the past yearly excess return (past return), idiosyncratic volatility (idio vola), and coskewness (coskew). A detailed description of the computation of these variables is given in the main text and in Appendix C. The sample covers all U.S. common stocks traded on the NYSE / AMEX and the sample period is from January 1969 to December 2012.

Table 4: Univariate Equal-Weighted Portfolio Sorts: EDL Risk and Returns

Panel A: EDL Risk				
Portfolio	(1) EDL risk	(2) Return _{t+2}	(3) CAPM _{t+2}	(4) Carhart _{t+2}
1 Weak EDL risk	0.04	5.77%	1.30%	-0.17%
2	0.11	7.46%	2.65%	1.17%
3	0.17	8.75%	3.70%	2.24%
4	0.25	9.16%	3.86%	2.42%
5 Strong EDL risk	0.39	9.77%	4.15%	2.86%
Strong - Weak	0.35	4.00%*** (3.66)	2.85%*** (2.80)	3.03%*** (2.90)

Panel B: EDL Risk₁				
Portfolio	(1) EDL risk ₁	(2) Return _{t+2}	(3) CAPM _{t+2}	(4) Carhart _{t+2}
1 Weak EDL risk ₁	0.00	8.11%	3.35%	1.88%
2	0.01	8.29%	3.37%	1.77%
3	0.04	7.39%	2.41%	0.95%
4	0.09	8.70%	3.49%	2.27%
5 Strong EDL risk ₁	0.19	8.43%	3.03%	1.65%
Strong - Weak	0.19	0.33% (0.40)	-0.32% (-0.40)	-0.23% (-0.28)

Panel C: EDL Risk₂				
Portfolio	(1) EDL risk ₂	(2) Return _{t+2}	(3) CAPM _{t+2}	(4) Carhart _{t+2}
1 Weak EDL risk ₂	0.00	5.73%	1.11%	-0.15%
2	0.02	7.26%	2.42%	1.20%
3	0.05	7.21%	2.27%	0.92%
4	0.09	9.37%	4.22%	2.82%
5 Strong EDL risk ₂	0.17	9.80%	4.43%	2.94%
Strong - Weak	0.17	4.08%*** (4.74)	3.32%*** (4.10)	3.09%*** (3.69)

Panel D: EDL Risk₃

Portfolio	(1) EDL risk ₃	(2) Return _{t+2}	(3) CAPM _{t+2}	(4) Carhart _{t+2}
1 Weak EDL risk ₃	0.00	6.38%	1.73%	0.28%
2	0.01	6.75%	1.98%	0.52%
3	0.04	7.50%	2.49%	0.93%
4	0.08	10.31%	5.01%	3.53%
5 Strong EDL risk ₃	0.16	9.97%	4.43%	3.25%
Strong - Weak	0.16	3.59%*** (3.87)	2.70%*** (3.08)	2.97%*** (3.39)

This table (with Panels A-D) reports equal-weighted annualized average week $t+2$ excess returns for portfolios sorted by EDL risk and the different EDL risk components EDL risk₁, EDL risk₂ and EDL risk₃. Each week t we rank stocks into quintiles (1-5) based on estimated EDL risk (or the respective EDL risk component) over the past three years and form equal-weighted portfolios at the beginning of each weekly period. We report annualized average returns in excess of the one-month T-Bill rate over the week $t + 2$, annualized CAPM-alphas based on Sharpe (1964)'s capital asset pricing model and annualized Carhart-alphas based on Carhart (1997)'s four factor model. The row labelled 'Strong - Weak' reports the difference between the returns and alphas of portfolio 5 and portfolio 1 with corresponding t-statistic. The sample covers all U.S. common stocks traded on the NYSE / AMEX and the sample period is from January 1969 to December 2012. t-statistics are in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively. We use Newey-West (1987) standard errors with four lags.

Table 5: Bivariate Equal-Weighted Portfolio Sorts**Panel A: EDL Risk and β_L Risk**

Portfolio	1 Weak β_L	2	3	4	5 Strong β_L	Average
1 Weak EDL risk	6.34%	4.78%	5.34%	6.36%	6.04%	5.77%
2	8.58%	5.55%	7.02%	7.49%	8.42%	7.41%
3	9.18%	7.27%	8.85%	9.85%	8.91%	8.81%
4	10.02%	8.26%	7.68%	10.21%	11.04%	9.44%
5 Strong EDL risk	9.80%	7.38%	8.62%	9.32%	12.14%	9.45%
Strong-Weak Return	3.46%** (2.38)	2.60%** (2.46)	3.28%*** (2.62)	2.96%** (2.22)	6.10%*** (3.94)	3.68%*** (4.15)
Strong-Weak CAPM	2.65%* (1.87)	2.04%* (1.94)	2.48%** (2.02)	2.11% (1.58)	5.15%*** (3.40)	2.89%*** (3.40)
Strong-Weak Carhart	2.09% (1.42)	1.94%* (1.82)	2.75%** (2.23)	2.62%* (1.86)	4.77%*** (3.11)	2.83%*** (3.27)

Panel B: EDL Risk and β_L^- Risk

Portfolio	1 Weak β_L^-	2	3	4	5 Strong β_L^-	Average
1 Weak EDL risk	6.16%	4.64%	4.78%	6.21%	6.96%	5.75%
2	7.17%	6.55%	6.94%	8.32%	8.25%	7.44%
3	9.46%	7.96%	8.59%	9.24%	8.61%	8.77%
4	8.11%	9.05%	8.02%	9.75%	11.27%	9.24%
5 Strong EDL risk	10.34%	7.69%	8.69%	10.03%	11.63%	9.68%
Strong-Weak Return	4.18%*** (2.86)	3.05%*** (2.82)	3.91%*** (3.02)	3.81%*** (2.81)	4.67%*** (2.87)	3.93%*** (4.27)
Strong-Weak CAPM	3.28%** (2.34)	2.37%** (2.23)	2.97%** (2.34)	2.91%** (2.15)	3.61%** (2.29)	3.03%*** (3.47)
Strong-Weak Carhart	2.99%** (2.10)	2.34%** (2.11)	2.93%** (2.34)	3.68%** (2.69)	3.19%* (1.96)	3.03%*** (3.40)

Panel C: EDL Risk and EDR Risk

Portfolio	1 Weak EDRR	2	3	4	5 Strong EDRR	Average
1 Weak EDL risk	3.46%	5.04%	6.92%	6.42%	8.73%	6.11%
2	4.27%	6.64%	7.84%	7.97%	11.26%	7.60%
3	5.84%	7.23%	10.16%	10.00%	10.86%	8.82%
4	5.80%	7.85%	9.50%	10.17%	11.65%	9.00%
5 Strong EDL risk	6.89%	8.47%	10.94%	9.70%	10.80%	9.36%
Strong-Weak Return	3.43%** (2.43)	3.43%** (2.47)	4.02%*** (2.78)	3.29%** (2.45)	2.07% (1.46)	3.25%*** (3.28)
Strong-Weak CAPM	2.39%* (1.75)	2.40%* (1.81)	2.92%** (2.10)	2.40%* (1.77)	1.30% (0.94)	2.28%** (2.42)
Strong-Weak Carhart	2.25% (1.59)	2.33%* (1.71)	2.96%** (2.10)	2.39%* (1.77)	1.39% (0.97)	2.26%** (2.37)

Panel D: EDL Risk and LPM Liquidity Risk

Portfolio	1 Weak LPMLR	2	3	4	5 Strong LPMLR	Average
1 Weak EDL risk	4.59%	5.28%	6.64%	6.04%	5.64%	5.64%
2	8.17%	5.77%	7.92%	8.50%	8.69%	7.81%
3	7.11%	7.91%	8.46%	8.99%	9.58%	8.41%
4	9.18%	9.62%	9.17%	9.02%	11.10%	9.62%
5 Strong EDL risk	7.71%	8.29%	9.32%	10.81%	11.38%	9.50%
Strong-Weak Return	3.12%** (1.98)	3.01%** (2.12)	2.68%** (2.19)	4.76%*** (3.61)	5.74%*** (3.62)	3.86%*** (3.84)
Strong-Weak CAPM	2.26% (1.44)	1.96% (1.46)	1.57% (1.39)	3.82%*** (3.04)	4.66%*** (3.04)	2.86%*** (3.08)
Strong-Weak Carhart	2.62% (1.64)	1.95% (1.44)	1.75% (1.48)	3.73%*** (2.85)	4.32%** (2.69)	2.87%*** (3.04)

Panel E: EDL Risk and Liquidity Tail Risk

Portfolio	1 Weak LTR	2	3	4	5 Strong LTR	Average
1 Weak EDL risk	4.33%	7.03%	7.15%	7.32%	10.70%	7.30%
2	8.54%	6.79%	9.26%	10.16%	9.30%	8.81%
3	10.59%	9.75%	10.34%	10.95%	10.28%	10.38%
4	10.48%	10.07%	10.25%	11.65%	10.57%	10.6%
5 Strong EDL risk	9.68%	10.42%	10.21%	12.43%	13.15%	11.18%
Strong-Weak Return	5.35%*** (3.27)	3.38%** (2.41)	3.06%** (1.97)	5.11%*** (3.32)	2.46% (1.38)	3.87%*** (3.45)
Strong-Weak CAPM	3.99%** (2.52)	2.15%* (1.69)	1.70% (1.16)	3.96%*** (2.61)	1.31% (0.77)	2.62%*** (2.55)
Strong-Weak Carhart	3.70%** (2.25)	1.82% (1.33)	1.75% (1.20)	3.78%** (2.39)	1.39% (0.79)	2.49%** (2.39)

This table reports the results of dependent equal-weighted portfolio sorts. First, we form quintile portfolios sorted on β_L risk (β_L^- risk, EDR risk, LPM liquidity risk, liquidity tail risk). Then, within each risk quintile, we sort stocks into equal-weighted portfolios based on EDL Risk. Panel A displays annualized average future returns of 25 β_L risk - EDL risk portfolio sorts, Panel B shows annualized average future returns of the 25 β_L^- - EDL risk sorts, Panel C shows the annualized average future returns of the 25 EDR risk - EDL risk portfolio sorts, Panel D shows the annualized average future returns of the 25 LPM liquidity risk (see Anthonisz and Putnins, 2016) - EDL risk portfolio sorts and Panel E shows the annualized average future returns of the 25 liquidity tail risk (see Wu, 2015) - EDL risk portfolio sorts. The row labelled 'Strong - Weak' reports the difference between the returns and alphas of portfolio 5 and portfolio 1 with corresponding t-statistic. The sample covers all U.S. common stocks traded on the NYSE / AMEX and the sample period is from January 1969 to December 2012. t-statistics are in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively. We use Newey-West (1987) standard errors with four lags.

Table 6: EDL Risk and Returns: Factor Models

Panel A: Factor Models							
	(1) EDL risk (PF5-1)	(2) EDL risk (PF5-1)	(3) EDL risk (PF5-1)	(4) EDL risk (PF5-1)	(5) EDL risk (PF5-1)	(6) EDL risk (PF5-1)	(7) EDL risk (PF5-1)
Marketrfr	0.134*** (4.52)	0.133*** (5.37)	0.133*** (5.41)	0.078*** (2.96)	0.108*** (4.39)	0.137*** (5.16)	0.141*** (5.87)
SMB		-0.033 (-0.99)	-0.033 (-0.99)	-0.026 (-0.79)	-0.064* (-1.70)	-0.043 (-1.21)	-0.031 (-0.97)
HML		0.045* (1.21)	0.045* (1.63)	0.101** (2.43)	0.060* (1.94)	0.063** (2.32)	0.101*** (3.39)
MOM		-0.118** (-2.10)	-0.118** (-2.08)	-0.127** (-2.23)	-0.112** (-2.16)	-0.103* (-1.72)	-0.096* (-1.84)
PS Liqui			-0.001 (-0.04)				
EDRR				0.163*** (3.25)			
Max					0.037 (0.97)		
Tail						-0.048 (-1.29)	
BAB							-0.103*** (-3.19)
const	0.238%*** (2.80)	0.253%*** (2.90)	0.294%*** (2.89)	0.210%** (2.30)	0.316%*** (2.86)	0.316%*** (3.09)	0.342%*** (3.35)
yearly alpha	2.70%	3.52%	3.52%	2.51%	3.80%	3.78%	4.10%
R^2	0.107	0.198	0.198	0.235	0.188	0.199	0.224

Panel B: Other Factor Models

Factor Model	Annualized α
Fama-French 5-Factor Model (Fama and French, 2015)	2.80%*** (2.86)
Novy-Marx 4-Factor Model (Novy-Marx, 2013)	4.04%*** (2.81)
Hou-Xue-Zhang 4-Factor Model (Hou et al., 2015)	3.08%*** (2.70)
Carhart 4-Factor Model + short- and long-term reversal	3.95%*** (2.98)
Carhart 4-Factor Model + leverage factor (Adrian et al., 2014)	3.75%*** (3.10)
Carhart 4-Factor Model + quality-minus-junk (Asness et al., 2015)	3.85%*** (3.07)
Carhart 4-Factor Model + undervalued-minus-overvalued (Hirshleifer and Jiang, 2010)	3.35%*** (3.34)
Carhart 4-Factor Model + LPM liquidity risk (Anthonisz and Putnins, 2016)	3.50%*** (3.01)
Carhart 4-Factor Model + liquidity tail risk (Wu, 2015)	3.77%*** (3.14)

This table reports monthly OLS-regression results of a trading strategy based on the return-difference between past strong EDL risk (quintile 5) and past weak EDL risk (quintile 1) portfolios on different factor models. The factors we use in Panel A include Marketrf, which is based on Sharpe (1964)'s capital asset pricing model, SMB and HML of the Fama and French (1993) three-factor model, MOM of the four-factor model by Carhart (1997), Pastor and Stambaugh (2003)'s traded liquidity risk factor (PS Liqui), Chabi-Yo et al. (2017)'s equal-weighted EDRR (EDRR) factor, Bali et al. (2011)'s equal-weighted lottery factor (Max), as well as the equally-weighted tail-risk factor (Tail) proposed by Kelly and Jiang (2014) and the betting-against-beta factor (BAB) proposed by Frazzini and Pedersen (2014). The factor models in Panel B include the the Fama and French (2015) five-factor model, the Hou et al. (2015) and Novy-Marx (2013) four-factor models as well as the Carhart (1997) four-factor model extended by the Fama and French short- and long-term reversal factors, the leverage factor from Adrian et al. (2014), the quality-minus-junk factor from Asnes et al. (2014), the undervalued-minus-overvalued factor from Hirshleifer and Jiang (2010), the lower partial moment liquidity risk factor from Anthonisz and Putnins (2016), and the Wu (2015) liquidity tail risk factor. Portfolios of the EDL risk trading strategy are rebalanced monthly. The sample covers all U.S. common stocks traded on the NYSE / AMEX and the sample period is from January 1969 to December 2012. t-statistics are in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively. We use Newey-West (1987) standard errors with one lag.

Table 7: Fama and MacBeth (1973) Regressions

	(1) Return _{t+2}	(2) Return _{t+2}	(3) Return _{t+2}	(4) Return _{t+2}	(5) Return _{t+2}	(6) Return _{t+2}
EDL risk	0.00184*** (3.73)	0.00137*** (4.49)	0.00137*** (4.28)	0.00145*** (4.49)	0.00133*** (4.15)	0.00132*** (4.14)
β_R		-0.00008 (-0.19)	0.00006 (0.16)		0.0001 (0.30)	0.0001 (0.40)
size		-0.00007 (-0.79)	-0.00018** (-2.54)	-0.00018** (-2.65)	-0.00017** (-2.39)	-0.00019** (-2.66)
btm		0.00039*** (2.89)	0.00032*** (2.27)	0.00032*** (2.26)	0.00024* (1.83)	0.00027* (1.93)
past return		0.00159*** (3.80)	0.00131*** (2.98)	0.00133*** (2.98)	0.00146*** (3.64)	0.00151*** (3.85)
β_L			0.00050 (0.15)		0.0007 (0.22)	0.0003 (0.00)
EDR risk			0.00265*** (6.54)	0.00264*** (6.21)	0.00262 (6.53)	0.00263 (6.64)
illiq			0.00010 (0.75)	0.00009 (0.62)	0.00020 (1.55)	0.00013 (1.03)
β_{Tail}			0.00794** (2.19)	0.00748** (2.04)	0.00782** (2.18)	0.00924** (2.47)
idio vola			-0.01391* (-1.73)	-0.01457* (-1.65)	-0.01433* (-1.77)	-0.0144* (-1.71)
coskew			0.00009 (0.20)	-0.00007 (-0.10)	0.00013 (0.20)	-0.00005 (-0.02)
β_L^-				-0.00132 (-0.88)		
β_L^+				-0.00006 (-0.03)		
β_R^-				0.00004 (0.14)		
β_R^+				0.00001 (0.08)		
LPM return					0.33574 (1.20)	
LPM liquidity risk					-0.04393 (-0.59)	
liquidity tail risk						0.0059** (1.97)
const	0.00113** (2.03)	0.00239 (1.33)	0.00510*** (3.83)	0.00531*** (4.14)	0.00546*** (4.10)	0.00551*** (4.12)
Avg. R ²	0.0025	0.0449	0.0647	0.0653	0.0677	0.0703

This table displays the results of multivariate Fama and MacBeth (1973) regressions. We report the results of regressions of weekly excess returns over the risk-free rate at week $t + 2$ on EDL risk, β_R , the log of market capitalization (size), the book-to-market ratio (btm), the past 12-month excess returns (past year return), β_L , EDR risk, illiquidity (illiq), β_{Tail} from Kelly and Jiang (2014), idiosyncratic volatility (idio vola), coskewness (*coskew*), β_R^- , β_R^+ , β_L^- , β_L^+ , LPM return and LPM liquidity risk as in Anthonisz and Putnins (2016), and Wu (2015)'s liquidity tail risk beta. All risk and firm characteristics are calculated using data available at (the end of) week t . A detailed description of the computation of these variables is given in the main text and in Appendix C. The sample covers all U.S. common stocks traded on the NYSE / AMEX and the sample period is from January 1969 to December 2012. t-statistics are in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively. We use Newey-West (1987) standard errors with four lags.

Table 8: Impact of EDL Risk in Dispersion-Sorted Samples

Panel A: Univariate Sorts

Dispersion Proxy	Low Dispersion				High Dispersion			
	Strong EDL risk	Weak EDL risk	5-1 Return	5-1 CAPM	5-1 Carhart	Strong EDL risk	Weak EDL risk	5-1 Return
Standard Deviation	8.76%	5.58%	3.18%*** (3.00)	1.91%*** (2.04)	1.95%*** (2.04)	10.56%	5.13%	5.42%*** (3.78)
Idio Vola	8.74%	5.65%	3.08%*** (2.93)	1.84%*** (1.99)	1.91%*** (2.02)	10.48%	4.69%	5.79%*** (3.89)
VaR	9.02%	5.39%	3.63%*** (3.32)	2.34%*** (2.43)	2.49%*** (2.54)	9.88%	5.53%	4.35%*** (3.20)
CoVar	8.99%	5.58%	3.41%*** (3.17)	2.15%*** (2.24)	2.28%*** (2.31)	9.94%	5.69%	4.25%*** (3.12)
Average	8.88%	5.55%	3.33%*** (3.13)	2.06%*** (2.20)	2.16%*** (2.25)	10.21%	5.26%	4.95%*** (3.59)
								3.97%*** (2.95)
								3.54%*** (2.52)

Panel B: Fama-MacBeth (1973) Regressions

	Standard Deviation		Idios. Vola		VaR		CoVar	
	Low Disp.	High Disp.	Low Disp.	High Disp.	Low Disp.	High Disp.	Low Disp.	High Disp.
EDL risk	0.00112*** (3.54)	0.00195*** (2.58)	0.00109*** (3.44)	0.00201*** (2.67)	0.00116*** (3.56)	0.00187*** (2.52)	0.00114*** (3.56)	0.00171*** (2.22)

This table displays the results of conditional univariate portfolio sorts and conditional multivariate Fama and MacBeth (1973) regressions. We sort stocks into two categories: Low dispersion stocks which display a standard deviation or idiosyncratic volatility (VaR or CoVar) of returns *and* liquidity shocks below (above) the respective median measure and high dispersion stocks which display a standard deviation or idiosyncratic volatility (VaR or CoVar) of returns *and* liquidity shocks above (below) the respective median measure. Panel A reports the results of univariate portfolio sorts based on the high/low dispersion sample. Panel B repeats regression (5) from Table 7 of weekly excess returns over the risk-free rate at week $t + 2$ on firm- and risk characteristics conditional on a stock's dispersion measures being below (above) the respective median. We only report the coefficient estimate for the impact of EDL risk. All other explanatory variables of regression specification (5) are included in the regressions, but their coefficient estimates are suppressed. A detailed description of the computation of these variables is given in the main text and in Appendix C. The sample covers all U.S. common stocks traded on the NYSE / AMEX and the sample period is from January 1969 to December 2012. t-statistics are in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively. We use Newey-West (1987) standard errors with four lags.

Table 9: Temporal Variation: Portfolio Sorts and Fama-MacBeth (1973) Regressions

Panel A: Univariate Sorts

	1969-1987			1988-2012		
	Return _{<i>t</i>+2}	CAPM	Carhart	Return _{<i>t</i>+2}	CAPM	Carhart
1 Weak EDL risk	4.55%	2.32%	1.01%	6.69%	0.76%	-0.64%
2	5.90%	3.57%	2.50%	8.65%	2.13%	0.69%
3	6.16%	3.75%	3.02%	10.73%	3.78%	2.32%
4	6.49%	4.02%	3.26%	11.19%	3.80%	2.49%
5 Strong EDL risk	6.04%	3.52%	3.33%	12.60%	4.57%	3.35%
5 Strong - Weak	1.49% (1.15)	1.19% (0.95)	2.32%* (1.78)	5.91%*** (3.60)	3.81%*** (2.57)	3.99%*** (2.66)

Panel B: Fama and MacBeth (1973) Regressions

	1969-1987		1988-2012	
	Return _{<i>t</i>+2}	(1)	Return _{<i>t</i>+2}	(5)
EDL risk	0.00072 (1.13)	0.00064 (1.41)	0.00269*** (3.75)	0.00181*** (4.19)

This tables reports the results of the impact of EDL risk on future returns during two subsamples. Panel A shows equal-weighted average returns and alphas of portfolios sorted by past EDL risk in the time period from January 1969 to December 1987, and from January 1988 to December 2012. Each week t we rank stocks into quintiles (1-5) based on estimated EDL risk over the last three years and form equal-weighted portfolios at the beginning of each weekly period. We reports annualized average returns in excess of the one-month T-Bill rate over the week $t + 2$. The row labelled 'Strong - Weak' reports the difference between the returns of portfolio 5 and portfolio 1 with corresponding statistical significance levels. Panel B displays the results of Fama and MacBeth (1973) regressions of weekly future excess returns on firm- and risk-characteristics in the period from 1969 to 1987 and from 1988 to 2012. We repeat regressions (1) and (5) from Table 7 for both subperiods. All control variables are included in the regression, but coefficient estimates are suppressed. The sample covers all U.S. common stocks traded on the NYSE / AMEX. t-statistics are in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively. We use Newey-West (1987) standard errors with four lags.

Table 10: Different Liquidity Proxies: Univariate Portfolio Sorts and FMB Regressions**Panel A: Univariate Portfolio Sorts**

Liquidity	Return _{t+2}	CAPM	Carhart
EDL risk 5-1	Low-Frequency (1969-2012)		
<i>illiq</i>	4.00%*** (3.66)	2.85%*** (2.80)	3.03%*** (2.90)
<i>Corwin</i>	2.28%** (2.15)	0.89% (0.89)	1.98%** (2.03)
<i>Zeros</i>	1.47%*** (2.69)	1.35%** (2.49)	1.60%*** (2.91)
<i>FHT</i>	3.40%*** (4.24)	2.80%*** (3.57)	3.10%*** (3.95)
EDL risk 5-1	High-Frequency (2002-2010)		
<i>EffSpr</i>	4.11%** (2.24)	3.53%** (2.14)	3.39%** (1.94)
<i>RelSpr</i>	1.72% (0.83)	0.81% (0.43)	1.24% (0.67)
<i>IntAmi</i>	5.53%** (2.03)	4.51%** (1.98)	3.82%* (1.80)
<i>PriImp</i>	4.67%** (2.18)	3.93%** (2.03)	3.78%* (1.85)

Panel B: Fama and MacBeth (1973) Regressions

	Low-Frequency (1969-2012)				High-Frequency (2002-2010)			
	(1) <i>Illiq</i>	(2) <i>Corwin</i>	(3) <i>Zeros</i>	(4) <i>FHT</i>	(5) <i>EffSpr</i>	(6) <i>RelSpr</i>	(7) <i>IntAmi</i>	(8) <i>PriImp</i>
EDL risk	0.00137*** (4.28)	0.00085*** (2.69)	0.00047 (0.98)	0.00167*** (4.49)	0.00135* (1.83)	0.00007 (0.14)	0.00192*** (2.59)	0.00171** (2.23)

This table reports results of univariate portfolio sorts and Fama and MacBeth (1973) regressions for different liquidity proxies. As high-frequency liquidity proxies we use the effective spread (*EffSpr*), the relative spread (*RelSpr*), the intraday Amihud measure (*IntAmi*), and the price impact measure (*PriImp*). As low-frequency liquidity proxies we use the Amihud Illiquidity Ratio (*illiq*), the Corwin measure (*Corwin*), the Zeros measure (*Zeros*) and the FHT measure (*FHT*). A detailed description of the computation of these variables is given in Appendix A. In Panel A we rank stocks into quintiles (1-5) based on estimated past EDL risk of the different liquidity proxies over the last three years and form equal-weighted portfolios at the beginning of each weekly period. We report differences in annualized returns, differences in the CAPM-Alpha based on Sharpe (1964)'s capital asset pricing model and differences in the Carhart-alpha based on Carhart (1997)'s four factor model between portfolio 5 and portfolio 1 with corresponding statistical significance levels. Panel B shows the results of regression specification (5) from Table 7 for different liquidity proxies. We only report the coefficient estimate for the impact of EDL risk. All other explanatory variables of specification (5) are included in the regressions, but their coefficient estimates are suppressed. The sample covers all U.S. common stocks traded on the NYSE / AMEX. The sample period for the low-frequency liquidity proxies is from January 1969 to December 2012. The sample period for the high-frequency liquidity proxies is from July 2002 to December 2010. t-statistics are in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively. We use Newey-West (1987) standard errors with four lags.

Table 11: Different Estimation Procedures: Univariate Portfolio Sorts and FMB Regressions

Panel A: Univariate Portfolio Sorts			
Procedure	Return _{t+2}	CAPM	Carhart
EDL risk 5-1	Estimation Horizons & Liquidity Shocks		
1y	2.91%*** (3.40)	2.05%** (2.39)	2.39%** (2.50)
2y	3.91%*** (3.43)	2.67%** (2.53)	2.94%*** (2.68)
5y	4.22%*** (3.09)	2.81%** (2.32)	2.56%** (2.16)
diff	5.66%*** (4.39)	4.34%*** (3.75)	3.91%*** (3.31)
EDL risk 5-1	Copula Functions		
C1	4.00%*** (3.66)	2.85%*** (2.80)	3.03%*** (2.90)
C2	4.19%*** (3.94)	3.07%*** (3.14)	3.22%*** (3.23)
C63	4.64%*** (4.27)	3.47%*** (3.47)	3.59%*** (3.50)
C64	4.10%*** (3.78)	2.93%*** (2.93)	3.10%*** (3.01)
Cw	5.24%*** (4.41)	3.91%** (3.58)	4.04%*** (3.61)
EDL risk 5-1	EDL risk Components		
EDLR ₁	0.33% (0.40)	-0.32% (-0.40)	-0.23% (-0.28)
EDLR ₂	4.08%*** (4.74)	3.32%*** (4.10)	3.09%*** (3.69)
EDLR ₃	3.59%*** (3.87)	2.70%*** (3.08)	2.97%*** (3.39)

Panel B: Fama and MacBeth (1973) Regressions

	Estimation Horizons & Liquidity Shocks				
	(1)	(2)	(3)	(4)	
	1y	2y	5y	diff	
EDL risk	0.00068*** (3.45)	0.00108*** (4.14)	0.00167*** (4.48)	0.00226*** (6.41)	
	Copula Functions				
	(5)	(6)	(7)	(8)	(9)
	C1	C2	C63	C64	Cw
EDL risk	0.00137*** (4.28)	0.00125*** (3.96)	0.00156*** (4.65)	0.00127*** (3.92)	0.00178*** (4.44)
	EDL risk Components (joint estimate)				
	(10)				
	EDLR ₁	EDLR ₂	EDLR ₃		
EDL risk _i	-0.00003 (-0.06)	0.00234*** (3.61)	0.00276*** (4.55)		

This table reports results of univariate portfolio sorts and Fama-MacBeth (1973) regressions for different estimation horizons, liquidity shocks, copula functions, and on the EDL risk component level. We estimate EDL risk with different estimation horizons of 1-year, 2-years, and 5-years, as well as based on liquidity-differences instead of -shocks from an AR-model. Furthermore we estimate EDL risk with different copulas (C1-C4 and Cw). We also analyze the component-wise effect of the three risk factors EDL risk₁, EDL risk₂, and EDL risk₃. A detailed description of the computation of these variables is given in the main text and Appendix C. In Panel A we rank stocks into quintiles (1-5) based on estimated past EDL risk of the different estimation horizons, different copulas and EDL risk components, and form equal-weighted portfolios at the beginning of each weekly period. We report differences in annualized returns, differences in the CAPM-Alpha based on Sharpe (1964)'s capital asset pricing model and differences in the Carhart-alpha based on Carhart (1997)'s four factor model between portfolio 5 and portfolio 1 with corresponding statistical significance levels. Panel B shows the results of regression specification (5) from Table 7 for different estimation procedures. We only report the coefficient estimate for the impact of EDL risk. In Specification (10) of Panel B, we adjust specification (5) from Table 7 by replacing EDL risk by its three components and estimating jointly. The sample covers all U.S. common stocks traded on the NYSE / AMEX. The sample period is from January 1969 to December 2012. t-statistics are in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively. We use Newey-West (1987) standard errors with four lags.

Table 12: Dependent Portfolio Sorts: EDL Risk and Firm Size – Value-Weighted

Panel A: EDL Risk and Size – Value-Weighted

Portfolio	1 Small	2	3	4	5 Large	Average
1 Weak EDL risk	6.95%	6.93%	5.85%	5.98%	3.69%	5.88%
2	7.68%	8.85%	7.47%	7.10%	5.10%	7.24%
3	6.84%	9.25%	10.05%	8.03%	5.65%	7.96%
4	9.41%	10.65%	9.66%	8.62%	6.37%	8.94%
5 Strong EDL risk	11.26%	10.44%	11.07%	9.32%	5.86%	9.59%
Strong-Weak Return	4.31%** (2.38)	3.51%** (2.42)	5.22%*** (3.54)	3.33%*** (2.60)	2.17% (1.49)	3.71%*** (3.50)
Strong-Weak CAPM	3.39%** (1.95)	2.62%* (1.85)	4.01%*** (2.94)	2.21%* (1.84)	1.06% (0.76)	2.66%*** (2.77)
Strong-Weak Carhart	3.54%** (2.00)	2.66%** (1.82)	4.51%*** (3.27)	1.96% (1.61)	0.22% (0.15)	2.58%*** (2.71)

Panel B: Factor Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
EDL risk-5-1	EDL risk-5-1	EDL risk-5-1	EDL risk-5-1	EDL risk-5-1	EDL risk-5-1	EDL risk-5-1	EDL risk-5-1
cons	0.222%*** (2.77)	0.215%*** (2.71)	0.259%** (2.47)	0.196%** (2.13)	0.296%*** (2.68)	0.262%** (2.44)	0.291%*** (2.83)
yearly alpha	2.66%	2.58%	3.10%	2.35%	3.56%	3.15%	3.49%
R ²	0.124	0.232	0.233	0.249	0.226	0.228	0.251

This table reports the results of dependent portfolio sorts. First, we form quintile portfolios sorted on market capitalization. Then, within each size quintile, we sort stocks into portfolios based on EDL Risk. Panel A displays annualized average future returns of 25 size - EDL risk portfolio sorts with value-weighted portfolios. The row labelled 'Strong - Weak' reports the difference between the returns, CAPM alphas, and Carhart-alphas of portfolio 5 and portfolio 1 with corresponding t-statistic. Portfolios of the EDL risk trading strategy are rebalanced weekly. In contrast, for Panel B, we perform these double sorts on the monthly level and report monthly OLS-regression results for the factor models from Table 6. The sample covers all U.S. common stocks traded on the NYSE / AMEX and the sample period is from January 1969 to December 2012. t-statistics are in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively. We use Newey-West (1987) standard errors with four lags in Panel A (weekly data) and with one lag in Panel B (monthly data).

Table 13: Different Regression Methods

Panel A: Different Regression Methods							
Regression	(1)	(2)	(3)	(4)	(5)	(6)	(7)
EDL risk	0.00137*** (4.24)	0.00117*** (3.60)	0.00214*** (8.88)	0.00214*** (7.99)	0.00243*** (8.57)	0.00243*** (8.89)	0.00240*** (8.56)
Controls	yes	yes	yes	yes	yes	yes	yes
Method	fmb	fmb	ols	ols	panel	panel	panel
Winsorized	yes	no	yes	yes	yes	yes	yes
Time-Fixed Effects			yes	yes	yes	yes	yes
Firm Effects			no	no	fixed	fixed	random
Clustered SE			firm	industry	no	firm	no
Newey-West SE	no	yes	no	no	no	no	no
R^2	0.065	0.064	0.195	0.187	0.202	0.202	

Panel B: Adjusted Returns			
	EDL risk (t-stat)	return adjustment	EDL risk (t-stat)
Return _{t+1} (weekly)	0.00157*** (4.90)	SIC-2 (weekly)	0.00096*** (3.52)
Return _{t+3} (weekly)	0.00150*** (4.71)	SIC-3 (weekly)	0.00085*** (2.83)
Return _{t+4} (weekly)	0.00148*** (4.77)	SIC-4 (weekly)	0.00074*** (3.27)
Monthly Return (monthly)	0.00447*** (3.24)	FF12 (monthly)	0.00468** (2.19)
DGTW (monthly)	0.00263* (1.72)	FF48 (monthly)	0.00451** (2.18)

Panel A reports the results of different multivariate regressions on a weekly frequency. Regression (1) repeats the baseline regression (5) from Table 7, but we now do not use Newey-West standard errors in the second stage of the Fama-MacBeth (1973) regressions. Regression (2) repeats the standard Fama-MacBeth (1973) regression, but we do not winsorize the independent variables. In regression (3) we perform a pooled OLS regression with time-fixed effects and standard errors clustered by stock. Regression (4) is identical, but we cluster standard errors by the SIC-2-digits classification. Regressions (5) and (6) perform panel regressions with firm-fixed effects. In regression (6) standard errors are additionally clustered by firm. Finally, in regression (7) we regress excess returns on the independent variables via a random-effect panel regression. Panel B reports the result of regression (5) of Table 7 with different return adjustments. We use weekly returns in $t+1$, $t+3$, and $t+4$, as well as monthly returns, DGTW alphas (results are displayed on the left side of Panel B), and industry-adjustments (results are displayed on the right side of Panel B). The sample period is from January 1969 to December 2012. ***, **, and * indicate significance at the one, five, and ten percent level, respectively. We use Newey-West (1987) standard errors with four lags for weekly data and with one lag for monthly data.