Ruenzi, Stefan; Ungeheuer, Michael; Weigert, Florian

Joint Extreme events in equity returns and liquidity and their cross-sectional pricing implications

Published in:
Journal of Banking and Finance

DOI:
10.1016/j.jbankfin.2020.105809

Published: 01/06/2020

Document Version
Peer-reviewed accepted author manuscript, also known as Final accepted manuscript or Post-print

Please cite the original version:
Ruenzi, S., Ungeheuer, M., & Weigert, F. (2020). Joint Extreme events in equity returns and liquidity and their cross-sectional pricing implications. *Journal of Banking and Finance*, *115*, 1-31. Article 105809. https://doi.org/10.1016/j.jbankfin.2020.105809

Joint Extreme Events in Equity Returns and Liquidity and their Cross-Sectional Pricing Implications

Stefan Ruenzi, Michael Ungeheuer and Florian Weigert[a]

First Version: February 2011

This Version: January 2020

Abstract

We merge the literature on downside return risk and liquidity risk and introduce the concept of extreme downside liquidity (EDL) risks. The cross-section of stock returns reflects a premium if a stock's return (liquidity) is lowest at the same time when the market liquidity (return) is lowest. This effect is not driven by linear or downside liquidity risk or extreme downside return risk and is mainly driven by more recent years. There is no premium for stocks whose liquidity is lowest when market liquidity is lowest.

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

JEL Classification Numbers: C12, C13, G01, G11, G12, G17.

---

[a]Stefan Ruenzi (corresponding author): Chair of International Finance at the University of Mannheim, Address: L9, 1-2, 68131 Mannheim, Germany, Telephone: +49-621-181-1640, e-mail: *ruenzi@bwl.uni-mannheim.de*. Michael Ungeheuer: Department of Finance, Aalto University, Address: P.O. Box 21210, 000765 Aalto, Finland, Telephone: +358 50 511 3290, E-mail: *michael.ungeheuer@aalto.fi*. Florian Weigert: University of Neuchâtel, Institute of Financial Analysis, Address: Rue A.-L. Breguet 2, 2000 Neuchâtel, Switzerland, Telephone: +41-32-718-1331, e-mail: *florian.weigert@unine.ch*. Florian Weigert is affiliated with the Centre for Financial Research, Cologne, and is thankful for their support. We thank Olga Lebedeva, Stefan Obernberger, and Christian Westheide for sharing their high-frequency data with us. We would also like to thank Yakov Amihud, Christian Dick, Jean-David Fermanian, Sermin Gungor, Allaudeen Hameed, Robert Korajczyk, Andre Lucas, Thomas Nitschka, Rachel Pownall, Erik Theissen, Julian Thimme, Monika Trapp, seminar participants at the University of Mannheim, the University of Sydney, and participants at the 2012 EEA Meeting, 2012 Erasmus Liquidity Conference, 2012 SMYE Meeting, 2013 Humboldt-Copenhagen Conference, 2013 Financial Risks International Forum, 2013 SGF Conference, 2013 EFA Meeting, 2013 Conference on Copulas and Dependence at Columbia University, 2013 FMA Meeting, 2013 Australasian Finance and Banking Conference, 2014 Risk Management Conference at Mont Tremblant and 2014 Conference on Extreme Events in Finance at Royaumont Abbey for their helpful comments. All errors are our own.

1 Introduction

The recent empirical asset pricing literature documents that investors care about the systematic crash-exposure of stock returns and shows that stocks with such exposures earn a significant risk premium (e.g., Kelly and Jiang, 2014; and Chabi-Yo et al., 2018). 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).[1] The aim of our paper is to merge these two important strands of the literature.

The starting point of our paper is the observation that liquidity is risky, shows commonality, and varies over time (Chordia et al., 2000; Hasbrouk and Seppi, 2001; Huberman and Halka, 2001; Koch et al., 2016; Watanabe and Watanabe, 2008). Moreover, liquidity is shown to behave differently in good and bad states of the world (Pastor and Stambough, 2003) with periods of low market liquidity coinciding with periods of low market returns (Hameed et al., 2010). During such bad times, margins are typically destabilizing while market illiquidity and investors' funding illiquidity reinforce each other, so that markets can suddenly dry up (Brunnermeier and Pedersen, 2009) and liquidity "evaporates" (Nagel, 2012).[2] Hence, the previous literature shows that liquidity is behaving asymmetrically with extreme downward spikes during periods of financial turmoil.

Our second basic assumption is investors' aversion to the crash risk of an asset. Chabi-Yo et al. (2018) find that investors demand additional compensation for holdings stocks that are crash-prone, i.e., stocks that have particularly bad returns exactly when the market crashes. They also theoretically show, that such a crash risk premium emerges in a stochastic discount factor framework under the main assumption that the first four derivatives of the

[1] There are more recent replication exercises showing weaker or no significant results (Holden and Nam, 2019, and Kazumori et al., 2019).

[2] Downward liquidity spirals on markets can also occur due to tighter risk management of financial institutions (Garleanu and Pedersen, 2007), predatory trading (Carlin et al., 2007) and the exceedance of loss limits (Morris and Shin, 2004).

utility function have alternating signs, i.e., investors show non-satiation, they are risk-averse, their absolute risk aversion is decreasing, and they are temperate.[3] Therefore, the previous literature documents that a stock's sensitivity to extreme market crashes matters for its pricing in the cross-section.

In this paper, we combine (i) the asymmetric, fragile nature of liquidity on financial markets with (ii) investors' aversion to crash risk and introduce different dimensions of extreme downside liquidity (EDL) risks. In particular, we hypothesize that investors do not only care about crash risk in market returns, but also care about crash risk in market liquidity and the interplay between return and liquidity during periods of market stress. Specifically, we expect them to dislike stocks that (i) become extremely illiquid exactly at the moment when markets are extremely illiquid (EDL risk_1), (ii) realize their lowest return exactly at the moment when markets are extremely illquid (EDL risk_2) and (iii) are extremely illiquid exactly at the moment when market returns are extremely low (EDL risk_3). Thus, we expect stocks with strong EDL risks to deliver a positive risk premium.

Our empirical approach is reminiscent (but different from) 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 risks 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 follow the methodology of Chabi-Yo et al. (2018) and Weigert (2016) to capture extreme downside risk with tail dependence coefficients and apply it to liquidity. We focus on the following three

[3]Experimental evidence supporting such higher order risk attitudes is provided in Noussair et al. (2014).

components of EDL risk:

(i) EDL risk_1 is defined as clustering in the lower left tail of the bivariate distribution between individual stock liquidity and market liquidity. We argue that 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 unattractive, while assets that remain relatively liquid in times of market stress are attractive assets to hold. This is particularly relevant for institutional investors that might be subject to asset fire sale problems or might strongly depend on funding liquidity conditions.[4]

(ii) EDL risk_2 is defined as clustering in the lower left tail of the bivariate distribution between the individual stock return and market liquidity. Such clustering would be particularly problematic for investors who face margin or solvency constraints as they usually have to liquidate some assets to raise cash when their wealth drops critically. If they hold assets with strong EDL risk_2, such liquidations will occur in 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) EDL risk_3 is defined as clustering in the lower left tail of the bivariate distribution between individual stock liquidity and the market return. We expect stock characterized by such clustering to be unattractive assets particularly for institutional investors (such as mutual fund managers) as they are often forced to sell in times of market return crashes because their investors withdraw funds (Coval and Stafford, 2007) or financial intermediaries withdraw from providing liquidity (Brunnermeier and Pedersen, 2009).

[4]During extreme market liquidity downturns, funding liquidity is often reduced as well (e.g., margin requirements may increase; see Brunnermeier and Pedersen, 2009) and institutional investors are often forced to liquidate assets and eventually realize additional liquidity costs.

If a selling investor holds securities with strong EDL risk_3, 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 risks 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 (e.g. individual stock liquidity) is in the extreme lower tail of its distribution, conditional on the realization of the other random variable (e.g. market liquidity) also being in the extreme lower tail of its distribution.[5]

As our main liquidity proxy we use innovations in the Amihud (2002) Illiquidity Ratio, analogous to Acharya and Pedersen, 2005.[6] Using weekly data from 1963 to 2012 we estimate lower tail dependence coefficients for (i) individual stock liquidity and market liquidity (EDL risk_1), (ii) individual stock return and market liquidity (EDL risk_2), and (iii) individual stock liquidity and the market return (EDL risk_3) for each stock i and week t in our sample.

We then relate the stocks' three EDL risks 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 risks and future excess returns. We document that there exists a positive impact of EDL risk_2 and EDL risk_3 on the cross-section of average future returns.

From 1969 to 2012, a portfolio that is long in stocks with strong EDL risk_2 (EDL risk_3) and short in stocks with weak EDL risk_2 (EDL risk_3) yields a significant average excess return of 4.04% (2.41%) p.a., while EDL risk_1 does not bear an economically or statistically significant

[5]In Tables C.1 and C.2 of the Appendix, we also investigate the asset pricing implications of extreme *upside* liquidity (EUL) risk measures. These EUL risk measures are defined as the tail dependence coefficients between (i) a stock's liquidity and market illiquidity (EUL risk_1), (ii) a stock's return and market illiquidity (EUL risk_2), and (iii) a stock's illiquidity and the market return (EUL risk_3). We show that these upward modifications of the EDL risks are all very close to zero and that these tail dependencies do not exhibit a systematic return impact. Hence, we do not consider them in the main part of the empirical analysis.

[6]We also employ several other low-frequency and high-frequency liquidity measures in robustness checks; see Section 4.1.

premium. These findings are consistent with investors mainly being worried about stocks realizing their worst individual returns when markets are extremely illiquid and stocks being extremely illiquid when the market crashes, but less about stocks being extremely illiquid when the market is extremely illiquid. The latter finding might be due to the fact that many investors do not have to trade in periods of extreme market illiquidity as long as returns are not also very low.

We confirm that the premium for the priced EDL risks is not explained by other risk- and firm characteristics. Hence, our results suggest that EDL risk_2 and EDL risk_3 are important determinants of the cross-section of expected stock returns.

When investigating the variation of the EDL risk premiums over time, we observe that the significant premiums are mainly realized during the second half of our sample period. These results suggest that investors have become more concerned about a stock's EDL risk_2 and EDL risk_3 during the second half of our sample. This finding is broadly 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 in line with the argument 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. (2018) show that the premium for a stock's extreme downside *return* risk also 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 different estimation horizons and procedures for the estimation of the tail dependence coefficients, and using different regression models as well as return adjustments. Furthermore, we find that our results do also hold in a value-weighted analysis, but only if we exclude the top vigintile of stocks according to their market capitalization, which are extremely liquid and for which liquidity-related risks thus are a minor concern to start with.

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.[7] 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 (or 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). 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. We contribute to

[7] More recent papers find weaker evidence for liquidity levels impacting future returns (e.g., **?** or **?**).

the existing literature by showing that new dimensions of liquidity risk are priced.

Closely related to our analysis are concurrent papers by Anthonisz and Putnins (2017) and Wu (2017). Anthonisz and Putnins (2017) extend the Acharya and Pedersen (2005) model and analyze whether the downside version of their liquidity betas explains returns. Specifically, they define lower partial moment (LPM) liquidity risks which are computed as the three Acharya and Pedersen (2005) liquidity risks conditional on the liquidity-adjusted market return being negative. They find that mainly the LPM liquidity risk component that is based on individual liquidity and market return co-movements bears a return premium (but not the others). While this particular component seems to be related to our EDL $risk_3$ (which is driven by joint occurences of extremely low market returns and extreme individual stock illiquidity), our results hold after controlling for the Anthonisz and Putnins (2017) measures. It is not surprising that the return premia for the EDL risks are distinct from the return premia for the LPM liquidity risk by Anthonisz and Putnins (2017): EDL risk is conceptually different from the LPM liquidity risk, as the latter places no particular emphasis on tail events. In contrast, EDL risk is concerned with the worst return and worst liquidity realizations. Furthermore, while the Anthonisz and Putnins (2017) measures are based on correlations between individual/market level returns/liquidity all conditional on liquidity-adjusted market returns being negative (i.e., they are measured within the same negative subspace for liquidity adjusted market returns), our three EDL risks are based on realizations of returns and liquidity in three different joint extreme states. Wu (2017) applies the return tail risk concept of Kelly and Jiang (2014) to liquidity and documents that stocks with strong sensitivities to an aggregate liquidity tail risk factor earn high expected returns. In our empirical analysis, we also explicitly control for the Wu (2017) liquidity tail risk sensitivity and find our results to hold.

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. (2018), Chabi-Yo et al. (2019), 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).[8] Chabi-Yo et al. (2018) 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.

[8]Further 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.[9] 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

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

where r_{td}^i and V_{td}^i 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

[9] We 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.[10]

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.[11] Hence,

[10] We 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.

[11] The 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 risks 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 risk$_1$ between individual stock liquidity and market liquidity, (ii) EDL risk$_2$ between individual stock return and market liquidity, and (iii) EDL risk$_3$ between individual stock liquidity and market returns. 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

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

where $u \in (0, 1)$ denotes the value of the distribution function, i.e., $\lim_{u \to 0+}$ indicates the limit if we approach the left tail of the distribution from above.[12] 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.

Based on Equation (6), we can then subsequently define the respective EDL risks

instead of estimated liquidity-shocks in Section 4.2.

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

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

$$\text{EDL risk}_1 := \text{EDL risk}_1(l_i, l_m) = \lim_{u \to 0+} P(l_i \leq F_{l_i}^{-1}(u) | l_m \leq F_{l_m}^{-1}(u)), \tag{7}$$

$$\text{EDL risk}_2 := \text{EDL risk}_2(r_i, l_m) = \lim_{u \to 0+} P(r_i \leq F_{r_i}^{-1}(u) | l_m \leq F_{l_m}^{-1}(u)), \tag{8}$$

$$\text{EDL risk}_3 := \text{EDL risk}_3(l_i, r_m) = \lim_{u \to 0+} P(l_i \leq F_{l_i}^{-1}(u) | r_m \leq F_{r_m}^{-1}(u)), \tag{9}$$

where r_i (r_m) denotes the stock's (market) excess return and l_i (l_m) denotes the stock's (market) liquidity.

The lower tail dependence coefficient between two variables can be expressed in terms of a copula function $C : [0.1]^2 \mapsto [0, 1]$.[13] 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

$$\lambda_L = \lim_{u \to 0+} \frac{C(u, u)}{u}, \tag{10}$$

if F_1 and F_2 are continuous. Equation (10) 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. (2018) 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}:

[13]Copula 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).

$$
\begin{aligned}
C(u_1, u_2, \Theta) &= w_1 \cdot C_{\lambda_L}(u_1, u_2; \theta_1) + w_2 \cdot C_{\lambda_I}(u_1, u_2; \theta_2) \\
&\quad + (1 - w_1 - w_2) \cdot C_{\lambda_U}(u_1, u_2; \theta_3), \qquad (11)
\end{aligned}
$$

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-likelihood value among the 64 different copulas.[14] We then use the copula with the best fit for the respective stock and EDL risks over the previous three years in the estimation of tail dependence coefficients using Equation (10). As this procedure is repeated for each stock i and week t, we end up with a panel of tail dependence coefficients EDL risk^1_{it}, EDL risk^2_{it} and EDL risk^3_{it} at the stock-week level. For a more detailed description of the estimation method, we refer to Appendix B. The level (rather than innovations) of the EDL risk measures can be directly used in our later asset pricing tests, as the LTDs are determined based on liquidity innovations already (see Section 2.1).

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

[14] Table 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 and 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.

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 risks (EDL risk^1_{it}, EDL risk^2_{it} and EDL risk^3_{it}) 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 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.[15] 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.[16]

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 1 provides summary statistics.

[Insert Table 1 about here]

We report the mean, the 25%, the 50%, the 75% quantile and the standard deviation

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

[16] For comparison, Ang et al. (2006a) use daily data to estimate downide 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.

for the three EDL risks, the monthly excess return over the risk-free rate, and other key variables in this study. The mean (median) of EDL risk_1 is 0.063 (0.035), the mean (median) of EDL risk_2 is 0.071 (0.046), and the mean (median) of EDL risk_3 is 0.054 (0.028). The respective standard deviation for EDL risk_1 (EDL risk_2, EDL risk_3) is 0.077 (0.078, 0.068).[17]

The mean monthly excess return across all stocks is 0.82%. We present the excess return in month $t+1$ as we will relate returns in this month to EDL risk measures determined in month t in our later asset pricing tests (Section 3). Summary statistics of additional firm characteristics are displayed in the rest of the table. For detailed descriptions of all variables, see Appendix D. We report cross-correlations between the key variables used in this study in Table 2.

[Insert Table 2 about here]

Our results reveal that the magnitude of the linear correlations between the different EDL risks and other independent variables is moderate. EDL risk_1 displays correlations with EDL risk_2 and EDL risk_3 of 0.12 and 0.24, respectively, while EDL risk_2 and EDL risk_3 show a correlation of 0.07. The low correlations show that the three EDL risks capture different dimensions of liquidity risk. All EDL risks are positively correlated with EDR risk (correlations of 0.13, 0.26, and 0.10), market beta (0.09, 0.10, and 0.15), and downside linear return risk (0.06, 0.11, and 0.07). Interestingly, all EDL risks are only weakly correlated with β_L (correlations of 0.02, -0.02, and 0.05) and β_L^- (correlations of 0.03, -0.03, and 0.14); this provides first evidence that they capture aspects of liquidity risk that are different from the liquidity risks analyzed in Acharya and Pedersen (2005).

The EDL risks are slightly negatively correlated with illiquidity and positively correlated with firm size. These associations might be caused by the greater systemic risk of large and

[17] We also compute the corresponding extreme upside liquidity (EUL) risk coefficients with upper tail dependence coefficients. The mean for EUL risk_1 (EDL risk_2, EDL risk_3) amounts to 0.021 (0.021, 0.027) and is much smaller than the corresponding EDL risk value. Tables C.2 and C.3 in the Appendix report that there is no systematic impact of any EUL risk component on average future stock returns. Our results on the impact of EDL risk_2 and EDL risk_3 on average future stock returns are unaffected when controlling for the EUL risks.

usually more liquid firms. The EDL risks measure 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 0.26 with illquidity and -0.21 with firm size).

To better understand the temporal variation of EDL risk, we investigate the development of aggregate EDL risk_1, EDL risk_2, and EDL risk_3 over time. Aggregate EDL risk_i ($i = 1, 2, 3$), is defined as the cross-sectional, value-weighted, average of EDL $\text{risk}_{i,j,t}$ over all stocks j in week t in our sample. Panel A of Figure 1 plots the time series of the aggregate EDL risks.

[Insert Figure 1 about here]

In contrast to the low cross-sectional correlations between the EDL risks, all aggregate EDL risk time series are positively related with pairwise correlation coefficients of 0.63 (aggregate EDL risk_1 and aggregate EDL risk_2), 0.56 (aggregate EDL risk_1 and aggregate EDL risk_3), and 0.58 (aggregate EDL risk_2 and aggregate EDL risk_3). The time-series exhibit occasional persistent spikes that seem to coincide with worldwide market crises: In particular, we observe peaks for EDL risk_1 and EDL risk_2 during 1987-1990 (the time period after Black Monday in October 1987, the largest one-day percentage decline in U.S. stock market history) and for all EDL risks during 2008-2011 (the Global Financial Crisis).

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_1, EDL risk_2, and EDL risk_3 in Fama and MacBeth (1973) regressions on the firm level and display the results in Table A.2 of the Appendix. We find that each realized EDL risk component significantly predicts the future EDL risk component, 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 month t to portfolio and individual stock excess returns over month $t+1$. Note that we only use data observable to the investor at the end of month t in order to predict stock returns in month $t+1$. Strictly separating the estimation window for the EDL risks and the subsequent return prediction window alleviates concerns related to overfitting. 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 month t we sort stocks into five quintiles based on their EDL risks (i.e., EDL risk_1, EDL risk_2, and EDL risk_3) 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 for these quintile portfolios as well as differences in average returns between quintile portfolio 5 (strong EDL risk_1, EDL risk_2, and EDL risk_3) and quintile portfolio 1 (weak EDL risk_1, EDL risk_2, and EDL risk_3) over month $t+1$. Moreover, we also evaluate portfolio alphas based on Carhart (1997)'s four factor model augmented by the Pastor and Stambaugh (2003) traded liquidity factor and the Sadka (2006) fixed-transitory and variable-permanent liquidity factors.[18] We use these augmented models instead of the basic CAPM or Carhart (1997) model as our benchmark models to control for standard systematic liquidity risk. For each sort, we also provide annualized spreads in returns and alphas between quintile portfolio 1 and

[18]To compute average alphas, we regress the monthly $t+1$ return of the respective EDL risk portfolios on the monthly CRSP US excess market return, SMB, HLM, and MOM factors as well as the Pastor and Stambaugh (2003) and Sadka (2006) liquidity risk factors. Data for the US excess market return, SMB, HLM, and MOM factors are provided on Kenneth French French's homepage. Data on the Pastor and Stambaugh (2003) traded liquidity risk factor is obtained from the homepage of Lubos Pastor. Data on the Sadka (2006) fixed-transitory and variable-permanent liquidity factors is obtained from the homepage of Ronnie Sadka.

quintile portfolio 5.

[Insert Table 3 about here]

We begin with univariate portfolio sorts based on EDL $risk_1$ in Panel A. Column (1) reports average EDL $risk_1$ coefficients of the stocks in the quintile portfolios. There is considerable cross-sectional variation in EDL $risk_1$; average EDL $risk_1$ ranges from 0.00 in the bottom quintile portfolio to 0.19 in the top quintile portfolio. However, we do not find any pricing patterns due to EDL $risk_1$ in columns (2) to (4): Returns and alphas of stocks with strong EDL $risk_1$ are almost identical to the returns and alphas of stocks with weak EDL $risk_1$, suggesting that investors are not that much concerned about stocks that are extremely illiquid when markets are extremely illiquid.

We proceed to analyze univariate portfolio sorts based on EDL $risk_2$ in Panel B. We observe, in column (1), that the dispersion between stocks with strong EDL $risk_2$ and weak EDL $risk_2$ is 0.17, and is thus similar to the dispersion observed in the case for EDL $risk_1$. More importantly, and in contrast to the results for EDL $risk_1$, column (2) shows that stocks with strong EDL $risk_2$ earn significantly higher average future returns than stocks with weak EDL $risk_2$. Stocks in the quintile with the highest (lowest) EDL $risk_2$ earn a monthly average excess return of 0.78% (0.44%). The return spread between quintile portfolio 5 and 1 is 0.34% per month (4.04% per annum), which is statistically significant at the 1% level (t-statistic of 4.52).[19] The results also show that the returns are monotonically increasing from the lowest to the highest EDL $risk_2$ 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 EDL $risk_2$ portfolio returns at the 1% significance level.

Columns (3) and (4) provide results when we look at average alphas based on the Carhart

[19] As 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 EDL $risk_2$ difference portfolio remain comfortably above zero.

(1997) 4-factor model augmented by the Pastor and Stambaugh (2003) traded liquidity factor and the Sadka (2006) fixed-transitory and variable-permanent liquidity factors instead of raw returns. We find that the spreads between quintile portfolios 5 and 1 amount to 0.34% and 0.41% per month (4.04% and 4.95% per annum) and are statistically significant at the 1% level (with t-statistics of 3.63 and 4.00) in both cases. Hence, accounting for Pastor and Stambaugh (2003)'s and Sadka (2006)'s liquidity risk factors does not reduce the return spread due to EDL risk_2, suggesting that EDL risk_2 is capturing a different dimension of liquidity than the linear systematic liquidity risk factors used here.[20]

We finally investigate univariate portfolio sorts based on EDL risk_3 in Panel C. Similar to the results obtained for EDL risk_2, we find significant pricing implications for EDL risk_3. Column (2) documents that stocks in the quintile with the highest EDL risk_3 earn future monthly returns of 0.75%, while stocks in the quintile with the lowest EDL risk_3 earn future monthly returns of 0.55%. The spread in monthly (annual) returns amounts to 0.20% (2.55%) and is statistically significant at the 5% level (t-statistic of 2.55).[21] These results are again not affected when we risk-adjust the returns by the Carhart (1997) four factor model augmented by the Pastor and Stambaugh (2003) traded liquidity factor and the Sadka (2006) fixed-transitory and variable-permanent liquidity factors in columns (3) and (4). The annualized spread in risk-adjusted returns is 2.55% and 3.17%, respectively, with statistical significance at the 5% level (t-statistics of 2.52 and 2.64).

In summary, the results from Table 3 provide evidence that the components EDL risk_2 and EDL risk_3 have an impact on the cross-section of expected stock returns. Stocks with strong EDL risk_2 (EDL risk_3) earn higher average future returns and liquidity-risk augmented Carhart (1997) alphas than stocks with weak EDL risk_2 (EDL risk_3). The finding

[20]Note that in our factor models we always include the SMB size factor of Fama and French (1993). The SMB factor shows a time-series correlation with the illiquidity level factor of Amihud(2002) of 0.97. Hence, we implicitly control for the illiquidity level in our factor regressions. We will also later explicitly control for the illiquidity level in Fama and MacBeth (1973) regressions in Section 3.4.

[21]Although the returns are not completely monotonically increasing from the lowest to the highest EDL risk_3 quintile, we confirm the monotonic relationship based on the Patton and Timmermann (2010) test. This test rejects the null hypothesis of a flat or decreasing pattern over the five EDL risk_3 portfolio returns at the 10% significance level.

that EDL risk_1 (commonality in liquidity) is not priced is analogous to results by Acharya and Pedersen (2005) for linear liquidity risk. In the following sections, we will focus on asset pricing results based on EDL risk_2 and EDL risk_3. Nevertheless, we will use a stock's EDL risk_1 as a control variable in our later multivariate regressions.

3.2 Bivariate Portfolio Sorts

The correlations in Table 2 document that EDL risk_2 and EDL risk_3 are correlated with other related (liquidity and return) risk measures and firm characteristics. For example, an increase in EDL risk_2 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_2 portfolios could be driven by differences in these other variables. To isolate the return premium of EDL risk_2 and EDL risk_3 from the impact of other related characteristics, we now conduct dependent equal-weighted portfolio double sorts. We start to investigate bivariate equal-weighted portfolio sorts based on EDL risk_2 and other variables in Table 4; as for the univariate sorts, we evaluate average excess returns over month $t+1$.

[Insert Table 4 about here]

In Panel A of Table 4, we investigate whether the EDL risk_2 premium is explained by Acharya and Pedersen (2005)'s corresponding linear liquidity risk component, β_{L2} (see Appendix D), which measures systematic variation between a stock's return and market liquidity. We first form five portfolios sorted by β_{L2}. Then, within each β_{L2} quintile, we sort stocks into five portfolios based on EDL risk_2.We report the average monthly $t+1$ portfolio returns in excess of the risk-free rate for the 25 $\beta_{L2} \times$ EDL risk_2 portfolios and find that strong EDL risk_2 stocks clearly outperform weak EDL risk_2 stocks in all β_{L2} quintiles. The return difference is, on average, 0.25% per month, which is statistically significant at the 1% level. Similar results are obtained when we adjust raw returns by the Pastor and Stambaugh (2003) and Sadka (2006) liquidity-risk augmented Carhart (1997) model. Differences in alphas are on average 0.26% and 0.31% per month, respectively, and are both statistically significant at the 1% level. Hence, regular linear β_{L2} liquidity risk as analyzed in Acharya and Pedersen (2005) cannot account for the reward earned by holding stocks with strong EDL risk_2.

In Panel B of Table 4, we analyze whether the EDL risk_2 premium is explained by the corresponding linear downside liquidity risk, β^-_{L2} (see Appendix D), which — like EDL risk_2 — focuses on systematic downside variation between a stock's return and market liquidity. However, the conceptional difference between EDL risk_2 and β^-_{L2} risk is that the latter focuses on systematic risk below the mean of market liquidity, while the former explicitly focuses on extreme events. We again find that in all β^-_{L2} quintiles strong EDL risk_2 stocks significantly outperform weak EDL risk_2 stocks with an average return of 0.31%. Average liquidity-risk augmented Carhart (1997) alphas are also significantly larger for strong EDL risk_2 stocks compared to weak EDL risk_2 stocks with spreads of 0.28% and 0.38% (t-statistics of 4.28 and 4.71). Thus, linear downside liquidity risk cannot account for the EDL risk_2 premium either.

In Panel C and Panel D of Table 4, we examine whether EDL risk_2 is different from extreme downside return risk, EDR risk (see Appendix D), and liquidity tail risk (as in Wu, 2017). We can confirm the findings of Chabi-Yo et al. (2018) and Wu (2017) that stocks with high EDR risk (liquidity tail risk) outperform stocks with low EDR risk (liquidity tail risk). More importantly in our context, we show that the pricing impact of EDL risk_2 is not subsumed by neither EDR risk nor liquidity tail risk. On average, the spread between stocks with strong EDL risk_2 and weak EDL risk_2 controlling for EDR risk (liquidity tail risk) is 0.27% (0.24%) per month and is statistically significant at the 1% level. Results are very similar when we evaluate alphas instead of returns.

Finally, Panel E investigates whether the EDL risk_2 premium can be explained by a stock's exposure to lower-partial moment (LPM) liquidity risk 2 (as in Anthonisz and Putnins, 2017) between a stock's return and market liquidity. At first sight, EDL risk_2 and LPM_2 liquidity risk seem to be conceptionally related. However, they have to be clearly distinguished since (i) EDL risk_2 focuses on extreme events instead of below mean events (as in the case of LPM_2 liquidity risk), and (ii) EDL risk_2 has different conditioning subsets (extremely low market liquidity instead of negative liquidity-adjusted market returns as in the case of the Anthonisz and Putnins (2017) LPM_2 liquidity risk). As a consequence, it is not surprising that we find empirical support that the impact of EDL risk_2 on future returns is not subsumed by the impact of LPM_2 liquidity risk. The average return and alpha differences between strong EDL risk_2 stocks and weak EDL risk_2 stocks are economically meaningful and statistically significant at the 1% level.

In the same way as for double-sorts based on EDL risk_2, we perform bivariate equal-weighted portfolio sorts based on EDL risk_3 and other liquidity and return risk measures. Results are shown in Table 5.

[Insert Table 5 about here]

As for the portfolio double sorts based on EDL risk_2, we observe that the pricing effect of EDL risk_3 is different from the impact of the corresponding linear liquidity risk component, β_{L3}, the corresponding linear downside liquidity risk component, β^-_{L3}, EDR risk, liquidity tail risk, and lower-partial moment (LPM) liquidity risk 3. Based on the respective double sorts, stocks with strong EDL risk_3 outperform stocks with weak EDL risk_3 by statistically significant 0.17% to 0.22% per month (with t-statistics ranging from 2.32 to 3.36). If we adjust returns for the Pastor and Stambaugh (2003) and Sadka (2006) liquidity-risk augmented Carhart (1997) models, these spreads range from 0.17% to 0.26% (with t-statistics ranging from 1.83 to 2.97).[22]

[22] In additional tests shown in Table C.3 of the Appendix, we also look at reversed bivariate equal-weighted portfolio sorts based on EDL risk_2 (first sort) and LPM liquidity risk_2 (second sort), as well as EDL risk_3 (first sort) and LPM liquidity risk_3 (second sort). We observe that the documented premium for Anthonisz and Putnins (2017)'s LPM liquidity risk_3 remains priced when we explicitly control for EDL risk_3 in these sorts. This result supports the notion that EDL risk and LPM liquidity risk are capturing different aspects of liquidity risk which are separately priced. Additional findings about the joint impact of EDL risk_3 and LPM liquidity risk_3 in multivariate regressions are reported in Section 3.4 and Table C.4 of the Appendix.

To summarize, dependent bivariate portfolio sorts provide strong evidence that EDL $risk_2$ and EDL $risk_3$ are priced in the cross-section of expected stock returns when explicitly controlling for β_{L2} and β_{L3}, β^-_{L2} and β^-_{L3}, EDR risk, liquidity tail risk (as in Wu, 2017), and LPM liquidity $risk_2$ and LPM liquidity $risk_3$ (as in Anthonisz and Putnins, 2017), respectively. So far, our analysis relies on return and alpha differences and we only control for the impact of systematic risk characteristics indirectly by double-sorting portfolios. To control for the exposure to other systematic risk factors, we now investigate whether the EDL $risk_2$ and EDL $risk_3$ premiums can be explained by alternative multivariate factor models suggested in the literature.

3.3 Factor Models

We regress the monthly $t + 1$ returns of the EDL $risk_2$ and EDL $risk_3$ quintile difference portfolio on various factors that have been shown to determine the cross-section of average stock returns.[23] We then investigate risk-adjusted monthly returns according to these factors. Table 6 reports the results for the EDL $risk_2$ strong-weak quintile difference portfolio (PF5-1).

[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 $risk_2$ quintile difference portfolio for its exposure to the market factor and the Carhart (1997) four-factor model. We find that the EDL $risk_2$ portfolio loads significantly positive on the market factor and significantly negative on the size factor. The risk-adjusted alpha is significantly positive at the 1% level and amounts to 0.30% per month (3.57% per annum) for the market model, and 0.32% per month (3.82% per annum) for the Carhart (1997) four-factor alpha.

Regressions (3) through (6) additionally control for the EDR risk factor of Chabi-Yo et al. (2018), the Bali et al. (2011) factor for lottery-type stocks, the Kelly and Jiang (2014)

[23]The formal definitions of all factors used are provided in Appendix D.

tail risk factor, and the U.S. equity betting-against-beta factor from Frazzini and Pedersen (2014), respectively. Again, the monthly (annual) alpha of the EDL $risk_2$ portfolio remains statistically significant at the 1% level in each case and ranges from 0.31% to 0.37% (3.74% to 4.50%).

Panel B of Table 6 reports annualized alphas for additional alternative factor models. We regress the EDL $risk_2$ quintile difference portfolio on the factors from the Fama and French (2015) five-factor model, the Novy-Marx (2013) and Hou et al. (2015) 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 Asness et al. (2018), the undervalued-minus-overvalued factor from Hirshleifer and Jiang (2010), the Anthonisz and Putnins (2017) LPM liquidity risk factor, the Wu (2017) liquidity tail risk factor, and the Stambaugh and Yuan (2017) mispricing factor. The alpha of the strong minus weak EDL $risk_2$ portfolio ranges from 3.14% p.a. to 4.46% p.a. and is always statistically significant at the 1% level.

We also examine risk-adjusted monthly returns for the EDL $risk_3$ quintile difference portfolio and report the results in Table 7.

[Insert Table 7 about here]

In the same way as for EDL $risk_2$, we find that none of the tested asset pricing factors can substantially reduce the alpha of the EDL $risk_3$ quintile difference portfolio. Dependent on the respective model, we report monthly (annual) alphas between 0.16% to 0.27% (1.86% to 3.25%) with t-statistics ranging from 2.13 to 3.26 in Panel A and annual alphas between 1.94% to 3.21% with t-statistics ranging from 2.10 to 3.27 in Panel B.[24]

Our results reveal that the premiums for EDL $risk_2$ and EDL $risk_3$ are 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-

[24] All of our results are also stable when we use the equal-weighted CRSP market return instead of the value-weighted CRSP market return in the factor model regressions. Results of these tests are reported in Table C.4 of the Appendix.

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

In our basic setting, we perform individual Fama and MacBeth (1973) regressions of excess stock returns over the risk-free rate in month $t+1$ on risk and firm characteristics measured at month t in the period from 1969 to 2012. Running Fama and MacBeth (1973) regressions on the individual firm level can lead to less precisely estimated risk factors in comparison to using portfolios as test assets. However, Ang et al. (2019) 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. Moreover, regressions on the individual stock level avoid biasing the results in favour of (or against) a particular model as a result of the arbitrary but necessary choice of sorting variables in the portfolio formation (see Anthonisz and Putnins, 2017).[25] Table 8 presents the regression results of future monthly excess returns on the EDL risks and various combinations of control variables.

[Insert Table 8 about here]

In regression (1), we include EDL risk_1, EDL risk_2, and EDL risk_3 as the only explanatory variables. Consistent with our results from portfolio sorts and multivariate factor models, EDL risk_2 and EDL risk_3 show highly statistically as well as economically positive impacts, while EDL risk_1 is not significant here (or in any of the following specifications): For example, stocks with top quintile EDL risk_2 (EDL risk_3) earn higher future returns of 3.08% per annum (2.11% per annum) as compared to bottom quintile EDL risk_2 (EDL risk_3) stocks.[26]

[25]Moreover, Lewellen et al. (2010) show that the use of 25 Fama and French (1993) size-B/M sorted portfolios gives a low hurdle in asset pricing tests because of the strong factor structure created in the construction of the portfolios.

[26]Top (bottom) quintile EDL risk_2 stocks have an average EDL risk_2 exposure of 0.17 (0.00). Hence, our regressions results indicate an annual return spread of $0.0151 \cdot 0.17 \cdot 12 = 3.08\%$. Top (bottom) quintile

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$_2$ and EDL risk$_3$ remain 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., 2018), 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$_2$ and does not reduce the impact of EDL risk$_3$ on future returns. Both main variables remain 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^+. Except from β_L^-, none of these variables shows any significant impact on returns. In contrast, our main result regarding the impact of EDL risk$_2$ and EDL risk$_3$ on future returns remains unchanged — EDL risk$_2$ and EDL risk$_3$ are statistically significant at the 1% level and have an economically significant positive impact. Top quintile EDL risk$_2$ (EDL risk$_3$) stocks earn higher future returns by about 2.10% per annum (2.15% per annum) than bottom quintile EDL risk$_2$ (EDL risk$_3$) 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 is positively related to future average returns (Chabi-Yo et al., 2018), whereas idio vola shows a negative impact (e.g., Ang et al., 2006b), while the Acharya and Pedersen (2005) β_L looses is not significance.

In regressions (5), (6), and (7), we add a stock's liquidity tail risk sensitivity (see Wu, 2017),

EDL risk$_3$ stocks have an average EDL risk$_3$ exposure of 0.16 (0.00). Hence, our regressions results indicate an annual return spread of $0.0110 \cdot 0.16 \cdot 12 = 2.11\%$.

the LPM return, LPM liquidity risk, as well as the LPM liquidity risks (see Anthonisz and Putnins, 2017, and Appendix D) to our model. Although some of these variables seem to be similar to the concept of EDL risk (see our discussion above), we empirically find that inclusion of these variables does not diminish the impact of EDL $risk_2$ and EDL $risk_3$ on future average stock returns. Both main variables remain statistically significant at the 1% level and economically meaningful in size, confirming that EDL risk a different dimension of extreme liquidity risk than these measures. Our empirical findings also confirm the results of Anthonisz and Putnins (2017) who observe a positive and statistically significant premium for LPM_3 liquidity risk. Based on economic significance, top quintile LPM_3 liquidity risk stocks earn higher future returns of 3.21% per annum, controlling for the full set of additional variables. Thus, the economic magnitude is slightly larger than the impact for EDL $risk_2$ and EDL $risk_3$ (with corresponding numbers of 2.10% and 2.15% per annum).[27]

We find no evidence for the Anthonisz and Putnins LPM liquidity risk 2 being priced, while EDL $risk_2$ is significant, which suggests that only co-occurences of extreme stock returns and market illiquidty have a pricing impact.

Finally, in regression (7), we use a stock's 6-month ahead excess return, to be fully consistent with the (non-standard) specification used in Anthonisz and Putnins (2017) (instead of the 1-month ahead excess return) as our dependent variable. We find that the impact of EDL $risk_2$ and EDL $risk_3$ does not disappear and both variables remain to be priced at the 5% significance level (in the case of EDL $risk_2$) and the 10% significance level (in the case of EDL $risk_3$). In this setting we can also confirm the significant pricing impact of a stock's illiquidity level (illiq) following Amihud (2002), while it is not significantly priced based on our standard 1-month holding horizon.

[27]We investigate the relationship between the components of EDL risk and the components of LPM liquidity risk in a multivariate setup more detailed in Table C.5 of the Appendix. Specifically, we compare the impact of the components of LPM liquidity risk on future returns when including / excluding the components of EDL risk. Our results reveal that EDL $risk_2$ and EDL $risk_3$ as well as LPM_3 liquidity risk are all individually priced in the cross-section of expected stock returns. Moreover, the inclusion of EDL $risk_2$ and EDL $risk_3$ in a multivariate regression does not affect the magnitude of the pricing impact of LPM_3 liquidity risk (and vice versa).

In summary, we provide strong evidence that EDL risk_2 and EDL risk_3 are priced in the cross-section of expected stock returns. The premiums for EDL risk_2 and EDL risk_3 are robust to various portfolio double sorts, hold for various asset pricing factor models, and remain signficant when controlling for a wide list of firm characteristics.

3.5 Temporal Differences in the EDL Risk Premium

We now investigate whether the premiums for EDL risk_2 and EDL risk_3 are 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) 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 premiums for EDL risk_2 and EDL risk_3 in the cross-section of stock returns after 1987. Panel A of Table 9 reports the monthly excess portfolio returns and alphas of portfolios sorted by EDL risk_2. We also report differences in quintile portfolio spreads between the time periods from January 1988 through December 2012 and January 1969 through December 1987.

[Insert Table 9 about here]

The EDL risk_2 premium between the two subperiods varies considerably. In the first subsample from 1969 through 1987, we only find very weak indications of a positive EDL risk_2 impact. The return spread between the strong EDL risk_2 and the weak EDL risk_2 portfolio is 0.07% per month and is not statistically significant at conventional levels. The results for the liquidity-risk augmented Carhart (1997) alphas are similar: The alpha spreads amount to 0.08% and 0.10% per month and are not statistically significant from zero.

In the post-crash period from 1988 through 2012, the premium for EDL $risk_2$ strongly increases. Stocks in the quintile with the highest (lowest) EDL $risk_2$ earn an monthly average excess return of 0.98% (0.43%). Hence, the monthly return spread between quintile portfolios 5 and 1 is 0.54% and statistically significant at the 1% level. We also find that this premium remains robust when we adjust raw returns for exposures to our usual risk factor models. The monthly spread with regard to the Carhart (1997) four factor model extended by the Pastor and Stambaugh (2003) traded liquidity factor is 0.50% (t-statistic of 3.99) and the monthly spread with regard to the Carhart (1997) four factor model extended by the Sadka (2006) fixed-transitory and variable-permanent liquidity factors is 0.48% (t-statistic of 3.99). We also observe that the difference in the quintile portfolio return and alpha spreads between the time periods from January 1988 through December 2012 and January 1969 through December 1987 are economically large and statistically significant at least at the 5% significance level.

Panel B of Table 9 repeats the temporal variation analysis for EDL $risk_3$. We obtain results that are conceptionally similar but economically and statistically weaker than for EDL $risk_2$. Specifically, we document that EDL $risk_3$ has a systematic impact in the latter sample period, but not prior to 1988. The difference in the quintile portfolio return spread between the time periods from January 1988 through December 2012 and January 1969 through December 1987 increases by 0.26% (t-statistic of 1.73). The differences in the quintile portfolio alpha spreads amount to 0.14% and 0.15%, but do not show statistical significance at conventional levels.

Panel C of Table 9 reports the regression results from specification (3) of Table 8 separately for the two subperiods. Our results reveal – in line with the findings of the portfolio sorts – that the point estimate for the impact of EDL $risk_2$ has more than doubled from the first to the second subperiod in our sample period (from an insignificant 0.0051 to a strongly significant 0.0128). We also observe that the point estimate of EDL $risk_3$ is rather stable through both periods with significant values of 0.099 (between 1969 to 1987) and 0.0106 (between 1988 to 2012).

Figure 2 shows the temporal variation of the cumulative alpha based on the Carhart (1997) four factor model extended by the Pastor and Stambaugh (2003) traded liquidity factor of the top EDL risk_2 (EDL risk_1, EDL risk_3) minus the bottom EDL risk_2 (EDL risk_1, EDL risk_3) portfolio during the whole sample from January 1969 through December 2012.[28]

[Insert Figure 2 about here]

The graph reveals that most of the premium for EDL risk_2 can be attributed to the second half of our sample period (i.e., the time period from January 1988 through December 2012). The strongest premium is realized in the years following 1987 and 2009, respectively, i.e. after 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_2 and EDL risk_3 stocks. Again, this finding is in line with the results of the empirical option literature mentioned above, which indicates increasing prices (and low expected returns) for securities that offer protection against strong market downturns after 1987, as well as with findings in Chabi-Yo et al. (2018) showing that extreme downside return risk premia also significantly increased after crisis periods.

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 risks. Nevertheless, to

[28] When computing the cumulative alphas for the top EDL risk - bottom EDL risks portfolio, no trading costs are taken into account.

assure the stability of our findings, we now test whether our results regarding the impact of EDL $risk_2$ and EDL $risk_3$ on future returns are robust to using different (low-frequency and high-frequency) 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*).[29] 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 advantage of these proxies is their lower measurement error, but they are only available to us for a relatively short period of time, making it very challenging to conduct meaningful asset pricing tests. We perform asset pricing tests for the high-frequency proxies in the time period from 2002 to 2010. Average time-series correlations between the high-frequency and low-frequency proxies are shown in Table A.1 in the Appendix. We find that the highest correlations exist between *IntAmi* and *PriImp* (value of 0.79), *EffSpr* and *PriImp* (value of 0.75), and *Zeros* and *FHT* (value of 0.70).[30]

In the same way as for the Amihud (2002) Illiquidity Ratio, we estimate liquidity shocks, and subsequently the EDL risks, for each firm i in each week t based on weekly returns and liquidity shocks over 3-year rolling windows. To investigate whether EDL $risk_2$ and EDL $risk_3$ are priced factors 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]

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

[30] We 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 coefficients for each stock. Thus, our asset pricing tests using high frequency proxies only start in January 2002.

Consistent with our previous results, Panel A shows that EDL $risk_3$ is significantly priced across all low-frequency measures in our study. The monthly (annualized) return and alpha spreads between quintile portfolios 1 and 5 range from 0.15% (1.80%) for the *Zeros* measure up to 0.33% (3.96%) for the *Corwin* measure. We obtain slighly weaker results for the pricing effect of EDL $risk_2$ across the low-frequency measures. Nevertheless it shows a significant effect for the *Corwin* and the *FHT* measure.

Moreover, we find at least indicative evidence for the pricing of EDL $risk_2$ and EDL $risk_3$ when investigating portfolio sorts for the high-frequency liquidity measures. All EDL $risk_2$ and EDL $risk_3$ raw and risk-adjusted return spreads are positive. In addition, we find a statistically significant impact of EDL $risk_2$ on future returns for *EffSpr* and *PriImp*, as well as a statistically significant impact of EDL $risk_3$ for *EffSpr*, *RelSpr*, *IntAmi*, and *PriImp*. This is a remarkable result given that our sample period for our asset pricing tests is only 9 years, which generally makes it very hard to detect any significant asset pricing patterns.

To confirm that our results are not driven by correlations with other explanatory variables, we repeat regression (3) of Table 8 for the EDL risks based on the alternative liquidity proxies. Our findings in Panel B indicate that the effect of EDL $risk_2$ and EDL $risk_3$ is stable across the different liquidity proxies and not driven by measurement error. All EDL risk coefficients are positive. Except for the *Zeros* measure, we always find a statistically and economically significant impact of EDL $risk_2$ and/or EDL $risk_3$ across the different liquidity proxies, indicating a quite robust impact of these EDL risks on future returns.

4.2 Estimation Procedures and Weighting Scheme

The estimation procedure of the EDL risk coeffcients 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 this 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 using weekly returns. Second, we use simple differences in stock liquidity instead of shocks from an AR(4) model (diff). This robustness test alleviates concerns that errors due to the estimation of the AR(4)-parameters drive results. Third, we use different copula functions in the estimation procedure of the EDL risks. 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.

To examine whether EDL risk_2 and EDL risk_3 are 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 our benchmark factor models, EDL risk_2 and EDL risk_3 are 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 monthly (annualized) EDL risk_2 spread in excess returns and alphas between quintile portfolios 5 and 1 ranges from 0.12% (1.44%) to 0.47% (5.64%) and is always significant at the 10% level. The monthly (annualized) EDL risk_3 spread in excess returns and alphas between quintile portfolios 1 and 5 ranges from 0.16% (1.92%) to 0.39% (4.68%). We also observe that return and alpha spreads remain positive and are statistically significant at least at the 5%-level across different estimation procedures.

In Panel B, we repeat regression (3) of Table 8 of future returns on the EDL risks (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 $risk_2$ and EDL $risk_3$ on future returns is stable across different estimation procedures even when controlling for a wide array of firm and risk characteristics. 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. Thus, we also examine value-weighted portfolio sorts in Table 12.

[Insert Table 12 about here]

Panel A reports the results of value-weighted univariate portfolio sorts based on EDL $risk_2$ and EDL $risk_3$. Based on raw returns, we find that stocks with strong EDL $risk_2$ (EDL $risk_3$) earn significantly higher average future returns than stocks with weak EDL $risk_2$ (EDL $risk_3$). The return spread between quintile portfolio 5 and 1 is 0.21% (0.14%) and statistically significant at the 10% level. However, when we risk-adjust the returns using the Carhart (1997) four-factor model augmented by the Pastor and Stambaugh (2003) traded liquidity factor and the Sadka (2006) fixed-transitory and variable-permanent liquidity factors, we observe that the spreads are shrinking and are statistically indifferent from zero. Hence, giving disproportionate weight to very large stocks in portfolio sorts reduces the impact of EDL $risk_2$ and EDL $risk_3$ on the cross-section of expected stock returns.[31]

[31]We argue that using equal-weighted portfolio sorts in asset pricing tests is the more natural methodology for our research question. First, our paper deals with asset pricing under extreme illiquidity. As already documented in the literature, very large stocks tend to be very liquid, so that a value-weighting scheme strongly over-weights stocks for which liquidity is less of a concern and the concept of EDL risk is eventually not really relevant. As an illustration, in our sample the firms in the largest size quintile make up 84.26% of the total market capitalization of all firms in an average cross-section. Thus, value-weighted sorts are driven predominantly by the very largest firms, for which illiquidity concerns are negligible. Second, Hou et al. (2018) show that the vast majority of 452 asset pricing patterns become insignificant when overweighting

To check which stocks are responsible for the shrinking alpha spread, we also conduct univariate value-weighted portfolio sorts where we exclude the top 5% (top 10%, top 20%) largest firms of our sample in each month t. We show that – in all specifications – the return and alpha spreads based on EDL $risk_2$ and EDL $risk_3$ between quintile portfolio 5 and 1 are economically large and statistically signficant at least at the 10% significance level as soon as we exclude the very largest stocks that otherwise dominate value-weighted returns. As an example, when excluding the top 5% largest stocks per month, the value-weighted portfolio of strong EDL $risk_2$ (EDL $risk_3$) stocks has higher risk-adjusted returns than the value-weighted portfolio of weak EDL $risk_2$ (EDL $risk_3$) stocks between 0.21% (0.26%) per month with t-statistics ranging from 1.88 to 3.01. Hence, the premium for EDL $risk_2$ and EDL $risk_3$ is strong for all stocks except the very largest.

We finally examine whether the significant value-weighted return spread of the quintile difference portfolio based on EDL $risk_2$ and EDL $risk_3$ is also robust to the inclusion of other factors proposed in the literatur. For this purpose, we regress the return spread on the risk factors also used in Panel A of Table 6 and Table 7. We observe that none of the factors can substantially shrink the alpha of the EDL $risk_2$ and EDL $risk_3$ quintile difference portfolio (when having excluded the top 5% of the largest firms). Dependent on the respective model, we report monthly (annual) alphas between 0.26% to 0.31% (3.13% to 3.71%) with t-statistics ranging from 2.93 to 3.68 for EDL $risk_2$ in Panel B and monthly (annual) alphas between 0.20% to 0.32% (2.36% to 3.80%) with t-statistics ranging from 2.44 to 3.52 for EDL $risk_3$ in Panel C.

large stocks, in particular for liquidity-related return premiums. We interpret their findings as evidence that any analysis of liquidity-related phenomena must give sufficient weight to illiquid (typically small firm) stocks, which are actually affected by these phenomena, to provide any insight. Thus, in order to gauge the importance of EDL $risk_2$ and EDL $risk_3$, we rely on an equal-weighted approach in the main part of our empirical analysis, giving a large-enough weight to illiquid stocks to make the effects of extreme illiquidity visible.

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 8 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.[32] 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_2 and EDL risk_3 are important explanatory factors and always statistically significant at the 1% level.

So far, we have used monthly excess returns in month $t + 1$ as our dependent variable in the asset pricing exercises. We now test the robustness of our results if we use different lags, namely monthly returns in $t + 2$, $t + 3$, and $t + 4$ as our dependent variable. Results in Panel B of Table 13 document a stable and statistically significant impact of EDL risk_2 and EDL risk_3 on future returns across the different lags and return horizons which decrease the longer the lag between the estimation and evaluation period becomes.

Next, we adjust the return of each stock by subtracting the return of its corresponding Daniel et al. (1997) characteristic-based benchmark (DGTW). Again, our main result of

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

significant premiums for EDL $risk_2$ and EDL $risk_3$ remains unaffected.

Finally, some extreme market downturns might be driven by specific industries. To investigate whether this is the case, we repeat our multivariate regressions with the full set of controls (i.e., regression (3) from Table 8), 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, as well as the Fama-French 12 (FF12) and 48 (FF48) industry classifications with monthly returns. For all classifications, the coefficient for EDL $risk_2$ and EDL $risk_3$ remains positive and statistically significant.

5 Conclusion

This study investigates whether investors receive compensation for holding stocks with high extreme downside liquidity (EDL) risks, i.e., stocks that display (i) clustering in the lower left tail of the bivariate distribution between individual stock liquidity and market liquidity (EDL $risk_1$), (ii) clustering in the lower left tail of the bivariate distribution between the individual stock return and market liquidity (EDL $risk_2$), and (iii) clustering in the lower left tail of the bivariate distribution between individual stock liquidity and the market return (EDL $risk_3$). We hypothesize that such stocks are unattractive assets to hold for crash-averse investors leading them to demand a premium for holding high 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 $risk_2$ and EDL $risk_3$, but not EDL $risk_1$. Stocks that are characterized by high EDL $risk_2$ (EDL $risk_3$) earn significantly higher future returns than stocks with low EDL $risk_2$ (EDL $risk_3$). The high future returns earned by stocks with high EDL $risk_2$ (EDL $risk_3$) can be explained neither by linear liquidity risk (as in Acharya and Pedersen, 2005), LPM liquidity risk (as in Anthonisz and Putnins, 2017) 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 for the EDL risks.

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. (2017) 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 $risk_2$ and EDL $risk_3$ 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):

$$c_t^i = min(0.25 + 0.30 \cdot illiq_t^i \cdot P_{t-1}^m, 30)\% \tag{12}$$

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:

$$c_t^i = \frac{1}{\text{days}_t^i - 1} \sum_{d=2}^{\text{days}_t^i} max\left(\frac{2 \cdot (e^{\alpha_{td}^i} - 1)}{e^{\alpha_{td}^i} + 1}, 0\right) \tag{13}$$

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 $hi^i_{t,d}$ and $lo^i_{t,d}$ stand for high- and low-prices on day d in week t for stock i, $tdhi^i_{t,d}$ and $tdlo^i_{t,d}$ stand for 2-day high- and low-prices on days $d-1$ and d in week t for stock i and days^i_t 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^i_t can be interpreted as the spread of stock i.

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

$$c^i_t = \frac{x^i_{td}}{\text{days}^i_t} \tag{14}$$

where x^i_{td} is the number of zero-return days and $days^i_t$ 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:

$$c^i_t = 2 \cdot \sigma^i_t \cdot N^{-1}\left(\frac{1 + Zeros2}{2}\right) \tag{15}$$

with

$$Zeros2 = \frac{x^i_t}{7}$$

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

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

$$c^i_t = \frac{1}{\text{days}^i_t} \sum_{d=1}^{\text{days}^i_t} \frac{1}{N^i_{td}} \sum_{n=1}^{N^i_{td}} RS^i_{tdn} \tag{16}$$

with

$$RS^i_{tdn} = \frac{A^i_{tdn} - B^i_{tdn}}{Q^i_{tdn}}$$

where A^i_{tdn}, B^i_{tdn} and $Q^i_{tdn} = \frac{A^i_{tdn}+B^i_{tdn}}{2}$ are prevailing ask quote, prevailing bid quote and quote midpoint price in transaction n of day d in week t. days^i_t is the number of days with available transactions of stock i in week t and N^i_{td} 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:

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

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:

$$c_t^i = \frac{1}{\text{days}_t^i} \sum_{d=1}^{\text{days}_t^i} \frac{1}{N_{td}^i} \sum_{n=1}^{N_{td}^i} PI_{tdn}^i \quad (18)$$

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:

$$c_t^i = \frac{1}{\text{days}_t^i} \sum_{d=1}^{\text{days}_t^i} \frac{1}{N_{td}^i} \sum_{n=1}^{N_{td}^i} IA_{tdn}^i \quad (19)$$

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., $\text{days}_t^i < 3$.[33]

[33] We make an exception for the week of September 11^{th} 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 risks (see Appendix B) in order to facilitate the interpretation of our extreme downside *liquidity* risks. 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 2011[34] – 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).

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. We observe that illiq and *Corwin* dislay the highest pairwise correlations with the high-frequency proxies.

[34]The 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.

Table A.1: Average Time-Series Correlations between Liquidity Proxy Levels

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

This table displays correlations between liquidity levels 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 sample covers all U.S. common stocks traded on the NYSE / AMEX. The sample period for proxy levels is from January 1996 to December 2010.

Table A.2: Persistence of EDL Risk

	(1) EDL risk_1	(2) EDL risk_1	(3) EDL risk_2	(4) EDL risk_2	(5) EDL risk_3	(6) EDL risk_3
EDL risk_1	0.0303***	0.0220***				
	(4.25)	(4.24)				
EDL risk_2			0.0147***	0.0092***		
			(3.49)	(2.88)		
EDL risk_3					0.0428***	0.0197***
					(5.64)	(4.29)
β_R		0.0060**		0.0021		0.0071***
		(2.13)		(0.71)		(2.94)
size		0.0039***		0.0015		0.0060
		(3.15)		(1.54)		(1.48)
btm		0.0024*		0.0014		0.0024*
		(1.77)		(1.08)		(1.69)
past return		-0.0038		-0.0006		0.0007
		(-1.45)		(-0.30)		(0.23)
β_L		-0.0063		-0.0068		0.0044
		(-0.99)		(-1.22)		(1.18)
EDR risk		0.0070		0.0057**		-0.0093**
		(1.52)		(2.08)		(-2.50)
illiq		-0.0106		0.0157		0.0997**
		(-0.96)		(1.04)		(2.37)
β_{Tail}		0.0080		0.0090		0.0045
		(0.54)		(1.23)		(0.43)
idio vola		-0.1009		-0.0213		-0.1284
		(-1.18)		(-0.26)		(-1.56)
coskew		0.0016		0.0029		-0.0053
		(0.37)		(0.90)		(-1.50)
const	0.0919***	0.0078	0.0666***	0.0346*	0.0728***	-0.0468
	(17.12)	(0.32)	(9.17)	(1.92)	(13.14)	(-1.44)
Avg. R^2	0.0039	0.0626	0.0031	0.0474	0.0065	0.0704

This table displays the results of multivariate Fama and MacBeth (1973) regressions. We report the results of regressions of weekly EDL risk_1, EDL risk_2, and EDL risk_3 estimated based on weeks $t+1$ to $t+156$ on EDL risk_1, EDL risk_2, and EDL risk_3 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 D. 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.

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. (2018).

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 $C_1(u_1, u_2)$, $C_2(u_1, u_2)$, ..., $C_n(u_1, u_2)$ are bivariate copula functions, then

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

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 risk$_1$). The estimation of the other EDL risks, namely EDL risk$_2$ (stock return and market liquidity) as well as EDL risk$_3$ (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 $j = 1, \ldots, 64$ 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 risk$_1$ and copula (1-A-IV) is the best fit for the distributions for EDL risk$_2$ as well as EDL risk$_3$. 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., 2018):

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

$$\widehat{F}_i(x) = \frac{1}{n+1}\sum_{k=1}^{n} \mathbb{1}_{l_{i,k} \leq x} \quad \text{and} \quad \widehat{F}_m(x) = \frac{1}{n+1}\sum_{k=1}^{n} \mathbb{1}_{l_{m,k} \leq x}. \tag{20}$$

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

$$\widehat{\Theta} = \text{argmax}_{\Theta}\, L(\Theta) \quad \text{with} \quad L(\Theta) = \sum_{k=1}^{n} \log\left(c(\widehat{F}_{i,l_{i,k}}, \widehat{F}_{m,l_{m,k}}; \Theta_j)\right), \tag{21}$$

where $L(\Theta)$ denotes the log-likelihood function and $c(\cdot,\cdot;\Theta)$ the copula densitiy. $\widehat{\Theta}$ 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)	$C_{\text{RGum}}(u_1, u_2) = u_1 + u_2 - 1 + \exp\left(-((-\log(\overline{u}_1))^\theta + (-\log(\overline{u}_2))^\theta)^{1/\theta}\right)$	$2 - 2^{1/\theta}$	–
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)	$C_{\text{RGal}}(u_1, u_2) = u_1 + u_2 - 1 + (\overline{u}_1) \cdot (\overline{u}_2) \cdot \exp\left(((-\log(\overline{u}_1))^{-\theta} + (-\log(\overline{u}_2))^{-\theta})^{-1/\theta}\right)$	$2^{-1/\theta}$	–
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)	$C_{\text{Pla}}(u_1, u_2; \theta) = \frac{1}{2}(\theta - 1)^{-1} \left\{1 + (\theta - 1)(u_1 + u_2) - [(1 + (\theta - 1)(u_1 + u_2))^2 - 4\theta u_1 u_2]^{1/2}\right\}$	–	–
F-G-M (D)	$C_{\text{Fgm}}(u_1, u_2; \theta) = u_1 u_2 (1 + \theta(1 - u_1)(\overline{u}_2))$	–	–
Joe (I)	$C_{\text{Joe}}(u_1, u_2; \theta) = 1 - ((\overline{u}_1)^\theta + (\overline{u}_2)^\theta - (\overline{u}_1)^\theta \cdot (\overline{u}_2)^\theta)^{1/\theta}$	–	$2 - 2^{1/\theta}$
Gumbel (II)	$C_{\text{Gum}}(u_1, u_2; \theta) = \exp\left(-((-\log(u_1))^\theta + (-\log(u_2))^\theta)^{1/\theta}\right)$	–	$2 - 2^{1/\theta}$
Galambos (III)	$C_{\text{Gal}}(u_1, u_2; \theta) = u_1 \cdot u_2 \cdot \exp\left(((-\log(u_1))^{-\theta} + (-\log(u_2))^{-\theta})^{-1/\theta}\right)$	–	$2^{-1/\theta}$
Rotated-Clayton (IV)	$C_{\text{RCla}}(u_1, u_2) = u_1 + u_2 - 1 + ((\overline{u}_1)^{-\theta} + (\overline{u}_2)^{-\theta} - 1)^{-1/\theta}$	–	$2^{-1/\theta}$

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 $\overline{u}_1 = 1 - u_1$ and $\overline{u}_2 = 1 - u_2$. 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%	(2-D-II)	0.00%	(3-B-II)	0.00%
(3-B-II)	0.00%	(2-B-I)	0.00%	(2-B-II)	0.00%
(3-B-I)	0.00%	(2-B-II)	0.00%	(2-B-I)	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: Additional Asset Pricing Results

Table C.1: Extreme Upside Liquidity Risk: Summary Statistics and Univariate Portfolio Sorts

Panel A: Summary Statistics

	Mean	Standard Deviation	10%-Percentile	50%-Median	90%-Percentile
EUL $risk_1$	0.0211	0.0201	0.0000	0.0200	0.0462
EUL $risk_2$	0.0212	0.0198	0.0000	0.0188	0.0429
EUL $risk_3$	0.0274	0.0232	0.0000	0.0200	0.0600
EDL $risk_1$	0.0632	0.0770	0.0000	0.0351	0.1803
EDL $risk_2$	0.0713	0.0779	0.0000	0.0461	0.1764
EDL $risk_3$	0.0543	0.0682	0.0000	0.0282	0.1557

Panel B: Univariate Portfolio Sorts

Portfolio	(1) EUL $risk_1$	(2) EUL $risk_2$	(3) EUL $risk_3$
1 Weak 1	0.61%	0.58%	0.66%
2	0.60%	0.66%	0.58%
3	0.64%	0.62%	0.63%
4	0.65%	0.61%	0.64%
5 Strong 5	0.69%	0.57%	0.68%
Strong - Weak	0.08%	−0.01%	0.02%
Return	(1.25)	(-0.29)	(0.32)
Strong-Weak	0.05%	0.01%	0.01%
Carhart + PS_{t+1}	(0.80)	(0.21)	(0.20)
Strong-Weak	0.06%	0.04%	−0.02%
Carhart + $Sadka_{t+1}$	(0.83)	(0.59)	(-0.31)

Panel A of this table displays summary statistics for EUL $risk_1$, EUL $risk_2$, EUL $risk_3$, EDL $risk_1$, EDL $risk_2$, and EDL $risk_3$. We report the mean, the standard deviation, the 10%-percentile, 50%-percentile (median), and 90%-percentile for each variable. Panel B of this table reports equal-weighted average monthly $t+1$ excess returns for portfolios sorted by EUL $risk_1$, EUL $risk_2$, and EUL $risk_3$. Each month t we rank stocks into quintiles (1-5) based on estimated EUL $risk_1$, EUL $risk_2$, and EUL $risk_3$ over the past three years and form equal-weighted portfolios at the beginning of each monthly period. We report monthly average returns in excess of the one-month T-Bill rate over the month $t+1$, alphas based on Carhart (1997)'s four factor model extended by the Pastor and Stambaugh (2003) traded liquidity factor and the Sadka (2006) fixed-transitory and variable-permanent liquidity factors. 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. Alphas based on Carhart (1997)'s four factor model extended by the Sadka (2006) fixed-transitory and variable-permanent liquidity factors range from April 1983 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 C.2: Fama and MacBeth (1973) Regressions: Extreme Upside Liquidity Risks

	Return_{t+1}
EDLR_1	-0.0015
	(-0.71)
EDLR_2	0.0100***
	(3.64)
EDLR_3	0.0110***
	(4.04)
EULR_1	-0.0003
	(-0.13)
EULR_2	-0.0002
	(-0.05)
EULR_3	0.0076
	(1.45)
β_R	0.0004
	(0.25)
size	-0.0014***
	(-4.63)
btm	0.0023***
	(3.03)
past return	0.0104***
	(5.65)
β_L	-0.0080
	(-0.59)
EDR risk	0.0088***
	(5.16)
illiq	-0.0211
	(-0.97)
β_{Tail}	0.0236
	(1.45)
idio vola	-0.0957***
	(-2.76)
coskew	-0.0002
	(-0.12)
Avg. R^2	0.0888

This table displays the results of multivariate Fama and MacBeth (1973) regressions. We report the results of regressions of monthly excess returns over the risk-free rate at month $t+1$ on EDLR_1, EDLR_2, EDLR_3, EULR_1, EULR_2, EULR_3, 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) month t. A detailed description of the computation of these variables is given in the main text and in Appendix D. 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 C.3: Reversed Bivariate Equal-Weighted Portfolio Sorts

Panel A: EDL risk$_2$ (first sort) and LPM liquidity risk$_2$ (second sort)

Portfolio	1 Weak EDLR$_2$	2	3	4	5 Strong EDLR$_2$	Average
1 Weak LPMLR$_2$	0.36%	0.40%	0.50%	0.53%	0.61%	0.48%
2	0.50%	0.63%	0.63%	0.78%	0.77%	0.66%
3	0.60%	0.70%	0.65%	0.78%	0.78%	0.70%
4	0.44%	0.66%	0.78%	0.68%	0.87%	0.69%
5 Strong LPMLR$_2$	0.31%	0.49%	0.52%	0.74%	0.87%	0.59%
Strong-Weak	−0.05%	0.10%	0.02%	0.22%	0.26%	0.11%
Return	(-0.28)	(0.52)	(0.12)	(1.25)	(1.34)	(0.70)
Strong-Weak	−0.20%	0.01%	−0.04%	0.10%	0.21%	0.02%
Carhart + PS$_{t+1}$	(-1.18)	(0.08)	(-0.24)	(0.57)	(1.19)	(0.13)
Strong-Weak	−0.30%	−0.08%	−0.10%	0.10%	0.16%	−0.04%
Carhart + Sadka$_{t+1}$	(-1.52)	(-0.39)	(-0.47)	(0.47)	(0.75)	(-0.29)

Panel B: EDL risk$_3$ (first sort) and LPM liquidity risk$_3$ (second sort)

Portfolio	1 Weak EDLR$_3$	2	3	4	5 Strong EDLR$_3$	Average
1 Weak LPMLR$_3$	0.23%	0.29%	0.32%	0.44%	0.48%	0.35%
2	0.36%	0.28%	0.38%	0.63%	0.55%	0.44%
3	0.48%	0.53%	0.55%	0.71%	0.80%	0.62%
4	0.85%	0.92%	0.83%	1.03%	1.08%	0.94%
5 Strong LPMLR$_3$	0.73%	0.81%	0.80%	1.18%	0.98%	0.90%
Strong-Weak	0.50%***	0.52%***	0.47%***	0.75%***	0.50%***	0.55%***
Return	(3.54)	(3.86)	(3.43)	(4.86)	(3.51)	(5.94)
Strong-Weak	0.54%***	0.57%***	0.45%***	0.79%***	0.54%***	0.58%***
Carhart + PS$_{t+1}$	(3.75)	(4.43)	(3.18)	(5.11)	(3.34)	(6.28
Strong-Weak	0.41%**	0.40%**	0.25%	0.82%***	0.41%**	0.46%***
Carhart + Sadka$_{t+1}$	(2.23)	(2.51)	(1.40)	(4.49)	(2.10)	(4.29)

This table reports the results of dependent equal-weighted portfolio sorts based on EDL risk$_2$ and LPM liquidity risk$_2$, as well as EDL risk$_3$ and LPM liquidity risk$_3$. Panel A displays monthly average future returns of 25 LPM liquidity risk$_2$ - EDL risk$_2$ portfolio sorts. We form quintile portfolios based on EDL risk$_2$. Then, within each risk quintile, we sort stocks into equal-weighted portfolios based on LPM liquidity risk$_2$. Panel B displays monthly average future returns of 25 LPM liquidity risk$_3$ - EDL risk$_3$ portfolio sorts. We form quintile portfolios based on EDL risk$_3$. Then, within each risk quintile, we sort stocks into equal-weighted portfolios based on LPM liquidity risk$_3$. 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. Alphas based on Carhart (1997)'s four factor model extended by the Sadka (2006) fixed-transitory and variable-permanent liquidity factors range from April 1983 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 C.4: Factor Models with Equal-Weighted Market Returns

Panel A: Factor Models with Equal-Weighted Market Returns (EDL risk$_2$)

	(1) EDL risk$_2$ (PF 5-1)	(2) EDL risk$_2$ (PF 5-1)	(3) EDL risk$_2$ (PF 5-1)	(4) EDL risk$_2$ (PF 5-1)	(5) EDL risk$_2$ (PF 5-1)	(6) EDL risk$_2$ (PF 5-1)	(7) EDL risk$_2$ (PF 5-1)	(8) EDL risk$_2$ (PF 5-1)
const	0.29%***	0.31%***	0.33%***	0.41%***	0.30%***	0.35%***	0.36%***	0.35%***
	(4.47)	(3.29)	(3.37)	(3.71)	(3.12)	(3.40)	(3.63)	(3.77)
yearly alpha	3.53%	3.67%	3.91%	4.98%	3.57%	4.26%	4.36%	4.21%

Panel B: Factor Models with Equal-Weighted Market Returns (EDL risk$_3$)

	(1) EDL risk$_3$ (PF 5-1)	(2) EDL risk$_3$ (PF 5-1)	(3) EDL risk$_3$ (PF 5-1)	(4) EDL risk$_3$ (PF 5-1)	(5) EDL risk$_3$ (PF 5-1)	(6) EDL risk$_3$ (PF 5-1)	(7) EDL risk$_3$ (PF 5-1)	(8) EDL risk$_3$ (PF 5-1)
const	0.13%*	0.20%**	0.18%**	0.23%**	0.19%**	0.23%***	0.18%**	0.24%***
	(1.82)	(2.52)	(2.13)	(2.27)	(2.27)	(2.60)	(2.14)	(2.82)
yearly alpha	1.53%	2.46%	2.22%	2.81%	2.22%	2.81%	2.21%	2.83%

Panel C: Other Factor Models (EDL $risk_2$ and EDL $risk_3$)

Factor Model	Annualized α EDL $risk_2$	Annualized α EDL $risk_3$
Fama-French 5-Factor Model (Fama and French, 2015)	3.00%*** (3.78)	1.42%* (1.67)
Novy-Marx four-factor Model (Novy-Marx, 2013)	4.14%*** (2.79)	2.66%** (2.25)
Hou-Xue-Zhang four-factor Model (Hou et al., 2015)	3.65%*** (3.64)	2.35%** (2.24)
Carhart 4-factor Model + short- and long-term reversal	3.90%*** (3.06)	2.59%** (2.41)
Carhart 4-factor Model + leverage factor (Adrian et al., 2014)	3.97%*** (3.23)	2.77%*** (2.66)
Carhart 4-factor Model + quality-minus-junk (Asness et al., 2015)	4.18%*** (3.61)	3.20%*** (3.05)
Carhart 4-factor Model + undervalued-minus-overvalued (Hirshleifer and Jiang, 2010)	4.04%*** (4.36)	2.11%** (2.22)
Carhart 4-factor Model + LPM liquidity risk (Anthonisz and Putnins, 2017)	3.74%*** (3.32)	2.49%** (2.54)
Carhart 4-factor Model + liquidity tail risk (Wu, 2015)	4.33%*** (3.61)	2.32%** (2.26)
Carhart 4-factor Model + mispricing (Stambaugh and Yuan, 2017)	4.55%*** (4.15)	2.66%** (2.55)

Panel A of this table reports monthly OLS-regression results of a trading strategy based on the return-difference between past strong EDL $risk_2$ (quintile 5) and past strong EDL $risk_2$ (quintile 1) portfolios on different factor models. Panel B of this table reports monthly OLS-regression results of a trading strategy based on the return-difference between past strong EDL $risk_3$ (quintile 5) and past strong EDL $risk_3$ (quintile 1) portfolios on different factor models. The factors we use in Panel A and Panel B are the equal-weighted CRSP market-return in excess of the risk-free rate in (1), SMB and HML of the Fama and French (1993) three-factor model, MOM of the four-factor model by Carhart (1997) in (2), Pastor and Stambaugh (2003)'s traded liquidity risk factor (PS Liqui) in (3), Sadka (2006)'s fixed-transitory and variable-permanent liquidity factors in (4), Chabi-Yo et al. (2018)'s equal-weighted EDRR (EDRR) factor in (5), Bali et al. (2011)'s equal-weighted lottery factor (Max) in (6), as well as the equally-weighted tail-risk factor (Tail) proposed by Kelly and Jiang (2014) in (7), and the betting-against-beta factor (BAB) proposed by Frazzini and Pedersen (2014) in (8). We only report the intercept of the regression and the respective annualized alpha. Panel C of this table reports additional factors alphas based on the strong minus weak trading strategy of EDL $risk_2$ and EDL $risk_3$. We use 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 Asness et al. (2018), the undervalued-minus-overvalued factor from Hirshleifer and Jiang (2010), the lower partial moment liquidity risk factor from Anthonisz and Putnins (2017), the Wu (2017) liquidity tail risk factor, and the two mispricing factors of Stambaugh and Yuan (2017). 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 four lags.

Table C.5: Fama and MacBeth (1973) Regressions: LPM liquidity risk and EDL risk

	(1) Return $t+1$	(2) Return $t+1$	(3) Return $t+1$	(4) Return $t+1$
EDL risk_1			-0.0035	-0.0042
			(-1.38)	(-1.57)
EDL risk_2			0.00967***	0.0100***
			(3.55)	(3.69)
EDL risk_3			0.00942***	0.00929***
			(3.34)	(3.30)
past return	0.0085***	0.0086***	0.0080***	0.0083***
	(4.16)	(4.29)	(3.99)	(4.12)
EDR risk	0.0067***	0.0065***	0.0061***	0.0059***
	(3.35)	(3.25)	(3.05)	(2.96)
illiq	-0.0012	0.0103	0.0353	0.0456
	(-0.02)	(0.18)	(0.56)	(0.73)
LPM return	-0.0009	0.0003	-0.0005	0.0006
	(-0.60)	(0.18)	(-0.36)	(0.36)
LPM liquidity risk	0.0027***		0.0031***	
	(4.60)		(4.27)	
LPM liquidity risk_1		-0.0019		0.0015
		(-0.29)		(0.20)
LPM liquidity risk_2		-0.0172		-0.0164
		(-1.24)		(-1.16)
LPM liquidity risk_3		0.0041***		0.0041***
		(4.28)		(4.28)
Avg. R^2	0.0546	0.0596	0.0611	0.0661

This table replicates the regression results of Anthonisz and Putnins (2017) and includes the EDL risks. The table displays the results of multivariate Fama and MacBeth (1973) regressions. We report the results of regressions of monthly excess returns over the risk-free rate at month $t+1$ on EDL risk_1, EDL risk_2, EDL risk_3, the past 12-month excess returns (past year return), EDR risk, illiquidity (illiq), as well as LPM return, LPM liquidity risk, LPM liquidity risk_1, LPM liquidity risk_2, and LPM liquidity risk_3, computed as in Anthonisz and Putnins (2017). All risk and firm characteristics are calculated using data available at (the end of) month t. A detailed description of the computation of these variables is given in the main text and in Appendix D. 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.

D 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 month$t$. 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
Aggregate EDL risk_1	Aggregate Extreme Downside Liquidity Risk 1. Value-weighted average of EDL risk (EDL risk_1) for each week over all stocks in the sample, as detailed in the main text.	CRSP, EST
Aggregate EDL risk_2	Aggregate Extreme Downside Liquidity Risk 2. Value-weighted average of EDL risk (EDL risk_2) for each week over all stocks in the sample, as detailed in the main text.	CRSP, EST
Aggregate EDL risk_3	Aggregate Extreme Downside Liquidity Risk 3. Value-weighted average of EDL risk (EDL risk_3) for each week over all stocks in the sample, as detailed in the main text.	CRSP, EST
EUL risk_1	Extreme Upside Liquidity Risk 1 of a stock. Lower tail dependence between stock liquidity-shocks and (value-weighted) market illiquidity-shocks, estimated based on weekly data from a 3-year rolling window.	CRSP, EST
EUL risk_2	Extreme Upside Liquidity Risk 2 of a stock. Lower tail dependence between stock returns and (value-weighted) market illiquidity-shocks, estimated based on weekly data from a 3-year rolling window.	CRSP, EST
EUL risk_3	Extreme Upside Liquidity Risk 3 of a stock. Lower tail dependence between stock illiquidity-shocks and (value-weighted) market returns, estimated based on weekly data from a 3-year rolling window.	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): $\beta_R^- = \frac{\text{COV}(r_i, r_m \mid r_m < \mu_m)}{\text{VAR}(r_m \mid r_m < \mu_m)}$, 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: $\beta_{L1}^- = \frac{\text{COV}(l_i, l_m \mid l_m < \mu_{l_m})}{\text{VAR}(r_m - l_m \mid l_m < \mu_{l_m})}$, where μ_{u_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: $\beta_{L2}^- = \frac{\text{COV}(r_i, l_m \mid l_m < \mu_{l_m})}{\text{VAR}(r_m - l_m \mid l_m < \mu_{l_m})}$.	CRSP, EST
β_{L3}^-	Downside liquidity beta 3, estimated based on a 3-year rolling window of weekly data: $\beta_{L3}^- = \frac{\text{COV}(l_i, r_m \mid r_m < \mu_{r_m})}{\text{VAR}(r_m - l_m \mid r_m < \mu_{r_m})}$, 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
Carhart + PS Alpha	Carhart (1997)'s four factor alpha extented by the Pastor and Stambaugh (2003) traded liquidity factor.	CRSP, OP, EST
Carhart + Sadka Alpha	Carhart (1997)'s four factor alpha extented by the Sadka (2006) fixed-transitory and variable-permanent liquidity factors.	CRSP, OP, 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: $coskew = \frac{E[(r_i - \mu_i)(r_m - \mu_m)^2]}{\sqrt{\text{VAR}(r_i)}\text{VAR}(r_m)}$.	CRSP, EST
LPM return	Lower partial co-moment between a stock return and the market as computed in Anthonisz and Putnins (2017), estimated based on a 6-month rolling window of daily data.	CRSP, EST
LPM liquidity risk$_1$	Lower partial co-moment between a stock's liquidity and market liquidity as computed in Anthonisz and Putnins (2017), estimated based on a 6-month rolling window of daily data.	CRSP, EST
LPM liquidity risk$_2$	Lower partial co-moment between a stock's return and market liquidity as computed in Anthonisz and Putnins (2017), estimated based on a 6-month rolling window of daily data.	CRSP, EST
LPM liquidity risk$_3$	Lower partial co-moment between a stock's liquidity and the market return as computed in Anthonisz and Putnins (2017), estimated based on a 6-month rolling window of daily data.	CRSP, EST
LPM liquidity risk	Joint LPM liquidity risk of a stock. $\text{LPM liquidity risk} = \text{LPM liquidity risk}_1 + \text{LPM liquidity risk}_2 + \text{LPM liquidity risk}_3$.	CRSP, EST
liquidity tail risk	Exposure to liquidity tail risk, as measured in Wu (2017), based on a 3-year rolling window of weekly data.	CRSP, EST
illiq	Amihud (2002) illiquidity ratio (average over last year).	CRSP, EST
past return	Last year's return for a given stock.	CRSP, EST

Variable Name	Description	Source
Marketrf	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
PS Liqui	Pastor and Stambaugh (2003)'s traded liquidity risk factor.	OP
Sadka Liqui	Sadka (2006)'s fixed-transitory and variable-permanent liquidity factors.	OP
EDRR	Chabi-Yo et al. (2018)'s equally-weighted EDR risk factor portfolio return.	OP
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

References

Acharya, V. and Pedersen, L. (2005) Asset pricing with liquidity risk, *Journal of Financial Economics* **77**, 375-410.

Acharya, V., Amihud, Y., and Bharat, S. (2013) Liquidity risk of corporate bond returns: conditional approach, *Journal of Financial Economics* **110**, 358-386.

Adrian, T., Etula, E., and Muir, T. (2014) Financial intermediaries and the cross-section of asset returns, *Journal of Finance* **69**, 2557-2596.

Agarwal, V., Ruenzi, S., and Weigert, F. (2017) Tail Risk in Hedge Funds: A Unique View from Portfolio Holdings, *Journal of Financial Economics* **125**, 610-637.

Amihud, Y. and Mendelson, H. (1986) Asset pricing and the bid-ask spread, *Journal of Financial Economics* **17**, 223-249.

Amihud, Y. (2002) Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* **5**, 31-56.

Ané, T. and Kharoubi, C. (2003) Dependence structure and risk measure, *Journal of Business* **76**, 411-438.

Ang, A. and Chen, J. (2002) Asymmetric correlations of equity portfolios, *Journal of Financial Economics* **63**, 443-494.

Ang, A., Chen, J., and Xing, Y. (2006a) Downside risk, *Review of Financial Studies* **19**, 1191-1239.

Ang, A., Hodrick, R.J., Xing, Y., and Zhang, X. (2006b) The cross-section of volatility and expected returns, *Journal of Finance* **61**, 259-299.

Ang, A., Liu, J., and Schwarz, K. (2019) Using stocks or portfolios in tests of factor models, *Journal of Financial and Quantitative Analysis*, Forthcoming.

Anthonisz, S.A. and Putnins, T.J. (2017) Asset pricing with downside liquidity risks, *Management Science* **63**, 2549-2572.

Asness, C.S., Frazzini, A., and Pedersen, L.H. (2018) Quality minus junk, *Review of Accounting Studies* **24**, 34-112.

Bali, T.G., Cakici, N. and Whitelaw, R.F. (2011) Maxing out: Stocks as lotteries and the cross-section of expected returns, *Journal of Financial Economics* **99**, 427-446.

Banz, R. (1981) The relation between return and market value of common stocks, *Journal of Financial Economics* **9**, 3-18.

Basu, S. (1983) The relationship between earnings yield, market value, and return for NYSE common stocks: Further evidence, *Journal of Financial Economics* **12**, 129-156.

Bates, D.S. (2008) The market for crash risk, *Journal of Economic Dynamics and Control* **32**, 2291-2321.

Bava, V.S. and Lindenberg, E.B. (1977) Capital market equilibrium in a mean-lower partial moment framework, *Journal of Financial Economics* **5**, 189-200.

Berkman, H., Jacobsen, B., and Lee, J.B. (2011) Time-varying rare disaster risk and stock returns, *Journal of Financial Economics* **101**, 313-332.

Brunnermeier, M. and Pedersen, L. (2009) Market liquidity and funding liquidity, *Review of Financial Studies* **22**, 2201-2238.

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

Carlin, B.I., Lobo, M.S., and Viswanathan, S. (2007) Episodic liquidity crises: Cooperative and predatory trading, *Journal of Finance* **62**, 2235-2274.

Chabi-Yo, F., Ruenzi, S., and Weigert, F. (2018) Crash sensitivity and the cross-section of expected stock returns, *Journal of Financial and Quantitative Analysis* **53**, 1059-1100.

Chabi-Yo, F., Huggenberger, M., and Weigert, F. (2019) Multivariate Crash Risk, unpublished working paper. University of Massachusetts at Amherst, University of Mannheim, and University of St. Gallen.

Chen, J., Joslin, S., and Tran N.K. (2012) Rare disasters and risk sharing with heterogeneous beliefs, *Review of Financial Studies* **25**, 2189-2224.

Cholette, L. and Lu, C.-C. (2011) The market premium for dynamic tail risk, unpublished working paper, University of Stavanger and National Chengchi University.

Chordia, T., Roll, R., and Subrahmanyam, A. (2000). Commonality in liquidity. *Journal of Financial Economics* **56**, 3-28.

Corwin, S.A. and Schultz, P. (2012) A simple way to estimate bid-ask spreads from daily high and low prices, *Journal of Finance* **67**, 719-759.

Coval, J. and Stafford, E. (2007) Asset fire sales (and purchases) in equity markets, *Journal* *of Financial Economics* **86**, 479-512.

Daniel, K., Grinblatt, M., Titman, S., and Wermers, R. (1997) Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* **52**, 1035-1058.

Daniel, K. and Titman, S. (1997) Evidence on the characteristics of cross sectional variation in stock returns, *Journal of Finance* **52**, 1-33.

Embrechts, P., McNeil, A., and Straumann, D. (2002) Correlation and dependence in risk management: properties and pitfalls, in: M.A.H. Dempster (ed.), *Risk Management: Value at Risk and Beyond*, Cambridge University Press, Cambridge, 176-223.

Fama, E.F. and French, K.R. (1993) Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* **33**, 3-56.

Fama, E.F. and French, K.R. (2015) A five-factor asset pricing model, *Journal of Financial Economics* **11**, 1-22.

Fama, E.F. and MacBeth, J.D. (1973) Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* **81**, 607-636.

Fong, K., Holden, C., and Trzcinka, C. (2017) What are the best liquidity proxies for global research, *Review of Finance* **21**, 1355-1401.

Frahm, G., Junker, M. and Schmidt, R. (2005) Estimating the tail-dependence coefficient: Properties and pitfalls, *Insurance: Mathematics and Economics* **37**, 80-100.

Frazzini, A. and Pedersen, L.H. (2014) Betting against beta, *Journal of Financial Economics* **111**, 1-25.

Garleanu, N. and Pedersen, L.H. (2007) Liquidity and risk management, *American Economic Review* **97**, 193-197.

Gennaioli, N., Shleifer, A., and Vishny, R. (2015) Neglected risks: The psychology of financial crises, *American Economic Review* **105**, 310-314.

Genest, C., Ghoudi, K., and Rivest, L.P. (1995) A semiparametric estimation procedure of dependence parameters in multivariate families of distributions, *Biometrika* **82**, 543-552.

Goyenko, R., Holden, C., and Trzcinka, C. (2009) Do liquidity measures measure liquidity? *Journal of Financial Economics* **92**, 153-181.

Hameed, A., Kang, W., and Viswanathan, S. (2010). Stock market declines and liquidity. *Journal of Finance* **65**, 257-293.

Harvey, C.R. and Siddique, A. (2000) Conditional skewness in asset pricing tests, *Journal of Finance* **55**, 1263-1295.

Hasbrouck, J. and Seppi, D.J. (2001) Common factors in prices, order flows and liquidity, *Journal of Financial Economics* **59**, 383-411.

Hasbrouck, J. (2009) Trading costs and returns for US equities: The evidence from daily data, *Journal of Finance* **64**, 1445-1477.

Hill, B. (1975) A simple general approach to inference about the tail of a distribution, *Annals of Statistics* **3**, 1163-1164.

Hirshleifer, D. and Jiang, D. (2010) A financing-based misvaluation factor and the cross-section of expected stock returns, *Review of Financial Studies* **23**, 3401-3436.

Hogan, W. and Warren, J. (1974) Towards the development of an equilibrium capital-market model based on semi-variance, *Journal of Financial and Quantitative Analysis* **9**, 1-11.

Hou, K., Xue, C., and Zhang, L. (2015) Digesting anomalies: an investment approach, *Review of Financial Studies* **28**, 650-705.

Hou, K., Xue, C., and Zhang, L. (2018) Replicating Anomalies, *Review of Financial Studies* Forthcoming.

Huberman, G. and Halka, D. (2001) Systematic liquidity, *Journal of Financial Research* **24**, 161-178.

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

Kelly, B. and Jiang, H. (2014) Tail risk and asset prices, *Review of Financial Studies* **27**, 2841-2871.

Koch, A., Ruenzi, S., and Starks, L. (2016) Commonality in liquidity: A demand-side explanation, *Review of Financial Studies* **29**, 1943-1974.

Lee, K. (2011) The world price of liquidity risk, *Journal of Financial Economics* **99**, 136-161.

Lesmond, D., Ogden, J., and Trzcinka, C. (1999) A new estimate of transaction costs, *Review of Financial Studies* **12**, 1113-1141.

Lewellen, J., Nagel, S., and Shanken, J. (2010) A skeptical appraisal of asset pricing tests, *Journal of Financial Economics* **96**, 175-194.

Longin, F. and Solnik, B. (2001) Extreme correlation of international equity markets, *Journal of Finance* **56**, 649-676.

McNeil, A.J., Frey, R., and Embrechts, P. (2005) *Quantitative risk management*, Princeton University Press.

Menkveld, A. and Wang, T. (2012) Liquileaks, unpublished working paper. VU University of Amsterdam and Tinbergen Institute.

Morris, S. and Shin, H.S. (2004) Liquidity black holes, *Review of Finance* **8**, 1-18.

Nagel, S. (2012) Evaporating liquidity, *Review of Financial Studies* **25**, 2005-2039.

Nelsen, R.B. (2006) *An introduction to copulas*, Springer Series in Statistics, Second Edition.

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

Noussair, C.N., Trautmann, S.T., and van de Kuilen, G. (2014) Higher order risk attitudes, demographics, and financial decisions, *Review of Economic Studies* **81**, 325-55.

Novy-Marx, R. (2013) The other side of value: The gross profitability premium, *Journal of Financial Economics* **108**, 1-28.

Pastor, L. and Stambaugh, R.F. (2003) Liquidity risk and expected returns, *Journal of Political Economy* **111**, 642-685.

Patton, A.J. (2004) On the out-of-sample importance of skewness and asymmetric dependence for asset allocation, *Journal of Financial Econometrics* **2**, 130-168.

Patton, A.J. and Timmermann, A. (2010) Monotonicity in asset returns: New tests with applications to the term structure, the CAPM, and portfolio sorts, *Journal of Financial Economics* **98**, 605-625.

Poon, S.H., Rockinger, M., and Tawn, J. (2004) Extreme value dependence in financial markets: Diagnostics, models, and financial implications, *Review of Financial Studies* **17**, 581-610.

Rodriguez, J.C. (2007) Measuring financial contagion: A copula approach, *Journal of Empirical Finance* **14**, 401-423.

Rubinstein, M. (1994) Implied binomial trees, *Journal of Finance* **49**, 771-813.

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

Sharpe, W.F. (1964) Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* **19**, 425-442.

Sibuya, M. (1960) Bivariate extreme statistics, *Annals of the Institute of Statistical Mathematics* **11**, 195-210.

Sklar, A. (1959) Fonctions de répartition à n dimensions et leurs marges, *Publications de l'Institut de Statistique de l'Université de Paris* **14**, 229-231.

Stambaugh, R.F., and Yuan, Y. (2017) Mispricing factors, *Review of Financial Studies* **30**, 1270-1315.

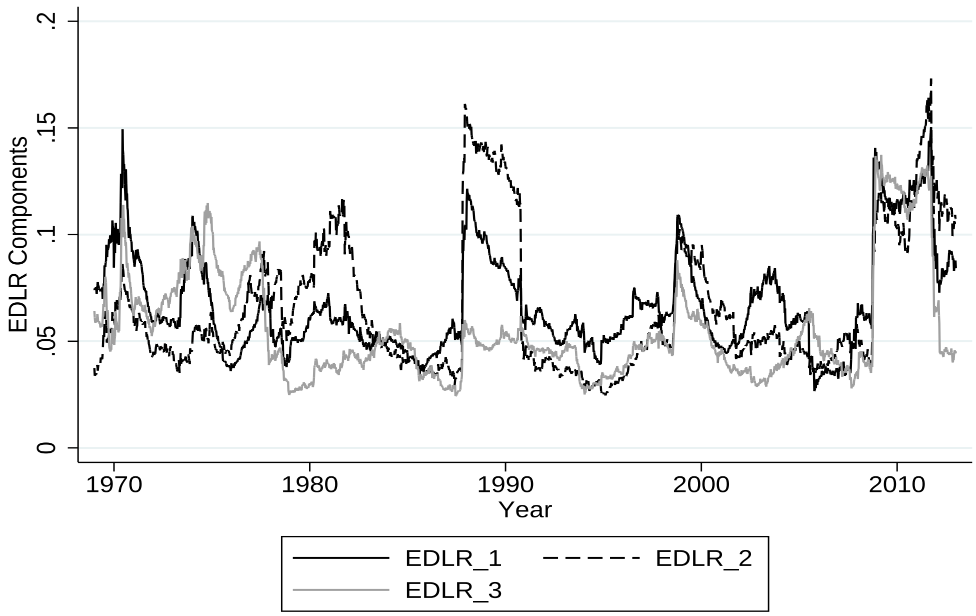
Tawn, J. (1988) Bivariate extreme value theory: models and estimation, *Biometrika* **75**, 397-415.

Watanabe, A., and Watanabe, M. (2008) Time-Varying Liquidity Risk and the Cross Section of Stock Returns, *Review of Financial Studies* **21**, 2449-2486.

Wu, Y. (2017) Asset pricing with extreme liquidity risk, unpublished working paper. Stevens Institute of Technology.

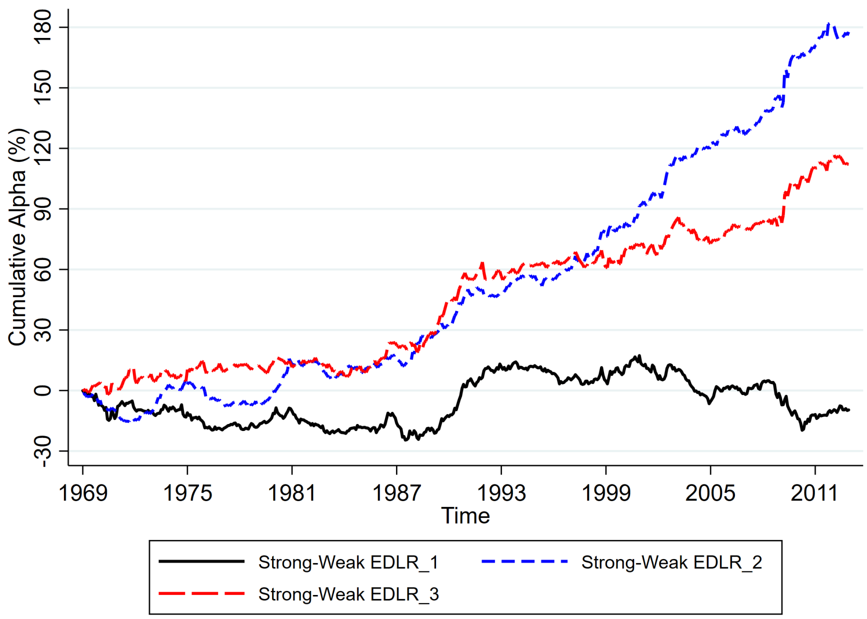
Weigert, F. (2016) Crash aversion and the cross-section of expected stock return worldwide, *Review of Asset Pricing Studies* **6**, 135-178.

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



This figure displays the evolution of aggregate EDL $risk_1$, aggregate EDL $risk_2$, and aggregate EDL $risk_3$ over time. Aggregate EDL $risk_1$, aggregate EDL $risk_2$, and aggregate EDL $risk_3$ in week t is defined as the value-weighted average of EDL $risk_1$ (EDL $risk_2$, EDL $risk_3$) over all stocks i in our sample. 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: Cumulative Alpha of a Trading Strategy Based on EDL $risk_1$, EDL $risk_2$, and EDL $risk_3$



This figure displays the evolution of the Carhart (1997) four factor alpha extended by the Pastor and Stambaugh (2003) traded liquidity factor of a cumulative trading strategy consisting of buying stocks with high EDL $risk_1$ (EDL $risk_2$, EDL $risk_3$) and selling stocks with low EDL $risk_1$ (EDL $risk_2$, EDL $risk_3$) with monthly 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 1: Summary Statistics

	Mean	25%-Quantile	50%-Median	75%-Quantile	Std. Dev.
Return_{t+1}	0.82%	−5.35%	0.14%	6.11%	12.26%
EDL risk_1	0.063	0.000	0.035	0.101	0.077
EDL risk_2	0.071	0.000	0.046	0.116	0.078
EDL risk_3	0.054	0.000	0.028	0.083	0.068
$\beta_L(\cdot 100)$	1.088	0.047	0.262	1.069	1.997
$\beta_L^-(\cdot 100)$	1.583	−0.026	0.163	1.393	3.877
EDRR	0.180	0.065	0.163	0.275	0.138
β_R	1.042	0.682	0.999	1.351	0.495
β_R^-	1.130	0.678	1.067	1.515	0.664
size	19.085	17.453	18.946	20.597	2.170
btm	0.818	0.390	0.646	1.036	0.646
illiq	1.00%	0.27%	0.33%	0.67%	1.84%
past return	13.97%	−12.00%	8.58%	31.80%	43.90%
idio vola	4.61%	3.09%	4.17%	5.72%	1.95%
coskew	−0.165	−0.320	−0.153	0.008	0.256

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. We present results for future monthly excess stock returns over the 1-month T-Bill rate (Return_{t+1}), EDL risk, EDL risk_1, EDL risk_2, EDL risk_3, 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 the computation of these variables is given in the main text and in Appendix D. 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 2: Correlations

	$EDLR_1$	$EDLR_2$	$EDLR_3$	β_L	β_L^-	EDRR	β_R	β_R^-	size	btm	illiq	past ret	idio vola	coskew	$Return_{t+1}$
EDL $risk_1$	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-	-
EDL $risk_2$	0.12	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-
EDL $risk_3$	0.24	0.07	1.00	-	-	-	-	-	-	-	-	-	-	-	-
β_L	0.02	-0.02	0.05	1.00	-	-	-	-	-	-	-	-	-	-	-
β_L^-	0.03	-0.03	0.14	0.35	1.00	-	-	-	-	-	-	-	-	-	-
EDRR	0.13	0.26	0.10	-0.04	-0.06	1.00	-	-	-	-	-	-	-	-	-
β_R	0.09	0.10	0.15	0.03	0.02	0.29	1.00	-	-	-	-	-	-	-	-
β_R^-	0.06	0.11	0.07	0.04	0.11	0.43	0.69	1.00	-	-	-	-	-	-	-
size	0.10	0.06	0.05	-0.21	-0.44	0.10	-0.03	-0.14	1.00	-	-	-	-	-	-
btm	-0.01	0.00	0.04	0.08	0.17	-0.07	-0.02	-0.03	-0.44	1.00	-	-	-	-	-
illiq	-0.07	-0.07	-0.06	0.26	0.35	-0.16	-0.14	-0.05	-0.54	0.31	1.00	-	-	-	-
past return	-0.04	-0.01	-0.04	0.01	0.02	0.01	0.01	0.03	0.07	-0.28	-0.03	1.00	-	-	-
idio vola	-0.01	0.00	0.03	0.17	0.31	-0.03	0.33	0.33	-0.48	0.18	0.42	0.07	1.00	-	-
coskew	-0.12	-0.23	0.02	0.03	0.04	-0.52	-0.04	-0.30	-0.04	0.06	0.04	0.02	0.05	1.00	-
$Return_{t+1}$	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	-0.01	0.03	0.00	0.01	0.00	0.01	1.00

This table displays linear correlations between the most important independent variables used in this study. As independent variables we use EDL $risk_1$, EDL $risk_2$, EDL $risk_3$, 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), coskewness (coskew), and the future monthly excess stock returns over the 1-month T-Bill rate ($Return_{t+1}$). A detailed description of the computation of these variables is given in the main text and in Appendix D. 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 3: Univariate Equal-Weighted Portfolio Sorts: EDL Risk Compnents and Returns

Panel A: EDL risk$_1$

Portfolio	(1) EDL risk$_1$	(2) Return$_{t+1}$	(3) Carhart + PS$_{t+1}$	(4) Carhart + Sadka$_{t+1}$
1 Weak EDL risk$_1$	0.00	0.64%	0.00%	0.00%
2	0.01	0.66%	0.03%	0.02%
3	0.04	0.58%	-0.04%	-0.04%
4	0.09	0.69%	0.08%	0.10%
5 Strong EDL risk$_1$	0.19	0.62%	-0.02%	0.02%
Strong - Weak	0.19	−0.02%	−0.02%	0.02%
		(-0.21)	(-0.25)	(0.22)
Annualized Spread		−0.16%	−0.21%	0.23%

Panel B: EDL risk$_2$

Portfolio	(1) EDL risk$_2$	(2) Return$_{t+1}$	(3) Carhart + PS$_{t+1}$	(4) Carhart + Sadka$_{t+1}$
1 Weak EDL risk$_2$	0.00	0.44%	-0.17%	-0.24%
2	0.02	0.56%	-0.07%	-0.05%
3	0.05	0.59%	-0.04%	-0.01%
4	0.09	0.68%	0.05%	0.10%
5 Strong EDL risk$_2$	0.17	0.78%	0.17%	0.17%
Strong - Weak	0.17	0.34%***	0.34%***	0.41%***
		(4.52)	(3.63)	(4.00)
Annualized Spread		4.04%	4.04%	4.95%

Panel C: EDL risk$_3$

Portfolio	(1) EDL risk$_3$	(2) Return$_{t+1}$	(3) Carhart + PS$_{t+1}$	(4) Carhart + Sadka$_{t+1}$
1 Weak EDL risk$_3$	0.00	0.55%	-0.08%	-0.07%
2	0.01	0.54%	-0.09%	-0.10%
3	0.03	0.55%	-0.05%	-0.06%
4	0.08	0.79%	0.13%	0.13%
5 Strong EDL risk$_3$	0.16	0.75%	0.14%	0.20%
Strong - Weak	0.16	0.20%**	0.21%**	0.26%**
		(2.55)	(2.52)	(2.64)
Annualized Spread		2.41%	2.55%	3.17%

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

This table reports equal-weighted average monthly $t+1$ excess returns for portfolios sorted by the different EDL risk components EDL risk_1 (Panel A), EDL risk_2 (Panel B), and EDL risk_3 (Panel C). Each month t we rank stocks into quintiles (1-5) based on the respective EDL risk component over the past three years and form equal-weighted portfolios at the beginning of each monthly period. We report average returns in excess of the one-month T-Bill rate over the month $t+1$, alphas based on Carhart (1997)'s four factor model extended by the Pastor and Stambaugh (2003) traded liquidity factor and the Sadka (2006) fixed-transitory and variable-permanent liquidity factors. 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 4: Bivariate Equal-Weighted Portfolio Sorts with EDL $risk_2$

Panel A: EDL $risk_2$ and β_{L2} Risk

Portfolio	1 Weak β_{L2}	2	3	4	5 Strong β_{L2}	Average
1 Weak EDL $risk_2$	0.42%	0.59%	0.54%	0.52%	0.32%	0.48%
2	0.45%	0.62%	0.58%	0.59%	0.41%	0.53%
3	0.59%	0.62%	0.69%	0.59%	0.52%	0.60%
4	0.60%	0.75%	0.76%	0.76%	0.63%	0.70%
5 Strong EDL $risk_2$	0.65%	0.74%	0.80%	0.75%	0.72%	0.73%
Strong-Weak Return	0.23%**	0.15%*	0.26%**	0.23%**	0.40%***	0.25%***
	(2.35)	(1.77)	(2.54)	(2.29)	(3.05)	(4.00)
Strong-Weak Carhart + PS_{t+1}	0.20%*	0.18%*	0.32%***	0.22%**	0.39%***	0.26%***
	(1.84)	(1.79)	(2.99)	(2.12)	(2.83)	(3.75)
Strong-Weak Carhart + $Sadka_{t+1}$	0.30%**	0.22%*	0.41%***	0.28%**	0.36%**	0.31%***
	(2.25)	(1.79)	(3.23)	(2.21)	(2.08)	(3.66)

Panel B: EDL $risk_2$ and β^-_{L2} Risk

Portfolio	1 Weak β^-_{L2}	2	3	4	5 Strong β^-_{L2}	Average
1 Weak EDL $risk_2$	0.41%	0.40%	0.50%	0.59%	0.33%	0.44%
2	0.47%	0.56%	0.56%	0.73%	0.55%	0.57%
3	0.46%	0.53%	0.69%	0.65%	0.55%	0.58%
4	0.51%	0.73%	0.73%	0.74%	0.76%	0.69%
5 Strong EDL $risk_2$	0.69%	0.76%	0.84%	0.79%	0.68%	0.75%
Strong-Weak Return	0.28%***	0.36%***	0.34%***	0.20%*	0.35%***	0.31%***
	(2.66)	(4.03)	(3.99)	(1.92)	(2.83)	(5.00)
Strong-Weak Carhart + PS_{t+1}	0.25%**	0.31%***	0.34%***	0.18%	0.34%***	0.28%***
	(2.07)	(3.19)	(3.66)	(1.55)	(2.64)	(4.28)
Strong-Weak Carhart + $Sadka_{t+1}$	0.38%**	0.38%***	0.39%***	0.24%*	0.46%***	0.38%***
	(2.53)	(3.87)	(3.33)	(1.75)	(2.86)	(4.71)

Panel C: EDL $risk_2$ and EDR Risk

Portfolio	1 Weak EDR Risk	2	3	4	5 Strong EDR Risk	Average
1 Weak EDL $risk_2$	0.23%	0.44%	0.52%	0.51%	0.64%	0.47%
2	0.29%	0.49%	0.65%	0.67%	0.73%	0.56%
3	0.38%	0.50%	0.62%	0.67%	0.80%	0.59%
4	0.43%	0.58%	0.77%	0.66%	0.95%	0.68%
5 Strong EDL $risk_2$	0.48%	0.70%	0.72%	0.86%	0.93%	0.74%
Strong-Weak Return	0.25%**	0.26%**	0.20%**	0.35%***	0.29%***	0.27%***
	(2.23)	(2.33)	(1.97)	(3.71)	(2.72)	(3.99)
Strong-Weak Carhart + PS_{t+1}	0.19%	0.27%**	0.24%**	0.41%***	0.29%**	0.28%***
	(1.56)	(2.05)	(2.01)	(3.65)	(2.30)	(3.23)
Strong-Weak Carhart + $Sadka_{t+1}$	0.18%	0.40%**	0.33%**	0.51%***	0.24%*	0.33%***
	(1.14)	(2.54)	(2.29)	(3.84)	(1.67)	(3.32)

Panel D: EDL risk$_2$ and Liquidity Tail Risk

Portfolio	1 Weak liqui tail risk	2	3	4	5 Strong liqui tail risk	Average
1 Weak EDL risk$_2$	0.32%	0.63%	0.61%	0.59%	0.77%	0.58%
2	0.75%	0.50%	0.77%	0.70%	0.84%	0.71%
3	0.76%	0.79%	0.68%	0.91%	0.81%	0.79%
4	0.82%	0.88%	0.88%	0.85%	0.91%	0.87%
5 Strong EDL risk$_2$	0.90%	0.88%	0.90%	0.97%	0.95%	0.92%
Strong-Weak	0.58%***	0.25%**	0.29%***	0.39%***	0.18%	0.34%***
Return	(4.52)	(2.22)	(2.69)	(3.70)	(1.34)	(4.23)
Strong-Weak	0.56%***	0.23%*	0.32%**	0.32%***	0.12%	0.31%***
Carhart + PS$_{t+1}$	(4.08)	(1.70)	(2.43)	(2.66)	(0.84)	(3.28)
Strong-Weak	0.52%***	0.20%	0.33%**	0.40%***	0.19%	0.33%***
Carhart + Sadka$_{t+1}$	(3.31)	(1.37)	(2.29)	(3.01)	(1.23)	(3.21)

Panel E: EDL risk$_2$ and LPM Liquidity Risk 2

Portfolio	1 Weak LPM$_2$ risk	2	3	4	5 Strong LPM$_2$ risk	Average
1 Weak EDL risk$_2$	0.39%	0.51%	0.68%	0.41%	0.37%	0.47%
2	0.35%	0.69%	0.59%	0.77%	0.43%	0.57%
3	0.46%	0.63%	0.68%	0.71%	0.62%	0.62%
4	0.54%	0.77%	0.77%	0.70%	0.75%	0.71%
5 Strong EDL risk$_2$	0.56%	0.69%	0.85%	0.79%	0.85%	0.75%
Strong-Weak	0.17%	0.18%*	0.17%*	0.38%***	0.48%***	0.28%***
Return	(1.52)	(1.95)	(1.91)	(3.59)	(3.47)	(4.53)
Strong-Weak	0.13%	0.19%*	0.17%*	0.34%***	0.52%***	0.27%***
Carhart + PS$_{t+1}$	(0.99)	(1.81)	(1.67)	(3.12)	(3.16)	(3.66)
Strong-Weak	0.25%	0.28%**	0.14%	0.52%***	0.55%***	0.35%***
Carhart + Sadka$_{t+1}$	(1.59)	(2.00)	(1.10)	(3.71)	(2.69)	(4.10)

This table reports the results of dependent equal-weighted portfolio sorts. First, we form quintile portfolios sorted on β_{L2} risk (β^-_{L2} risk, EDR risk, liquidity tail risk, LPM$_2$ liquidity risk). Then, within each risk quintile, we sort stocks into equal-weighted portfolios based on EDL risk$_2$. Panel A displays monthly average future returns of 25 β_{L2} risk - EDL risk$_2$ portfolio sorts, Panel B shows monthly average future returns of the 25 β^-_{L2} - EDL risk$_2$ sorts, Panel C shows the monthly average future returns of the 25 EDR risk - EDL risk$_2$ portfolio sorts, Panel D shows the monthly average future returns of the 25 liquidity tail risk (see Wu, 2017) - EDL risk$_2$ portfolio sorts, and Panel E shows the monthly average future returns of the 25 LPM$_2$ liquidity risk (see Anthonisz and Putnins, 2017) - EDL risk$_2$ portfolio sorts. The row labelled 'Strong - Weak' reports the difference between the returns and alphas of portfolio 5 and portfolio 1 with corresponding t-statistics. 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 with EDL risk_3

Panel A: EDL risk_3 and β_{L3} Risk

Portfolio	1 Weak β_{L3}	2	3	4	5 Strong β_{L3}	Average
1 Weak EDL risk_3	0.63%	0.45%	0.53%	0.52%	0.73%	0.57%
2	0.54%	0.34%	0.49%	0.57%	0.63%	0.51%
3	0.62%	0.52%	0.59%	0.65%	0.66%	0.61%
4	0.86%	0.63%	0.80%	0.80%	0.69%	0.76%
5 Strong EDL risk_3	0.91%	0.60%	0.70%	0.75%	0.75%	0.74%
Strong-Weak	0.27%**	0.14%*	0.17%	0.23%**	0.02%	0.17%**
Return	(2.10)	(1.75)	(1.60)	(2.14)	(0.16)	(2.32)
Strong-Weak	0.27%*	0.13%	0.23%*	0.24%**	−0.03%	0.17%**
Carhart + PS_{t+1}	(1.68)	(1.47)	(1.86)	(2.07)	(-0.26)	(2.09)
Strong-Weak	0.16%	0.25%**	0.32%**	0.19%	0.03%	0.19%**
Carhart + Sadka_{t+1}	(0.85)	(2.15)	(2.19)	(1.30)	(0.17)	(1.99)

Panel B: EDL risk_3 and β^-_{L3} Risk

Portfolio	1 Weak β^-_{L3}	2	3	4	5 Strong β^-_{L3}	Average
1 Weak EDL risk_3	0.53%	0.42%	0.44%	0.68%	0.62%	0.54%
2	0.51%	0.47%	0.54%	0.58%	0.71%	0.56%
3	0.59%	0.54%	0.55%	0.72%	0.63%	0.61%
4	0.67%	0.66%	0.71%	0.77%	0.77%	0.72%
5 Strong EDL risk_3	0.83%	0.75%	0.65%	0.85%	0.72%	0.76%
Strong-Weak	0.29%**	0.33%***	0.21%**	0.16%	0.10%	0.22%***
Return	(2.52)	(4.10)	(2.34)	(1.49)	(0.73)	(3.36)
Strong-Weak	0.23%*	0.31%***	0.25%**	0.20%	0.08%	0.21%***
Carhart + PS_{t+1}	(1.88)	(3.65)	(2.45)	(1.62)	(0.59)	(2.97)
Strong-Weak	0.23%	0.38%***	0.43%***	0.14%	0.06%	0.25%***
Carhart + Sadka_{t+1}	(1.52)	(3.61)	(3.41)	(0.88)	(0.35)	(2.87)

Panel C: EDL risk_3 and EDR Risk

Portfolio	1 Weak EDR Risk	2	3	4	5 Strong EDR Risk	Average
1 Weak EDL risk_3	0.30%	0.42%	0.73%	0.59%	0.79%	0.57%
2	0.40%	0.44%	0.51%	0.58%	0.75%	0.54%
3	0.23%	0.40%	0.61%	0.76%	0.81%	0.56%
4	0.55%	0.84%	0.76%	0.77%	0.95%	0.77%
5 Strong EDL risk_3	0.55%	0.78%	0.75%	0.81%	0.82%	0.74%
Strong-Weak	0.25%**	0.36%***	0.02%	0.22%**	0.03%	0.18%**
Return	(2.09)	(3.18)	(0.19)	(2.08)	(0.27)	(2.37)
Strong-Weak	0.22%*	0.37%***	0.05%	0.22%*	0.07%	0.18%**
Carhart + PS_{t+1}	(1.78)	(3.04)	(0.36)	(1.88)	(0.56)	(2.24)
Strong-Weak	0.32%**	0.36%**	0.07%	0.24%*	0.15%	0.23%**
Carhart + Sadka_{t+1}	(2.03)	(2.40)	(0.47)	(1.71)	(1.03)	(2.35)

Panel D: EDL $risk_3$ and Liquidity Tail Risk

Portfolio	1 Weak liqui tail risk	2	3	4	5 Strong liqui tail risk	Average
1 Weak EDL $risk_3$	0.72%	0.65%	0.66%	0.68%	0.67%	0.68%
2	0.65%	0.63%	0.62%	0.75%	0.83%	0.70%
3	0.57%	0.61%	0.80%	0.68%	0.80%	0.69%
4	0.88%	0.87%	0.97%	0.97%	1.03%	0.94%
5 Strong EDL $risk_3$	0.82%	0.86%	0.84%	0.98%	0.99%	0.90%
Strong-Weak	0.10%	0.21%*	0.18%	0.30%***	0.32%**	0.22%***
Return	(0.79)	(1.81)	(1.60)	(2.80)	(2.35)	(2.82)
Strong-Weak	0.09%	0.21%*	0.13%	0.32%***	0.28%**	0.21%**
Carhart + PS_{t+1}	(0.70)	(1.69)	(1.12)	(2.82)	(1.99)	(2.47)
Strong-Weak	0.09%	0.22%	0.19%	0.42%***	0.41%**	0.26%***
Carhart + $Sadka_{t+1}$	(0.54)	(1.53)	(1.34)	(3.25)	(2.48)	(2.73)

Panel E: EDL $risk_3$ and LPM Liquidity Risk 3

Portfolio	1 Weak LPM_3 risk	2	3	4	5 Strong LPM_3 risk	Average
1 Weak EDL $risk_3$	0.18%	0.39%	0.52%	0.85%	0.88%	0.56%
2	0.41%	0.31%	0.54%	0.82%	0.73%	0.56%
3	0.29%	0.37%	0.63%	0.84%	0.85%	0.60%
4	0.47%	0.59%	0.69%	1.17%	1.05%	0.79%
5 Strong EDL $risk_3$	0.43%	0.51%	0.75%	1.07%	0.95%	0.74%
Strong-Weak	0.25%*	0.13%	0.23%**	0.22%**	0.07%	0.18%**
Return	(1.91)	(1.33)	(2.25)	(2.14)	(0.55)	(2.57)
Strong-Weak	0.21%*	0.12%	0.26%*	0.29%***	0.04%	0.19%**
Carhart + PS_{t+1}	(1.66)	(1.25)	(1.94)	(2.66)	(0.24)	(2.41)
Strong-Weak	0.21%	0.21%*	0.29%*	0.46%***	0.01%	0.23%**
Carhart + $Sadka_{t+1}$	(1.24)	(1.69)	(1.79)	(3.35)	(0.05)	(2.52)

This table reports the results of dependent equal-weighted portfolio sorts. First, we form quintile portfolios sorted on β_{L3} risk (β^-_{L3} risk, EDR risk, liquidity tail risk, LPM_3 liquidity risk). Then, within each risk quintile, we sort stocks into equal-weighted portfolios based on EDL $risk_3$. Panel A displays monthly average future returns of 25 β_{L3} risk - EDL $risk_3$ portfolio sorts, Panel B shows monthly average future returns of the 25 β^-_{L3} - EDL $risk_3$ sorts, Panel C shows the monthly average future returns of the 25 EDR risk - EDL $risk_3$ portfolio sorts, Panel D shows the monthly average future returns of the 25 liquidity tail risk (see Wu, 2017) - EDL $risk_3$ portfolio sorts, and Panel E shows the monthly average future returns of the 25 LPM_3 liquidity risk (see Anthonisz and Putnins, 2017) - EDL $risk_3$ portfolio sorts. The row labelled 'Strong - Weak' reports the difference between the returns and alphas of portfolio 5 and portfolio 1 with corresponding t-statistics. 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$_2$ and Returns: Factor Models

Panel A: Factor Models

	(1) EDL risk$_2$ (PF5-1)	(2) EDL risk$_2$ (PF5-1)	(3) EDL risk$_2$ (PF5-1)	(4) EDL risk$_2$ (PF5-1)	(5) EDL risk$_2$ (PF5-1)	(6) EDL risk$_2$ (PF5-1)
Marketrf	0.0912*** (6.14)	0.1070*** (4.83)	0.1035*** (4.39)	0.0870*** (4.32)	0.1119*** (4.65)	0.1157*** (5.37)
SMB		-0.0627** (-2.24)	-0.0633** (-2.27)	-0.1009*** (-2.88)	-0.0658** (-2.06)	-0.0596** (-2.22)
HML		0.0511 (1.37)	0.0514 (1.44)	0.0773 (1.61)	0.0568 (1.42)	0.1172*** (2.74)
MOM		-0.0548 (-0.98)	-0.0560 (-1.15)	-0.0496 (0.97)	-0.0547 (-0.93)	-0.0294 (-0.57)
EDRR			0.0275 (0.69)			
Max				0.0445 (1.21)		
Tail					-0.0166 (-0.62)	
BAB						-0.1215*** (-3.88)
const	0.30%*** (4.29)	0.32%*** (3.63)	0.31%*** (3.41)	0.34%*** (3.56)	0.37%*** (3.96)	0.37%*** (4.15)
Annualized Alpha	3.57%	3.82%	3.74%	4.08%	4.50%	4.50%
R^2	0.068	0.119	0.119	0.128	0.124	0.167

Panel B: Other Factor Models

Factor Model	Annualized α
Fama-French 5-Factor Model (Fama and French, 2015)	3.14%*** (3.98)
Novy-Marx 4-Factor Model (Novy-Marx, 2013)	4.19%*** (3.15)
Hou-Xue-Zhang 4-Factor Model (Hou et al., 2015)	3.65%*** (3.64)
Carhart 4-Factor Model + short- and long-term reversal	4.18%*** (3.28)
Carhart 4-Factor Model + leverage factor (Adrian et al., 2014)	4.13%*** (3.53)
Carhart 4-Factor Model + quality-minus-junk (Asness et al., 2015)	3.89%*** (3.67)
Carhart 4-Factor Model + undervalued-minus-overvalued (Hirshleifer and Jiang, 2010)	3.95%*** (4.60)
Carhart 4-Factor Model + LPM liquidity risk (Anthonisz and Putnins, 2017)	3.88%*** (3.63)
Carhart 4-Factor Model + liquidity tail risk (Wu, 2015)	4.46%*** (3.97)
Carhart 4-Factor Model + mispricing (Stambaugh and Yuan, 2017)	4.17%*** (4.10)

This table reports monthly OLS-regression results of a trading strategy based on the return-difference between past high EDL risk$_2$ (quintile 5) and past low EDL risk$_2$ (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), Chabi-Yo et al. (2018)'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 Asness et al. (2018), the undervalued-minus-overvalued factor from Hirshleifer and Jiang (2010), the lower partial moment liquidity risk factor from Anthonisz and Putnins (2017), the Wu (2017) liquidity tail risk factor, and the two mispricing factors of Stambaugh and Yuan (2017). 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 four lags.

Table 7: EDL risk_3 and Returns: Factor Models

Panel A: Factor Models

	(1) EDL risk_3 (PF5-1)	(2) EDL risk_3 (PF5-1)	(3) EDL risk_3 (PF5-1)	(4) EDL risk_3 (PF5-1)	(5) EDL risk_3 (PF5-1)	(6) EDL risk_3 (PF5-1)
Marketrf	0.1077***	0.1053***	0.0925***	0.0936***	0.1115***	0.1109***
	(4.26)	(5.09)	(4.36)	(4.24)	(4.97)	(5.31)
SMB		-0.0415	-0.0316	-0.0638*	-0.0422	-0.0395
		(-1.23)	(-0.99)	(-1.69)	(-1.15)	(-1.22)
HML		0.0292	0.0502	0.0446	0.0520	0.0722*
		(0.79)	(1.34)	(1.00)	(1.31)	(1.76)
MOM		-0.1216***	-0.1431***	-0.1186***	-0.1122***	-0.1051***
		(-3.08)	(-3.76)	(-3.21)	(-2.67)	(-2.79)
EDRR			0.1018**			
			(2.56)			
Max				0.0260		
				(0.87)		
Tail					0.0127	
					(0.44)	
BAB						-0.0789***
						(-2.70)
const	0.16%**	0.23%***	0.21%***	0.25%***	0.22%***	0.27%***
	(2.13)	(2.96)	(2.61)	(2.89)	(2.59)	(3.26)
Annualized Alpha	1.86%	2.81%	2.52%	2.96%	2.60%	3.25%
R^2	0.083	0.193	0.270	0.195	0.196	0.211

Panel B: Other Factor Models

Factor Model	Annualized α
Fama-French 5-Factor Model (Fama and French, 2015)	1.94%** (2.10)
Novy-Marx 4-Factor Model (Novy-Marx, 2013)	2.90%*** (2.62)
Hou-Xue-Zhang 4-Factor Model (Hou et al., 2015)	2.35%** (2.24)
Carhart 4-Factor Model + short- and long-term reversal	3.00%*** (2.77)
Carhart 4-Factor Model + leverage factor (Adrian et al., 2014)	3.07%*** (3.00)
Carhart 4-Factor Model + quality-minus-junk (Asness et al., 2015)	3.21%*** (3.27)
Carhart 4-Factor Model + undervalued-minus-overvalued (Hirshleifer and Jiang, 2010)	2.39%*** (2.65)
Carhart 4-Factor Model + LPM liquidity risk (Anthonisz and Putnins, 2017)	2.82%*** (2.95)
Carhart 4-Factor Model + liquidity tail risk (Wu, 2015)	2.75%*** (2.75)
Carhart 4-Factor Model + mispricing (Stambaugh and Yuan, 2017)	2.76%*** (2.81)

This table reports monthly OLS-regression results of a trading strategy based on the return-difference between past high EDL risk_3 (quintile 5) and past low EDL risk_3 (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), Chabi-Yo et al. (2018)'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 Asness et al. (2018), the undervalued-minus-overvalued factor from Hirshleifer and Jiang (2010), the lower partial moment liquidity risk factor from Anthonisz and Putnins (2017), the Wu (2017) liquidity tail risk factor, and the two mispricing factors of Stambaugh and Yuan (2017). 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 four legs.

Table 8: Fama and MacBeth (1973) Regressions

	(1) Return $t+1$	(2) Return $t+1$	(3) Return $t+1$	(4) Return $t+1$	(5) Return $t+1$	(6) Return $t+1$	(7) Return $t+1$	(8) Return $(t+1, t+6)$
EDL risk_1	-0.0026	-0.0031	-0.0015	-0.0015	-0.0012	-0.0025	-0.0019	-0.0007
	(-0.90)	(-1.55)	(-0.71)	(-0.69)	(-0.56)	(-0.95)	(-0.79)	(-0.07)
EDL risk_2	0.0151***	0.0124***	0.0099***	0.0103***	0.0101***	0.0096***	0.0099***	0.0259**
	(4.34)	(4.63)	(3.57)	(3.78)	(3.66)	(3.29)	(3.42)	(2.13)
EDL risk_3	0.0110***	0.0101***	0.0104***	0.0112***	0.0103***	0.0082***	0.0081***	0.0136*
	(3.02)	(4.30)	(3.82)	(4.07)	(3.83)	(2.85)	(2.83)	(1.78)
β_R		-0.0008	0.0004		0.0003	-0.0017	-0.0016	-0.0017
		(-0.44)	(0.23)		(0.18)	(-1.13)	(-1.08)	(-0.26)
size		-0.0003	-0.0014***	-0.0014***	-0.0014***	-0.0015***	-0.0014***	-0.0063***
		(-0.66)	(-4.62)	(-4.95)	(-4.57)	(-4.64)	(-4.87)	(-3.51)
btm		0.0026***	0.0024***	0.0023***	0.0024***	0.0027***	0.0027***	0.0123***
		(3.46)	(3.08)	(2.99)	(3.13)	(3.39)	(3.35)	(2.72)
past return		0.0116***	0.0104***	0.0102***	0.00151***	0.0090***	0.0091***	0.0356***
		(6.66)	(5.60)	(5.31)	(5.60)	(4.68)	(4.76)	(3.36)
β_L			-0.0065		-0.0080	0.0050	0.011	-0.1212
			(-0.49)		(-0.60)	(0.27)	(0.67)	(-1.20)
EDR risk			0.0088***	0.0095***	0.0087***	0.0079***	0.0076***	0.0247***
			(5.16)	(5.20)	(5.09)	(4.46)	(4.31)	(3.46)
illiq			-0.0217	-0.0213	-0.0220	0.0423	0.0058	0.4599***
			(-0.99)	(-0.96)	(-1.01)	(0.50)	(1.05)	(2.62)
β_{Tail}			0.0231	0.0226	0.0285*	0.0242	0.0243	0.1674*
			(1.42)	(1.40)	(1.71)	(1.30)	(1.32)	(1.83)
idio vola			-0.0945***	-0.0886**	-0.0953***	-0.0819**	-0.0787**	-0.0245
			(-2.72)	(-2.26)	(-2.76)	(-2.28)	(-2.19)	(-0.14)
coskew			-0.0001	-0.0020	-0.0002	-0.0002	-0.0003	-0.0059
			(-0.08)	(-0.71)	(-0.11)	(-0.14)	(-0.19)	(-0.63)
β_L^-				–0.0127**				
				(-2.13)				
β_L^+				-0.0054				
				(-0.85)				
β_R^-				-0.0008				
				(-0.75)				
β_R^+				0.0007				
				(0.93)				
liqui tail risk					0.0211*			
					(1.68)			
LPM return						0.0021*	0.0030**	0.0044
						(1.88)	(2.18)	(0.91)
LPM liqui risk						0.00164*		
						(1.94)		
LPM liqui risk_1							-0.0035	-0.0876
							(-0.40)	(-1.34)
LPM liqui risk_2							-0.0013	-0.0336
							(-1.05)	(-0.64)
LPM liqui risk_3							0.0029**	0.0221***
							(2.07)	(4.94)
Avg. R^2	0.0054	0.0641	0.0857	0.0858	0.0923	0.1063	0.1113	0.1273

This table displays the results of multivariate Fama and MacBeth (1973) regressions. We report the results of regressions of monthly excess returns over the risk-free rate at month $t+1$ on EDL risk_1, EDL risk_2, EDL risk_3, 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^+, Wu (2017)'s liquidity tail risk beta, as well as LPM return, LPM liquidity risk, LPM liquidity risk_1, LPM liquidity risk_2, and LPM liquidity risk_3, as in Anthonisz and Putnins (2017). All risk and firm characteristics are calculated using data available at (the end of) month t. A detailed description of the computation of these variables is given in the main text and in Appendix D. 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: EDL risk_2

	1969-1987			1988-2012		
	Return_{t+2}	Carhart + PS_{t+1}	Carhart + Sadka_{t+1}	Return_{t+1}	Carhart + PS_{t+1}	Carhart + Sadka_{t+1}
1 Weak EDL risk_2	0.45%	0.03%	−0.02%	0.43%	−0.26%	−0.23%
2	0.39%	−0.04%	−0.09%	0.68%	−0.04%	−0.01%
3	0.41%	−0.02%	−0.02%	0.73%	0.00%	0.03%
4	0.43%	0.01%	0.01%	0.87%	0.14%	0.17%
5 Strong EDL risk_2	0.51%	0.12%	0.08%	0.98%	0.24%	0.25%
5 Strong - Weak	0.07%	0.08%	0.10%	0.54%***	0.50%***	0.48%***
	(0.84)	(1.02)	(0.69)	(4.77)	(3.99)	(3.99)
Difference: 1988-2012 minus 1969-1987				0.47%***	0.42%***	0.38%**
				(3.43)	(3.50)	(2.23)

Panel B: Univariate Sorts: EDL risk_3

	1969-1987			1988-2012		
	Return_{t+2}	Carhart + PS_{t+1}	Carhart + Sadka_{t+1}	Return_{t+1}	Carhart + PS_{t+1}	Carhart + Sadka_{t+1}
1 Weak EDL risk_2	0.41%	−0.03%	−0.03%	0.66%	−0.05%	−0.02%
2	0.41%	−0.02%	−0.02%	0.63%	−0.09%	−0.06%
3	0.40%	−0.01%	−0.01%	0.67%	−0.03%	−0.02%
4	0.60%	0.17%	0.17%	0.94%	0.16%	0.19%
5 Strong EDL risk_2	0.46%	0.10%	0.10%	0.97%	0.22%	0.26%
5 Strong - Weak	0.05%	0.13%	0.13%	0.31%***	0.27%**	0.28%**
	(0.54)	(1.43)	(1.43)	(2.67)	(2.22)	(2.46)
Difference: 1988-2012 minus 1969-1987				0.26%*	0.14%	0.15%
				(1.73)	(1.15)	(0.72)

Panel C: Fama and MacBeth (1973) Regressions

	1969-1987			1988-2012	
	Return_{t+1}	Return_{t+1}		Return_{t+1}	Return_{t+1}
EDL risk_2	0.0051	0.0128***	EDL risk_3	0.0099***	0.0106***
	(1.53)	(3.23)		(2.89)	(2.77)

This tables reports the results of the impact of EDL risk_2 and EDL risk_3 on future returns and alphas during two subsamples. Panel A shows equal-weighted average monthly returns and alphas of portfolios sorted by past EDL risk_2. in the time period from January 1969 to December 1987, and from January 1988 to December 2012. Each month 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 monthly period. We report average returns in excess of the one-month T-Bill rate over the month $t+1$, alphas based on Carhart (1997)'s four factor model extended by the Pastor and Stambaugh (2003) traded liquidity factor and the Sadka (2006) fixed-transitory and variable-permanent liquidity factors. The row labelled 'Strong - Weak' reports the difference between the returns of portfolio 5 and portfolio 1 with corresponding statistical significance levels. Panel B shows the corresponding equal-weighted average returns and alphas of portfolios sorted by past EDL risk_3. Panel C displays the results of Fama and MacBeth (1973) regressions of monthly future excess returns on firm- and risk-characteristics in the period from 1969 to 1987 and from 1988 to 2012. We repeat regression (3) from Table 8 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	$Return_{t+1}$	Car + PS	Car + Sadka	Liquidity	$Return_{t+2}$	Car + PS	Car + Sadka
EDL $risk_2$ 5-1	Low-Frequency (1969-2012)			EDL $risk_3$ 5-1	Low-Frequency (1969-2012)		
illiq	0.34%***	0.34%***	0.41%***	*illiq*	0.20%**	0.21%**	0.26%***
	(4.52)	(3.63)	(4.00)		(2.55)	(2.52)	(2.69)
Corwin	0.16%*	0.19%*	0.12%	*Corwin*	0.27%***	0.26%***	0.33%***
	(1.78)	(1.92)	(1.00)		(4.85)	(4.42)	(4.78)
Zeros	−0.05%	−0.04%	−0.09%	*Zeros*	0.17%***	0.15%***	0.19%***
	(-0.82)	(-0.72)	(-1.16)		(3.17)	(2.75)	(2.76)
FHT	0.11%	0.15%*	0.20%**	*FHT*	0.20%***	0.21%***	0.27%***
	(1.57)	(1.92)	(2.03)		(3.14)	(2.99)	(2.96)
EDL $risk_2$ 5-1	High-Frequency (2002-2010)			EDL $risk_3$ 5-1	High-Frequency (2002-2010)		
EffSpr	0.48%**	0.46%***	0.49%***	*EffSpr*	0.35%**	0.27%**	0.22%*
	(2.47)	(2.59)	(2.77)		(2.38)	(2.19)	(1.82)
RelSpr	0.07%	0.02%	0.01%	*RelSpr*	0.25%	0.27%*	0.23%*
	(0.38)	(0.13)	(0.05)		(1.51)	(1.92)	(1.68)
IntAmi	0.31%	0.17%	0.16%	*IntAmi*	0.28%**	0.22%*	0.21%*
	(1.28)	(0.82)	(0.83)		(1.93)	(1.68)	(1.66)
PriImp	0.40%*	0.35%*	0.33%*	*PriImp*	0.15%**	0.12%	0.13%
	(1.81)	(1.67)	(1.69)		(2.18)	(1.47)	(1.25)

Panel B: Fama and MacBeth (1973) Regressions

	Low-Frequency (1969-2012)				High-Frequency (2002-2010)			
	(1) *Illiq*	(2) *Corwin*	(3) *Zeros*	(4) *FHT*	(5) *EffSpr*	(6) *RelSpr*	(7) *IntAmi*	(8) *PriImp*
EDL $risk_2$	0.0099***	0.0032	0.0011	0.0060*	0.0218**	0.0056	0.0200*	0.0188**
	(3.57)	(1.15)	(0.16)	(1.73)	(2.49)	(0.93)	(1.91)	(2.10)
EDL $risk_3$	0.0104***	0.0135***	0.0044	0.0106***	0.0180***	0.0098*	0.0123**	0.0136***
	(3.82)	(5.70)	(1.04)	(3.65)	(2.93)	(1.93)	(2.31)	(2.58)

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 $risk_2$ and EDL $risk_3$ 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 monthly returns, as well as differences in montly alphas based on Carhart (1997)'s four factor model extended by the Pastor and Stambaugh (2003) traded liquidity factor and Carhart (1997)'s four factor model extended by the Sadka (2006) fixed-transitory and variable-permanent liquidity factors between portfolio 5 and portfolio 1 with corresponding statistical significance levels. Panel B shows the results of regression specification (3) from Table 8 for different liquidity proxies. We only report the coefficient estimate for the impact of EDL $risk_2$ and EDL $risk_3$. 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

	EDL $risk_2$ 5-1			EDL $risk_3$ 5-1		
Procedure	$Return_{t+2}$	Car + PS	Car + Sadka	$Return_{t+2}$	Car + PS	Car + Sadka
	Estimation Horizons & Liquidity Shocks					
1y	0.13%**	0.12%*	0.15%*	0.16%***	0.21%***	0.26%***
	(1.96)	(1.76)	(1.72)	(2.81)	(3.16)	(3.37)
2y	0.22%***	0.19%**	0.27%***	0.22%**	0.27%***	0.32%***
	(3.10)	(2.48)	(3.13)	(2.40)	(2.86)	(2.94)
5y	0.24%***	0.22%**	0.29%**	0.39%***	0.32%**	0.39%**
	(2.59)	(1.95)	(2.32)	(3.12)	(2.37)	(2.49)
diff	0.39%***	0.39%***	0.47%***	0.26%**	0.26%**	0.29%**
	(4.71)	(3.63)	(3.79)	(2.37)	(2.45)	(2.33)
	Copula Functions					
C1	0.34%***	0.34%***	0.41%***	0.20%**	0.21%**	0.26%***
	(4.52)	(3.63)	(4.00)	(2.55)	(2.52)	(2.64)
C2	0.29%***	0.30%***	0.35%***	0.21%***	0.23%***	0.29%***
	(4.03)	(3.36)	(3.40)	(2.63)	(2.76)	(2.98)
C63	0.30%***	0.30%***	0.37%***	0.20%**	0.24%***	0.26%***
	(4.37)	(3.66)	(4.03)	(2.51)	(2.70)	(2.61)
C64	0.25%***	0.24%***	0.26%***	0.23%***	0.24%***	0.30%***
	(3.59)	(2.87)	(2.70)	(3.17)	(2.87)	(3.06)
Cw	0.51%***	0.50%**	0.65%***	0.50%***	0.50%***	0.58%***
	(5.60)	(4.70)	(5.67)	(5.44)	(4.93)	(4.69)

Panel B: Fama and MacBeth (1973) Regressions

	Estimation Horizons & Liquidity Shocks				
		(1)	(2)	(3)	(4)
		1y	2y	5y	diff
EDL $risk_2$		0.0020	0.0049**	0.0095***	0.0142***
		(1.18)	(2.11)	(2.87)	(4.95)
EDL $risk_3$		0.0052***	0.0089***	0.0126***	0.0085***
		(3.74)	(4.78)	(3.83)	(3.58)
	Copula Functions				
	(5)	(6)	(7)	(8)	(9)
	C1	C2	C63	C64	Cw
EDL $risk_2$	0.0099***	0.0109***	0.0086***	0.0066**	0.0153***
	(3.57)	(3.78)	(3.21)	(2.32)	(4.00)
EDL $risk_2$	0.0104***	0.0079***	0.0061**	0.0080***	0.0123***
	(3.82)	(3.23)	(2.48)	(3.18)	(3.76)

This table reports results of univariate portfolio sorts and Fama-MacBeth (1973) regressions for different estimation horizons, liquidity shocks, and copula functions. We estimate EDL $risk_2$ and EDL $risk_3$ 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 based on weekly return data. Furthermore we estimate EDL risk with different copulas (C1-C4 and Cw). In Panel A we rank stocks into quintiles (1-5) based on estimated past EDL $risk_2$ and EDL $risk_3$ of the different estimation horizons, and different copulas, and form equal-weighted portfolios at the beginning of each monthly period. We report differences in monthly returns, differences in alphas based on Carhart (1997)'s four factor model extended by the Pastor and Stambaugh (2003) traded liquidity factor and Carhart (1997)'s four factor model extended by the Sadka (2006) fixed-transitory and variable-permanent liquidity factors between portfolio 5 and portfolio 1 with corresponding statistical significance levels. Panel B shows the results of regression specification (3) from Table 8 for different estimation procedures. We only report the coefficient estimate for the impact of EDL $risk_2$ and EDL $risk_3$. 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: Value-Weighted Portfolio Sorts

Panel A: Univariate Portfolio Sorts

	EDL $risk_2$				EDL $risk_3$			
	$Return_{t+1}$	Excluding Top 5%	Excluding Top 10%	Excluding Top 20%	$Return_{t+1}$	Excluding Top 5%	Excluding Top 10%	Excluding Top 20%
1 Weak	0.32%	0.41%	0.50%	0.50%	0.36%	0.42%	0.48%	0.52%
2	0.39%	0.45%	0.50%	0.51%	0.33%	0.45%	0.51%	0.46%
3	0.40%	0.56%	0.60%	0.61%	0.41%	0.52%	0.56%	0.58%
4	0.54%	0.64%	0.71%	0.76%	0.54%	0.63%	0.69%	0.82%
5 Strong	0.53%	0.64%	0.70%	0.79%	0.50%	0.66%	0.74%	0.78%
Strong-Weak	0.21%*	0.23%***	0.20%**	0.29%***	0.14%*	0.24%***	0.26%***	0.26%***
Return	(1.89)	(2.96)	(2.54)	(3.91)	(1.76)	(3.01)	(3.16)	(2.91)
Strong-Weak	0.14%	0.21%**	0.19%*	0.29%***	0.07%	0.22%***	0.29%***	0.28%***
Car + PS	(1.11)	(2.15)	(1.92)	(3.17)	(0.83)	(2.58)	(3.01)	(2.98)
Strong-Weak	0.08%	0.21%*	0.22%*	0.30%***	0.13%	0.26%**	0.37%***	0.33%***
Car + Sadka	(0.56)	(1.88)	(1.93)	(2.84)	(1.20)	(2.40)	(3.09)	(2.89)

Panel B: EDL $risk_2$ and Returns: Factor Models Excluding Top 5% of the Largest Stocks

	(1) EDL $risk_2$ (PF5-1)	(2) EDL $risk_2$ (PF5-1)	(3) EDL $risk_2$ (PF5-1)	(4) EDL $risk_2$ (PF5-1)	(5) EDL $risk_2$ (PF5-1)	(6) EDL $risk_2$ (PF5-1)
const	0.26%***	0.27%***	0.26%***	0.30%***	0.31%**	0.30%***
	(3.68)	(3.12)	(2.93)	(3.37)	(3.30)	(3.39)
Annualized Alpha	3.13%	3.26%	3.14%	3.65%	3.71%	3.65%

Panel C: EDL $risk_3$ and Returns: Factor Models
Excluding Top 5% of the Largest Stocks

	(1) EDL $risk_3$ (PF5-1)	(2) EDL $risk_3$ (PF5-1)	(3) EDL $risk_3$ (PF5-1)	(4) EDL $risk_3$ (PF5-1)	(5) EDL $risk_3$ (PF5-1)	(6) EDL $risk_3$ (PF5-1)
const	0.20%**	0.29%***	0.27%***	0.32%***	0.31%***	0.32%***
	(2.44)	(3.26)	(3.09)	(3.43)	(3.25)	(3.52)
Annualized Alpha	2.36%	3.46%	3.30%	3.80%	3.71%	3.87%

Panel A of this table reports value-weighted average monthly $t+1$ excess returns for portfolios sorted by EDL $risk_2$ and EDL $risk_3$. Each month t we rank stocks into quintiles (1-5) based on the respective EDL risk component over the past three years and form value-weighted portfolios at the beginning of each monthly period. We report average returns in excess of the one-month T-Bill rate over the month $t+1$, alphas based on Carhart (1997)'s four factor model extended by the Pastor and Stambaugh (2003) traded liquidity factor and the Sadka (2006) fixed-transitory and variable-permanent liquidity factors. We report results for portfolio sorts with all stocks as for portfolio sorts where we exclude the top 5% (10%, 20%) largest stocks for each month t in the sample. The row labelled 'Strong - Weak' reports the difference between the returns and alphas of portfolio 5 and portfolio 1 with corresponding t-statistic. Panel B of this table reports monthly OLS-regression results of a trading strategy based on the value-weighted return-difference between past strong EDL $risk_2$ (quintile 5) and past weak EDL $risk_2$ (quintile 1) portfolios on different factor models. Panel C of this table reports monthly OLS-regression results of a trading strategy based on the value-weighted return-difference between past strong EDL $risk_3$ (quintile 5) and past weak EDL $risk_3$ (quintile 1) portfolios on different factor models. The factors we use in Panels B and C 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), Chabi-Yo et al. (2018)'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). In Panels B and C, we exclude the top 20% largest stocks for each month t in the sample. We only report the intercept of the regression and the respective annualized alpha. 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 four lags.

Table 13: Different Regression Methods

Panel A: Different Regression Methods

Regression	(1)	(2)	(3)	(4)	(5)	(6)	(7)
EDL $risk_2$	0.0099***	0.0101***	0.0120***	0.0153***	0.0151***	0.0143***	0.00115***
	(3.57)	(3.63)	(3.35)	(4.00)	(4.10)	(4.89)	(3.56)
EDL $risk_3$	0.0104***	0.0104***	0.0161***	0.0158***	0.0158***	0.0105***	0.0117***
	(3.82)	(3.80)	(3.56)	(3.69)	(4.04)	(3.89)	(3.42)
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

Panel B: Adjusted Returns

	EDL $risk_2$ (t-stat)	EDL $risk_3$ (t-stat)	return adjustment	EDL $risk_2$ (t-stat)	EDL $risk_3$ (t-stat)
$Return_{t+1}$	0.0099***	0.0104***	SIC-2	0.0083***	0.0092***
	(3.57)	(3.82)		(3.65)	(4.67)
$Return_{t+2}$	0.0062***	0.0079**	SIC-3	0.0076***	0.0081***
	(2.65)	(2.33)		(3.24)	(3.89)
$Return_{t+3}$	0.0056**	0.0055*	SIC-4	0.0069***	0.0078***
	(2.01)	(1.86)		(3.01)	(3.05)
$Return_{t+4}$	0.0043*	0.0051*	FF12	0.0068***	0.0091***
	(1.66)	(1.75)		(2.81)	(3.64)
DGTW	0.0066***	0.0097***	FF48	0.0075***	0.0083***
	(2.68)	(3.73)		(3.25)	(3.25)

Panel A reports the results of different multivariate regressions on a monthly frequency. Regression (1) repeats the baseline regression (3) from Table 8, 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 (3) of Table 8 with different return adjustments. We use monthly returns in $t+1$ (baseline scenario), $t+2$, $t+3$, and $t+4$, as well as 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.