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Crash Sensitivity and the Cross Section of Expected Stock Returns

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Abstract

This article examines whether investors receive compensation for holding crash-sensitive stocks. We capture the crash sensitivity of stocks by their lower-tail dependence (LTD) with the market based on copulas. We find that stocks with strong LTD have higher average future returns than stocks with weak LTD. This effect cannot be explained by traditional risk factors and is different from the impact of beta, downside beta, coskewness, cokurtosis, and Kelly and Jiang's (2014) tail risk beta. Hence, our findings are consistent with the notion that investors are crash-averse.

I. Introduction

In this article, we examine the potential impact of crash aversion on the pricing of the cross section of individual stocks. Stock market crashes lead to significant wealth destruction and eventually to severe contractions of consumption possibilities. Thus, assets that exhibit particularly bad returns during market crashes (i.e., crash-sensitive stocks) are eventually unattractive assets for crash-averse investors: Their value deteriorates most at exactly the moment when investor wealth is particularly low and they should thus bear a return premium.

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Our study documents that crash-sensitive stocks indeed deliver higher returns than crash-insensitive stocks.

To measure crash sensitivity at the individual asset level, we need a dependence concept that allows us to focus on joint extreme events. Standard asset pricing models since Sharpe (1964) and Lintner (1965) argue that the joint distribution of individual stock returns and the market portfolio return determines the cross section of expected stock returns. According to the empirical interpretation of the traditional capital asset pricing model (CAPM), a stock's expected return only depends on its beta, that is, its scaled linear correlation with the market, without any focus on tail events. However, the correlation alone cannot characterize the full dependence structure of nonnormally distributed random variables such as realized stock returns (Embrechts, McNeil, and Straumann (2002)). Particularly, it cannot capture clustering in the lower tail of the bivariate return distribution between individual securities and the market, which is important if investors are crash-averse. Thus, we develop a novel proxy for stock individual crash sensitivity using copula methods based on extreme value theory. Specifically, we capture stock individual crash sensitivity based on the extreme dependence between individual stock returns and market returns in the lower-left tail of their joint distribution (also called lower-tail dependence, LTD) and investigate its influence on the cross section of individual stock returns.[1]

Based on a rolling-window estimation using daily return data for U.S. stocks from 1963 to 2012, we calculate copula-based LTD coefficients for each stock and month. We find that stocks with previously weak LTD (i.e., stocks that displayed only weak LTD or no LTD with the market at all in the previous 12 months) have significantly higher returns than strong-LTD stocks during extreme market downturns. Hence, weak-LTD stocks indeed offer some protection against market crashes.

In our main asset pricing tests, we relate individual LTD to average returns in a predictive setting. Our empirical results using portfolio sorts and multivariate regression analysis at the individual firm level show a strong positive impact of LTD in month t on future excess returns in month $t+1$. A value-weighted portfolio consisting of stocks with the strongest LTD delivers higher average future returns of 0.360% per month than a portfolio of stocks with the weakest LTD. This amounts to an annualized spread of 4.32%. Similar results are obtained after controlling for the exposure to systematic risk factors and the impact of various firm characteristics.

The impact of LTD has to be distinguished from the impact of downside beta documented by Ang, Chen, and Xing (2006) as well as from the impact of other higher co-moments. Downside beta focuses on individual securities' exposure to market returns conditional on below-average market returns and is motivated by disappointment aversion (Gul (1992)). LTD is conceptually different from

[1]A positive influence of LTD on returns is expected (but not empirically shown) in Poon, Rockinger, and Tawn (2004): "If tail events are systematic as well, one might expect the extremal dependence between the asset returns and the market factor returns to also command a risk premium" (p. 586).

downside beta, as the latter places no particular emphasis on tail events.[2] Consequently, downside beta captures general downside risk (or disappointment) aversion rather than crash aversion. In contrast, LTD captures the dependence in the extreme left tail of return distributions; it focuses on how individual securities behave during the worst market return realizations within a given period. We find a strong impact of LTD after controlling for the impact of the Ang et al. (2006) downside beta as well as alternative definitions of downside beta as discussed by Post, van Vliet, and Lansdorp (2012). We can also show that the risk premium associated with LTD is not explained by coskewness (Harvey and Siddique (2000)), cokurtosis (Fang and Lai (1997)), idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang (2006)), or a stock's lottery characteristics (Bali, Cakici, and Whitelaw (2011)) and holds after controlling for other systematic risk factors suggested in the literature.

Furthermore, we document that the risk premium for LTD is higher following large stock market declines. This result is consistent with the theoretical predictions of Chen, Joslin, and Tran (2012). They show that disaster risk premia can increase substantially when the risk-sharing capacity of the "optimists" in their model is reduced, and they argue that this is likely to be the case in the aftermath of a crisis. Our findings also are in line with an argument recently made by Gennaioli, Shleifer, and Vishny (2015) that investors fear a future crash more when there was a recent crash that they still remember.

To motivate our use of copula-based LTD coefficients as a relevant risk measure for investors in a stringent way, in Appendix A, we introduce a theoretical asset pricing model. We show that some simple regularity assumptions on the representative investor's utility function are sufficient for LTD to be priced in a stochastic discount factor framework. The main assumptions necessary for this result are that the first four derivatives of the utility function have altering signs; that is, investors show non-satiation, they are risk-averse, their absolute risk aversion is decreasing (which is equivalent to investors liking skewness), and they are "temperate" (which is equivalent to investors disliking kurtosis; see Eeckhoudt and Schlesinger (2006)). Although our theoretical framework illustrates that these assumptions are sufficient to generate a risk premium for strong-LTD stocks, we expect this finding to be reinforced if one would enrich our basic theoretical model with additional behavioral aspects.[3]

Our theoretical model also predicts a negative return premium for the upper-tail dependence (UTD) between an individual stock's return and the market return. Our empirical analysis shows that high-UTD stocks indeed earn a negative return premium, but, as also predicted by the model, the effect is smaller in absolute

[2]Downside betas conditional on very low market returns (instead of just below-mean market returns, as in Ang et al. (2006)), are intuitively more closely related to LTD. However, they cannot be estimated reliably, as we show in Section III.D.1.

[3]For example, the accumulated evidence from experiments designed to verify the cumulative prospect theory by Kahneman and Tversky (1979) shows that individuals are loss-averse and distort the probabilities of low-probability outcomes (like market crashes) heavily upward (e.g., Abdellaoui (2002)). More recently, Polkovnichenko and Zhao (2013) confirm this pattern using market data from traded financial options to derive empirical probability-weighting functions. He and Zhou (2013) show that this can have important implications for investors' optimal portfolio choice and leads to demand for portfolio insurance.

terms than the impact of LTD and not statistically significant at the 10% level in most asset pricing tests.

Our study contributes to several strands of the asset pricing literature. First, it is related to the literature on rare-disaster risk that has caught a lot of attention in the economics and finance literature in recent years (e.g., Barro (2006), (2009), Pindyck and Wang (2013)). Bollerslev and Todorov (2011) find that much of the aggregate equity risk premium is a compensation for the risk of extreme events, and Gabaix (2012) shows that time-varying rare-disaster risk can explain the equity premium puzzle (as well as several other puzzles in macro-finance). Similarly, there is now a small number of recent articles that examine the time-series relationship between tail risk and *aggregate* stock market returns (e.g., Bali, Demirtas, and Levy (2009), Bollerslev and Todorov (2011), and Kelly and Jiang (2014)). They find that proxies for tail risk can predict aggregate market returns.

Second, our study is related to the theoretical and empirical literature on downside risk and loss aversion. Downside risk aversion is already discussed by Roy (1952), who argues that investors display "safety first" preferences, and by Markowitz (1959), who suggests using the semivariance as a measure of risk. Many subsequent contributions analyze the impact of higher co-moments on expected returns.[4] Kahneman and Tversky (1979) argue that individuals evaluate outcomes relative to reference points and show that individuals are loss-averse. Although aversion to losses and downside risk aversion are discussed extensively in the literature, only a few articles investigate the effect of loss or disappointment aversion on expected asset returns (Barberis and Huang (2001), Benartzi and Thaler (1995), Barberis, Huang, and Santos (2001), Ang, Bekaert, and Liu (2005), and Lettau, Maggiori, and Weber (2014)). However, these articles (as well as the study by Ang et al. (2006) discussed earlier) are concerned with general downside risk aversion rather than crash aversion.

Crash aversion has still caught relatively little attention in the cross-sectional asset pricing literature.[5] The only other articles we are aware of that investigate the impact of crash sensitivity (or tail risk exposure) on the cross section of individual stock returns are the articles by Kelly and Jiang (2014), Cholette and Lu (2011), Van Oordt and Zhou (2016), and Bali, Cakici, and Whitelaw (2014). Kelly and Jiang (2014) successfully predict aggregate market returns by applying the tail risk estimator of Hill (1975) to the cross section of all daily stock returns in a given month.[6] Consistent with our results, they also document that a long-short portfolio that is based on individual stocks' exposure to an aggregate tail risk factor that hedges against tail events delivers significantly negative returns. Our article differs from Kelly and Jiang (2014) conceptually: We capture crash

[4]Extensions of the basic CAPM that allow for preferences for skewness and lower partial moments of security and market returns are developed by Kraus and Litzenberger (1976) and Bawa and Lindenberg (1977). Kraus and Litzenberger (1976), Friend and Westerfield (1980), and Harvey and Siddique (2000) document that investors dislike a stock's negative coskewness with the market return. Fang and Lai (1997) and Dittmar (2002) show that stocks with high cokurtosis earn high average returns.

[5]Exceptions are Berkman, Jacobsen, and Lee (2011), who find that industries that are sensitive to a real crisis index deliver higher returns, and Agarwal, Ruenzi, and Weigert (2017), who show that the crash sensitivity of hedge funds drives the cross-sectional differences between them.

[6]Similar results are obtained by Cholette and Lu (2011).

sensitivity using lower-tail dependence between a stock and the market. Thus, our proxy for the crash sensitivity of an individual stock has the advantage of being directly based on the joint distribution of its return and the market return. It is only weakly positively correlated with the Kelly and Jiang (2014) tail risk beta. Not surprisingly, we can thus empirically show that the impact of LTD on future stock returns is not subsumed by the impact of the Kelly and Jiang (2014) tail risk beta. Furthermore, and in contrast to our results and those of Kelly and Jiang (2014), Van Oordt and Zhou (2016) measure tail risk of stocks based on tail betas but do not find evidence of higher returns associated with high tail risk. We attribute the conflicting findings to our more precise estimation procedure based on copula functions (see Section II) instead of estimating LTD nonparametrically (as in Van Oordt and Zhou (2016)). Motivated by the underdiversified portfolio holdings of individual investors, Bali et al. (2014) introduce a new hybrid measure of stock return tail covariance risk. They document a positive and significant relation between hybrid tail covariance risk and expected stock returns.

Finally, we contribute to the literature on the application of extreme value theory and copulas in finance. Despite its long history in statistics, multivariate extreme value theory has been applied to the analysis of financial markets only recently.[7] It is mainly used to describe dependence patterns across different markets and assets (Longin and Solnik (2001), Patton (2004), and Elkamhi and Stefanova (2015)). However, to the best of our knowledge, ours is the first article to investigate extreme dependence structures in the bivariate distribution of individual and market returns based on copulas. Our application details how to fit flexible combinations of basic parametric copulas to this bivariate distribution and how to derive the corresponding tail dependence coefficients. The copula approach has the advantage that extreme dependence is not estimated based on a small number of observations in the tail exclusively but that information from the whole joint distribution can be used. Furthermore, our approach updates dependence estimates frequently, thus allowing us to capture the potentially dynamic nature of tail dependence in an extremely flexible framework.

The rest of this article is organized as follows: Section II presents evidence on the existence of tail dependence between individual stock and market returns, explains the estimation procedure for tail dependence coefficients, and introduces our data. Section III demonstrates that stocks with strong lower-tail dependence earn high future average returns. Section IV concludes and briefly discusses the implications of our results.

[7]Longin and Solnik (2001) use extreme value theory to model the bivariate return distributions between different international equity markets. Ané and Kharoubi (2003) propose to model the dependence structure of international stock index returns via parametric copulas, whereas Poon et al. (2004) present a general framework for identifying joint-tail distributions based on multivariate extreme value theory. Patton (2004) uses copula theory to model the time-varying dependence structures of stock returns, and Patton (2009) applies copula functions to assess different definitions of market neutrality for hedge funds. Finally, Elkamhi and Stefanova (2015) use copulas to show that accounting for extreme asset comovements is important for portfolio hedging.

II. Tail Dependence and Copula Methodology

Most of the standard empirical asset pricing literature focuses on risk factors based on linear correlation coefficients. However, this measure of stochastic dependence is not typically able to completely characterize the dependence structure of nonnormally distributed random variables (Embrechts et al. (2002)). It has been widely recognized for a long time that many financial time series, including stock returns, are nonnormally distributed (see, e.g., Mandelbrot (1963) and Fama (1965)). For example, they are often characterized by leptokurtosis. This is problematic because when we are dealing with a fat-tailed bivariate distribution $F(x_1,x_2)$ of two random variables X_1 and X_2, the linear correlation (and consequently the standard beta estimate) fails to capture the dependence structure in the extreme lower-left and upper-right tail. As an example, consider the illustrations of 2,000 simulated bivariate realizations based on different dependence structures between (X_1,X_2) shown in Figure 1.

In all models, X_1 and X_2 have standard normal marginal distributions and a linear correlation of 0.8, but other aspects of the dependence structure are clearly different. In Graph A of Figure 1 we first show an example in which we did not allow for clustering in either tail of the distribution. Graphs B–D show examples of increased dependence in the upper-right tail, in the lower-left tail, and symmetric increased dependence in both tails, respectively. Still, all of these bivariate distributions are characterized by a linear correlation coefficient of 0.8. These examples show that it is often not possible to describe the dependence structure by the linear correlation alone.

Now, we characterize two measures of dependence as limiting cases of conditional probabilities: Consider two bivariate returns (X_1,X_2), where X_1 is the return of an individual stock, and X_2 is the market return with corresponding marginal cumulative distributions F_{X_1} and F_{X_2}. We define

$$(1) \qquad P_l(q) \quad = \quad \Pr\left[X_1 < F_{X_1}^{-1}(q)\,|\,X_2 < F_{X_2}^{-1}(q)\right]$$

as a tail dependence measure in the left tail. X_1 and X_2 are said to be asymptotically independent (dependent) in the left tail if $P_l(q)$ has a limit that is equal (not equal) to 0 as q approaches 0 from the right. We define lower-tail dependence (LTD) as

$$(2) \qquad \text{LTD} \quad \equiv \quad \lim_{q\to 0^+} P_l(q).$$

Similarly, we define

$$(3) \qquad P_r(q) \quad = \quad \Pr\left[X_1 > F_{X_1}^{-1}(q)\,|\,X_2 > F_{X_2}^{-1}(q)\right]$$

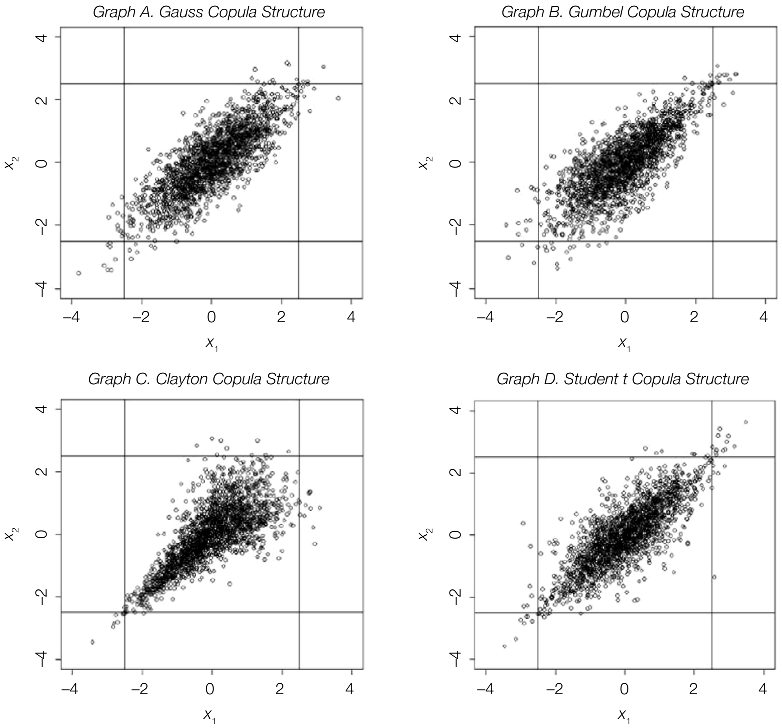
and

$$(4) \qquad \text{UTD} \quad \equiv \quad \lim_{q\to 1^-} P_r(q)$$

as our measure of upper-tail dependence (UTD).

FIGURE 1
Different Copula Dependence Structures

Figure 1 displays 2,000 random variates from four bivariate distributions with standard normal marginal distributions. The Gauss copula (Graph A), the Gumbel copula (Graph B), the Clayton copula (Graph C), and the Student *t* copula (Graph D) determine the dependence structure. These copulas are defined in Table IA.I of the Internet Appendix. In each case, the linear correlation is set to 0.8.



In Section II.A, we detail how we estimate measures of tail dependence based on copulas.[8] Then, we describe the development of aggregate tail dependence over time (Section II.B) and assess whether our suggested tail dependence coefficients are persistent and useful for hedging against extreme outcomes (Section II.C).

A. Copula-Based Estimation of Tail Dependence Coefficients

The main idea of our estimation framework is to model the *whole* dependence structure between individual stock returns and the market return using copulas. We first estimate the marginal distributions of an individual stock return and the market return nonparametrically by their scaled empirical distribution

[8]Because copula concepts are not yet regularly used in standard asset pricing applications, we provide a short intuitive introduction into the concept in Section A of the Internet Appendix (available at www.jfqa.org). For a more detailed overview on the use of copulas in econometrics and finance, see Fan and Patton (2014).

functions. Then, we estimate parameters of different copulas to compute coefficients of tail dependence (i.e., LTD and UTD) based on closed-form solutions.[9]

Unfortunately, most basic copulas do not allow for modeling of LTD and UTD simultaneously. Hence, we work with flexible convex combinations of copulas.[10] Specifically, we use combinations of simple parametric copulas that either exhibit no tail dependence (the Gauss, the Frank, the FGM, and the Plackett copula), lower-tail dependence (the Clayton, the rotated Gumbel, the rotated Joe, and the rotated Galambos copula), or upper-tail dependence (the Gumbel, the Joe, the Galambos, and the rotated Clayton copula). To allow for maximum flexibility in modeling dependence structures, we consider all $4\times4\times4=64$ possible convex combinations that consist 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}:

$$(5)\quad C(u_1,u_2,\Theta) = w_1\times C_{\text{LTD}}(u_1,u_2;\theta_1) + w_2\times C_{\text{NTD}}(u_1,u_2;\theta_2)+(1-w_1-w_2)\times C_{\text{UTD}}(u_1,u_2;\theta_3),$$

where Θ denotes the set of the basic copula parameters θ_i, $i=1,2,3$ and the weights w_1 and w_2.[11]

Our estimation approach for LTD and UTD then follows a 3-step procedure. First, based on daily return data for the market and each stock, we estimate a set of copula parameters Θ_j for $j=1,\ldots,64$ different copulas $C_j(\cdot,\cdot;\Theta_j)$ between the respective marginal distribution of an individual stock return r_i and the market return r_m for each month based on a rolling window of 12 months (Section II.A.1). We explicitly use a short time horizon of 12 months in the estimation of the copula parameters to account for time-varying dependence in the bivariate distribution of r_i and r_m. An alternative approach to account for time variation in dependence would be to specify a dynamic (conditional) copula model similar to Patton (2006) and Jondeau and Rockinger (2006). In this setting, the functional form of the copula remains fixed over time, whereas the copula parameters vary according to some prespecified stochastic process. However, although this is a valid approach for capturing the dynamic nature of the copula parameters, the approach uses a

[9]Table IA.I of the Internet Appendix shows the parametric forms and related tail dependencies of the basic copulas used in this study. Alternatives to this approach include a purely nonparametric approach (as suggested by Poon et al. (2004), which relies only on observations from the tail) and a fully parametric approach. Nonparametric test procedures enable us to test for the existence of tail dependence; in the Internet Appendix (Table IA.II), we show that the existence of LTD cannot be rejected for more than 60% of the firm-month observations in our sample using the bottom 1% daily return observations as a cutoff. However, purely nonparametric point estimates for tail dependence coefficients are not very precise (Frahm, Junker, and Schmidt (2005)). Hence, in the following, we rely on an estimation framework using nonparametric margins and parametric copula functions to obtain more precise estimates for LTD and UTD. To avoid the risk of model misspecification, we consider 64 different copula models in our selection and estimation process.

[10]Tawn (1988) shows that every convex combination of existing copula functions is again a copula. Thus, if $C_1(u_1,u_2)$, $C_2(u_1,u_2),\ldots,C_n(u_1,u_2)$ are bivariate copula functions, then $C(u_1,u_2)= w_1\cdot C_1(u_1,u_2)+w_2\cdot C_2(u_1,u_2)+\cdots+w_n\cdot C_n(u_1,u_2)$ is again a copula for $w_i\geq 0$ and $\sum_{i=1}^{n} w_i=1$.

[11]These convex combinations are similar to other copulas such as the BB1–BB7 copulas suggested in Joe (1997), but they offer more flexibility. Particularly, because our convex combinations also contain one copula that is asymptotically independent, ours is an extremely flexible and efficient way to model dependence structures and is less prone to model misspecification.

fixed functional form of the copula function itself. We decided in favor of our more flexible (unconditional) copula framework because it enables us to choose the best parametric copula (i.e., the parametric copula that minimizes the distance to the empirical copula) at each point in time.

Second, we follow Ané and Kharoubi (2003) and select the appropriate parametric copula $C^*(\cdot,\cdot;\Theta^*)$ by minimizing the distance between the different estimated parametric copulas $C_j(\cdot,\cdot;\widehat{\Theta}_j)$ and the empirical copula $\widehat{C}$ based on the integrated Anderson–Darling (IAD) distance (see Section II.A.2). Third, we compute the tail dependence coefficients LTD and UTD implied by the estimated parameters Θ^* of the selected copula $C^*(\cdot,\cdot;\Theta^*)$ (Section II.A.3).

1. Estimation of the Marginal Distribution and the Copula Parameters

The estimation of the set of copula parameters Θ_j for the different copula combinations $C_j(\cdot,\cdot;\Theta_j)$ is performed as follows: Let $\{r_{i,k},r_{m,k}\}_{k=1}^{n}$ be a random sample from the bivariate distribution $F(r_i,r_m)=C(F_i(r_i),F_m(r_m))$ between an individual stock return r_i and the market return r_m, where n denotes the number of daily return observations in a given period.[12] We estimate the marginal distributions F_i and F_m of an individual stock return r_i and the market return r_m nonparametrically by their scaled empirical distribution functions

$$(6)\quad \widehat{F}_i(x) = \frac{1}{n+1}\sum_{k=1}^{n}\mathbb{1}_{r_{i,k}\le x} \quad \text{and} \quad \widehat{F}_m(x) = \frac{1}{n+1}\sum_{k=1}^{n}\mathbb{1}_{r_{m,k}\le x}.$$

The estimation of F_i and F_m by their empirical counterparts avoids an incorrect specification of the marginal distributions (see Fermanian and Scaillet (2005) and Charpentier, Fermanian, and Scaillet (2007)). We then estimate the set of copula parameters Θ_j. Each convex combination requires the estimation of five parameters: one parameter θ_i $(i=1,2,3)$ for each of the three basic copulas and the two weights w_1 and w_2. Because we assume a parametric form of the copula functions, the parameters Θ_j can be estimated via the canonical maximum-likelihood procedure (Genest, Ghoudi, and Rivest (1995)):

$$(7)\quad \widehat{\Theta}_j = \underset{\Theta_j}{\operatorname{argmax}}\, L_j(\Theta_j) \quad \text{with } L_j(\Theta_j) = \sum_{k=1}^{n}\ln(c_j(\widehat{F}_{i,r_{i,k}},\widehat{F}_{m,r_{m,k}};\Theta_j)),$$

where $L_j(\Theta_j)$ denotes the log-likelihood function, and $c_j(\cdot,\cdot;\Theta_j)$ denotes the copula density. Assuming that $\{r_{i,k},r_{m,k}\}_{k=1}^{n}$ is an independent and identically distributed (IID) random sample, $\widehat{\Theta}$ is a consistent and asymptotic normal estimate of the set of copula parameters Θ under standard regularity conditions (e.g., Genest et al. (1995)).[13]

[12]In computing the market return r_m, we exclude stock i, so the market return r_m is slightly different for each stock's time-series regression. This removes potential endogeneity problems when calculating LTD and UTD coefficients for each stock.

[13]Obviously, daily return data often violate the assumption of an IID random sample. Thus, an alternative approach to the problem of non-IID data due to serial correlation in the first and the second moment of the time series would be to specify, for example, generalized autoregressive conditional heteroscedasticity (GARCH) models for the univariate processes and analyze the dependence structure of the residuals. In Section III.D.4 we check this alternative approach: Results for the LTD and UTD coefficients based on filtered residuals and subsequent asset pricing implications are very similar to our main results using unfiltered data.

2. How to Select the Right Copula

So far we have pointed out an estimation procedure under the assumption that the copula $C_j(\cdot,\cdot;\Theta_j)$ is known up to a set of parameters Θ_j. The choice of the copula $C^*(\cdot,\cdot;\Theta^*)$ obviously affects the resulting bivariate distribution and the resulting tail dependence coefficients LTD and UTD. However, most applications presented in the literature do not discuss this issue and rely on an arbitrary choice of the copula. To avoid this problem, we follow Ané and Kharoubi (2003) and use the empirical copula function introduced by Deheuvels (1981) to evaluate the fit of different parametric copulas. We proceed as follows: Let $\{R_{i,k}, R_{m,k}\}_{k=1}^{n}$ denote the rank statistic of $\{r_{i,k}, r_{m,k}\}_{k=1}^{n}$; that is, the smallest individual stock (market) return observation of $r_{i,k}$ $(r_{m,k})$ has rank $R_{i,k}=1$ $(R_{m,k}=1)$, and the largest individual stock (market) return observation of $r_{i,k}$ $(r_{m,k})$ has rank $R_{i,k}=n$ $(R_{m,k}=n)$.

Deheuvels (1981) introduces the empirical copula $\widehat{C}_{(n)}$ on the lattice

$$L = \left[\left(\frac{t_i}{n}, \frac{t_m}{n}\right),\ t_i = 0,1,\ldots,n,\ t_m = 0,1,\ldots,n\right]$$

by the following equation:

$$\text{(8)} \qquad \widehat{C}_{(n)}\left(\frac{t_i}{n}, \frac{t_m}{n}\right) = \frac{1}{n}\sum_{k=1}^{n} \mathbb{1}_{R_{i,k}\le t_i} \times \mathbb{1}_{R_{m,k}\le t_m}.$$

We compute integrated Anderson–Darling distances $D_{j,\text{IAD}}$ between the parametric copulas $C_j(\cdot,\cdot;\widehat{\Theta}_j)$ and the empirical copula $\widehat{C}_{(n)}$ via

$$\text{(9)} \qquad D_{j,\text{IAD}} = \sum_{t_i=1}^{n}\sum_{t_m=1}^{n} \frac{\left(\widehat{C}_{(n)}\left(\frac{t_i}{n}, \frac{t_m}{n}\right) - C_j\left(\frac{t_i}{n}, \frac{t_m}{n}; \widehat{\Theta}_j\right)\right)^2}{C_j\left(\frac{t_i}{n}, \frac{t_m}{n}; \widehat{\Theta}_j\right) \times \left(1 - C_j\left(\frac{t_i}{n}, \frac{t_m}{n}; \widehat{\Theta}_j\right)\right)}.$$

Hence, we calculate the distance between the predicted value of the parametric copulas $C_j(\cdot,\cdot;\widehat{\Theta}_j)$ and the empirical copula $\widehat{C}_{(n)}$ for every grid point on the lattice L. The estimation of the tail dependence coefficients LTD and UTD is based on the estimated parameters Θ^* of the copula combination $C^*(\cdot,\cdot;\Theta^*)$, which minimizes $D_{j,\text{IAD}}$.

The result of our empirical implementation of this procedure shows that all combinations are chosen regularly, and no specific copula clearly dominates, which highlights the advantage of picking the copula function that describes the data best rather than just using one specific ad hoc copula. The respective frequencies are summarized in Table IA.III in the Internet Appendix. The three copula combinations that are most often selected are the Clayton–Gauss–Galambos copula (5.96%), the Clayton–Gauss–rotated Clayton copula (5.75%), and the rotated Galambos–Gauss–rotated Clayton copula (5.73%).[14]

[14] In a robustness check, we select the best parametric copula based on estimated log-likelihood values instead of integrated Anderson–Darling distances. We confirm that the copula combinations most frequently picked are the Clayton–Gauss–Galambos copula (5.91%), the Clayton–Gauss–rotated Clayton copula (5.78%), and the rotated Galambos–Gauss–rotated Clayton copula (5.75%) using this alternative selection criterion. Asset pricing results are also very similar (see Table 9).

3. Computation of Tail Dependence Coefficients Based on Convex Combinations of Copulas

Finally, we compute the tail dependence coefficients LTD and UTD implied by the estimated parameters Θ^* of the selected copula $C^*(\cdot,\cdot;\Theta^*)$. The computation of LTD and UTD is straightforward for the basic copulas used in our study (the respective closed-form solutions for tail dependence coefficients are shown in Table IA.I in the Internet Appendix). The lower- and upper-tail-dependence coefficient of the convex combination is calculated as the weighted sum of the LTD and UTD coefficients from the individual copulas, respectively, where the weights from equation (5) are used (i.e., $\text{LTD}^* = w_1^* \times \text{LTD}(\theta_1^*)$ and $\text{UTD}^* = (1 - w_1^* - w_2^*) \times \text{UTD}(\theta_3^*)$). Because this procedure is repeated for each stock and month based on an annual estimation horizon, we end up with a panel of tail dependence coefficients $\text{LTD}_{i,t}^*$ and $\text{UTD}_{i,t}^*$ at the month-firm level.

Our empirical approach to estimate LTD has three advantages: i) It uses the whole body of data of the bivariate distribution of individual and market returns (thus avoiding the imprecision of tail dependence estimates relying on nonparametric methods that only focus on tail observations). ii) It is very flexible because the convex copula combination that best describes the data can be selected (in contrast to approaches using a predefined specific functional form for the dependence structure) and because it allows for asymmetric tail dependencies in the upper and lower tail. iii) It is able to capture the dynamic nature of the dependence relationship by frequently updating the procedure for copula fitting and parameter selection.

B. Data, Summary Statistics, and the Evolution of Aggregate Tail Dependence

Our sample consists of all common stocks (Center for Research in Security Prices (CRSP) share codes 10 and 11) from CRSP trading on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers Automated Quotations (NASDAQ) between Jan. 1, 1963, and Dec. 31, 2012. So that our results are not driven by very small stocks, we exclude return data from firms that are in the bottom 1% of market capitalization of all stocks in the previous year. Furthermore, we require at least 100 valid daily return observations per year. Overall, there are 2,613,440 firm-month observations after we apply these filters. The number of firms in each month over our sample period ranges from 1,904 to 6,778. Summary statistics are provided in Table 1.

The first four columns of Table 1 show the mean as well as the 25%, the 50%, and the 75% quantiles for key variables (pooled over all stocks and months). The mean (median) yearly excess return over the risk-free rate of all stocks in our sample is 0.67% (−0.13%), and the mean (median) LTD coefficient is 0.10 (0.07). We also observe considerable variation in LTD, with an interquartile range of nearly 0.15. The mean (median) of UTD is 0.07 (0.04) and is significantly lower than the mean (median) of LTD. The general tendency for stronger asymptotic dependence in the left tail than in the right tail of the distributions is consistent with the well-documented finding that return correlations generally increase

TABLE 1
Summary Statistics

Table 1 presents summary statistics for the main variables used in this study (pooled over all stocks and months). The first five columns show the mean, the 25% quantile, the 50% quantile (median), the 75% quantile, and the standard deviation of each variable. The last three columns display mean values of the variables conditional on lower-tail dependence (LTD) being above (below) its 50% quantile, as well as the difference and corresponding statistical significance level. We present results for yearly excess stock returns over the 1-month T-bill rate (return), lower-tail dependence (LTD), upper-tail dependence (UTD), beta (β), downside beta (β^-), upside beta (β^+), the natural log of market capitalization (SIZE), book-to-market ratio (BOOK_TO_MARKET), illiquidity (ILLIQ), idiosyncratic volatility (IDIO_VOLA), coskewness (COSKEW), cokurtosis (COKURT), the maximum daily return over the past 1 year (MAX), and the Kelly and Jiang (2014) tail risk beta (β_{TAIL}). A detailed description of the computation of these variables is given in the main text and in Appendix B. The sample covers all U.S. common stocks traded on the NYSE/AMEX/NASDAQ, and the sample period is from Jan. 1963 to Dec. 2012. *t*-statistics are in parentheses and are computed using Newey and West (1987) standard errors with 4 monthly lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variable	Mean	25% Quantile	Median	75% Quantile	Standard Deviation	Above LTD Median	Below LTD Median	Above – Below
Return	0.67%	−7.20%	−0.13%	6.78%	0.214	0.80%	0.57%	0.23%***
LTD	0.100	0.011	0.069	0.158	0.104	0.180	0.019	0.161***
UTD	0.065	0.000	0.036	0.103	0.082	0.075	0.056	0.019***
β	0.737	0.278	0.658	1.120	0.635	0.904	0.556	0.348***
β^-	0.854	0.313	0.785	1.325	0.871	1.141	0.542	0.599***
β^+	0.635	0.081	0.571	1.155	0.951	0.733	0.527	0.206***
SIZE	11.260	9.670	11.080	12.690	2.151	11.660	10.790	0.870***
BOOK_TO_MARKET	0.827	0.337	0.625	1.069	0.865	0.756	0.908	−0.152***
ILLIQ	0.175	0.021	0.252	0.300	0.132	0.151	0.206	−0.055***
IDIO_VOLA	0.541	0.285	0.432	0.666	0.387	0.507	0.577	−0.070***
COSKEW	−0.092	−0.172	−0.056	0.045	0.294	−0.170	−0.008	−0.162***
COKURT	1.474	0.329	0.913	1.769	2.723	2.118	0.776	1.342***
MAX	17.41%	8.19%	12.90%	20.98%	0.154	16.94%	17.95%	−1.01%***
β_{TAIL}	0.058	−0.015	0.043	0.118	0.153	0.035	0.003	0.032***

in down markets.[15] The rest of the table provides information on the summary statistics regarding other firm characteristics and return patterns that we later use in our empirical analysis. All variable definitions are contained in Appendix B.

The last three columns of Table 1 show the average characteristics of stocks with, respectively, above and below values of LTD in a given month, as well as the difference between the two. Excess returns over the risk-free rate for high-LTD stocks are 0.80% per annum, whereas they are significantly lower at 0.57% per annum for low-LTD stocks. The difference amounts to 0.23% per annum and is statistically significant at the 1% level. At the same time, high-LTD stocks also have significantly higher regular betas (β), downside betas (β^-), and tail betas (β_{TAIL}); tend to be somewhat larger and more liquid; and have lower book-to-market ratios.

Cross-correlations between the independent variables used in our later analysis are shown in Table 2 and confirm these patterns.

The correlation between LTD and UTD is relatively moderate, at 0.15, which shows that firms with strong tail dependence in one tail of the distribution do not necessarily exhibit strong tail dependence in the other tail. This finding also justifies our flexible modeling approach for tail dependence, which allows for asymmetric tail dependence in the upper and lower tail. LTD is correlated with downside beta with a correlation coefficient of 0.38, with regular beta with a correlation coefficient of 0.34, and with the Kelly and Jiang (2014) tail risk beta

[15]In the Internet Appendix, we also look at 5-year subperiods. We find that UTD is significantly weaker than LTD in each period (Table IA.IV). Increased extreme dependence among international markets during bear markets is also documented by Longin and Solnik (2001) and Poon et al. (2004).

TABLE 2
Correlations

Table 2 presents linear correlations between select variables used in this study: lower-tail dependence (LTD), upper-tail dependence (UTD), beta (β), downside beta (β^-), upside beta (β^+), the natural log of market capitalization (SIZE), book-to-market ratio (BOOK_TO_MARKET), illiquidity (ILLIQ), past return, idiosyncratic volatility (IDIO_VOLA), coskewness (COSKEW), cokurtosis (COKURT), the maximum daily return over the past 1 year (MAX), and tail risk beta (β_{TAIL}). A detailed description of the computation of these variables is given in the main text and in Appendix B. The sample covers all U.S. common stocks traded on the NYSE/AMEX/NASDAQ, and the sample period is from Jan. 1963 to Dec. 2012.

	LTD	UTD	β	β^-	β^+	SIZE	BOOK_TO_ MARKET	ILLIQ	PAST_ RETURN	IDIO_ VOLA	COSKEW	COKURT	MAX	β_{TAIL}
LTD	1.00	—	—	—	—	—	—	—	—	—	—	—	—	—
UTD	0.15	1.00	—	—	—	—	—	—	—	—	—	—	—	—
β	0.34	0.28	1.00	—	—	—	—	—	—	—	—	—	—	—
β^-	0.38	0.05	0.72	1.00	—	—	—	—	—	—	—	—	—	—
β^+	0.16	0.40	0.71	0.37	1.00	—	—	—	—	—	—	—	—	—
SIZE	0.33	0.30	0.29	0.12	0.24	1.00	—	—	—	—	—	—	—	—
BOOK_TO_MARKET	−0.09	−0.04	−0.12	−0.09	−0.06	−0.32	1.00	—	—	—	—	—	—	—
ILLIQ	−0.33	−0.29	−0.37	−0.18	−0.29	−0.82	0.24	1.00	—	—	—	—	—	—
PAST_RETURN	0.08	−0.00	0.15	0.14	0.09	0.11	−0.19	−0.02	1.00	—	—	—	—	—
IDIO_VOLA	−0.18	−0.16	−0.03	0.05	−0.07	−0.50	0.07	0.35	−0.10	1.00	—	—	—	—
COSKEW	−0.36	0.16	−0.00	−0.18	0.15	−0.05	0.07	0.05	−0.05	0.06	1.00	—	—	—
COKURT	0.37	0.22	0.23	0.17	0.22	0.22	−0.08	−0.22	0.02	−0.15	−0.77	1.00	—	—
MAX	−0.11	−0.13	0.02	0.06	−0.03	−0.39	0.04	0.28	0.10	0.62	0.06	−0.12	1.00	—
β_{TAIL}	0.07	−0.08	0.02	0.06	−0.02	−0.15	0.00	0.12	0.02	0.16	−0.02	−0.03	0.11	1.00

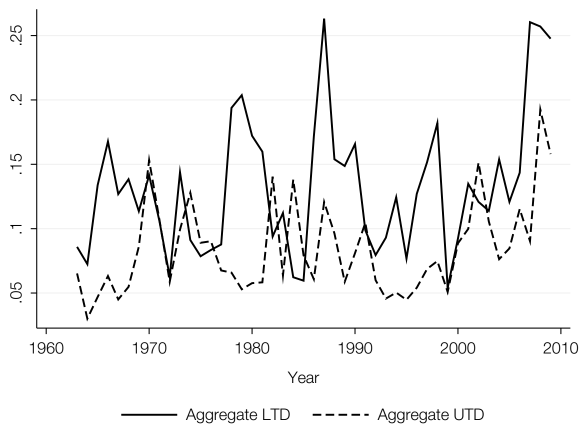
with a correlation of 0.07. LTD is also related to other co-moments, as can be seen from the strongly positive (negative) correlation with cokurtosis (coskewness). We carefully take into account the impact of these correlations in our later analysis.

To get some idea about the temporal variation of tail dependence, we investigate the time series of *aggregate* LTD. We define aggregate LTD, $\text{LTD}_{m,t}$, as the yearly cross-sectional, value-weighted average of $\text{LTD}_{i,t}$ over all stocks i in our sample. In Figure 2, we plot the time series of $\text{LTD}_{m,t}$.

FIGURE 2

Aggregate Tail Dependence over Time

Figure 2 displays the evolution of aggregate lower-tail dependence (LTD) and aggregate upper-tail dependence (UTD), over time. Aggregate LTD (UTD) is defined as the yearly cross-sectional equal-weighted average of the individual LTD coefficients, $\text{LTD}_{i,t}$ (UTD coefficients, $\text{UTD}_{i,t}$) between stock returns and market returns over all stocks i in year t in our sample. The sample covers all U.S. common stocks traded on the NYSE/AMEX/NASDAQ, and the sample period is from Jan. 1963 to Dec. 2012.



There is no particular time trend in $\text{LTD}_{m,t}$.[16] However, the graph does exhibit occasional spikes in $\text{LTD}_{m,t}$ that roughly correspond to worldwide financial market crises. The highest values in $\text{LTD}_{m,t}$ correspond to 1987, the year of "Black Monday," with the largest 1-day percentage decline in U.S. stock market history, and to the years 2007 through 2011, the years of the recent worldwide financial crisis. This pattern suggests that $\text{LTD}_{m,t}$, similar to return correlations, increases in times of financial crises. Consistent with this argument, the time-series correlation between LTD and the market return is −0.08, and the time-series correlation between LTD and market volatility is 0.32. Figure 2 also plots aggregate UTD, $\text{UTD}_{m,t}$, defined as the yearly cross-sectional, value-weighted average of $\text{UTD}_{i,t}$. The time series of $\text{LTD}_{m,t}$ and $\text{UTD}_{m,t}$ are not significantly correlated. We find that in 33 of 49 years of our sample, $\text{LTD}_{m,t}$ exceeds $\text{UTD}_{m,t}$.

[16]Performing an augmented Dickey–Fuller test rejects the null hypothesis that $\text{LTD}_{m,t}$ contains a unit root with a p-value smaller than 2%.

C. Persistence in LTD and Cross-Sectional Drivers

To hedge against market crashes from an ex ante point of view, investors may be inclined to pay for weak-LTD stocks in the expectation that this behavior will be repeated in the future. A natural question is whether these expectations are rational. To investigate the cross-sectional persistence in LTD, we report the results of an LTD transition matrix in Figure 3.

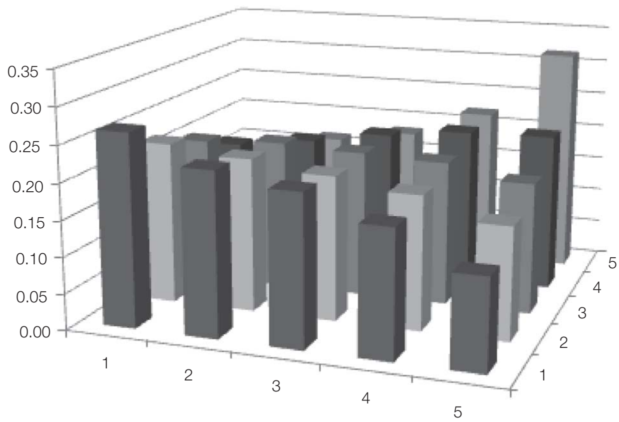
This figure visualizes the relative frequency by which a stock is sorted into LTD quintile portfolio i in year t given that it was in the LTD quintile portfolio j in year $t-1$ over our sample period from 1963 to 2012. If LTD coefficients were completely random, then all the frequencies should be approximately 20% because a high-/low-LTD coefficient in year $t-1$ should say nothing about LTD in year t. Instead, our results indicate clear persistence in LTD, particularly for the extreme portfolios: Stocks that are sorted into portfolio 5 (1) at year $t-1$ show up again in portfolio 5 (1) with a likelihood of 31.61% (26.60%). However, at the same time, there is also a substantial probability that the LTD of a stock changes over time, highlighting the dynamic nature of LTD.[17]

As in Bali, Brown, and Tang (2017), we also test the persistence of LTD using Fama–MacBeth (1973) regressions at the individual firm level in Table IA.VI of the corresponding Internet Appendix. Regressing LTD in year t on LTD in year $t-1$ in a univariate model delivers a coefficient estimate of 0.208 with a high statistical significance (t-statistic = 11.46) and hence indicates substantial persistence. We then expand the model and investigate whether other variables also display predictive power on a stock's LTD. For this purpose, we add the control

FIGURE 3

LTD Transition Matrix

Figure 3 provides a visual depiction of the lower-tail dependence (LTD) transition matrix. It shows the relative frequency at which a stock is sorted into LTD quintile portfolio i in year t given that it was in LTD quintile portfolio j in year $t-1$. The sample covers all U.S. common stocks traded on the NYSE/AMEX/NASDAQ, and the sample period is from Jan. 1963 to Dec. 2012.



[17]We report the underlying numbers of the LTD transition matrix in Table IA.V of the Internet Appendix.

variables used later in our asset pricing tests as well as a firm's leverage, cash-flow volatility, distress risk (estimated by a firm's Altman's (1968) Z-score), and research and development (R&D) expenses as potential cross-sectional drivers of LTD in the regression setup (see specifications 2–4 in Table IA.VI of the Internet Appendix). Our results are intuitive: LTD in year t is significantly positively related to a firm's beta, size, Kelly and Jiang's (2014) tail risk beta, and distress risk in year $t-1$; it is significantly negatively related to a firm's coskewness and idiosyncratic volatility in year $t-1$. We also investigate whether specific industries are more prone to LTD than others. Over the sample period from 1963 to 2012, we find that, on average, aggregate LTD for the Fama and French 12 industries is highest for manufacturing firms, financials, and consumer durables.

Finally, we also check whether weak LTD stocks offer insurance to investors on some of the most relevant financial crisis days in our sample period, namely, "Black Monday" (Oct. 19, 1987), the Asian crisis (Oct. 27, 1997), the burst of the dot-com bubble (Apr. 14, 2000), and the recent Lehman crises (Oct. 15, 2008). As expected (and opposite of what we expect in the overall sample and will later show in Table 3), weak-LTD stocks strongly *out*perform strong-LTD stocks on each of these individual crisis days. Detailed results of these tests are displayed in Table IA.VII of the Internet Appendix.

III. Crash Sensitivity and Future Returns

In the main part of the empirical analysis, we look at the relationship between tail dependence coefficients and future monthly security returns. Our asset pricing tests are completely out-of-sample and hence avoid in-sample problems such as overfitting. We estimate a stock's monthly individual LTD and UTD coefficients based on a rolling window over a period of 12 months. Using this horizon trades off two concerns: First, we need a sufficiently large number of observations to get reliable estimates for our tail dependence coefficients. Second, motivated by the fact that several studies document that risk exposures (like regular beta) are non-stable (see, e.g., Fama and French (1992), Ang and Chen (2007)), we need to account for time-varying extreme dependence risk by using an estimation window that is not too long. To avoid the impact of autocorrelation and heteroscedasticity in our models, we determine statistical significance in portfolio sorts and multivariate regressions using Newey and West (1987) standard errors.

A. Portfolio Sorts

1. Univariate Sorts

To examine whether tail dependence in the form of LTD and UTD has an impact on the cross section of future stock returns, we first look at simple univariate portfolio sorts. For each month t, we sort stocks into five quintile portfolios based on their LTD and UTD estimated over the previous 12 months. Panel A of Table 3 reports the results of value-weighted sorts based on LTD.[18]

[18]Equal-weighted portfolio results are discussed in Section III.D.4.

TABLE 3
Univariate Value-Weighted Portfolio Sorts

Panels A and B of Table 3 report results from univariate portfolio sorts based on lower-tail dependence (LTD) and upper-tail dependence (UTD). In each month, we rank stocks into quintiles (1–5) and form value-weighted portfolios based on the respective tail dependence measure. The column labeled "Return" reports the future average monthly return in excess of the 1-month T-bill rate of the portfolios. The column labeled "CAPM Alpha" ("CAR Alpha," "FF5 Alpha") reports the future average monthly alpha with regard to the Sharpe (1964) capital asset pricing model (Carhart (1997) 4-factor model, Fama and French (2015) 5-factor model). The row labeled "Strong – Weak" reports the difference between the returns of portfolio 5 and portfolio 1, with corresponding statistical significance levels. Panel C reports the results from univariate portfolio sorts based on LTD (i) during different market conditions (positive/negative market return, high/low market volatility, economic activity based on CFNAI > 0 / CFNAI < 0); (ii) when we apply more stringent constraints on our stock sample and explicitly screen out small (bottom 10% NYSE size breakpoint), illiquid (bottom 10% NYSE illiquidity breakpoint), and low-nominal-price stocks (<5 USD current stock price); and (iii) when we use 2-, 3-, and 6-month-ahead returns in the portfolio sorts. The sample covers all U.S. common stocks traded on the NYSE/AMEX/NASDAQ, and the sample period is from Jan. 1963 to Dec. 2012. t-statistics are in parentheses and are computed using Newey and West (1987) standard errors with 4 monthly lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Portfolio	LTD	Return	CAPM Alpha	CAR Alpha	FF5 Alpha
Panel A. Lower-Tail Dependence (LTD)					
1 Weak LTD	0.00	0.296%	−0.129%*	−0.108%	−0.323%***
2	0.03	0.315%	−0.141%*	−0.074%	−0.169%**
3	0.08	0.380%	−0.075%*	−0.067%	−0.150%*
4	0.15	0.508%	+0.045%	+0.038%	+0.004%
5 Strong LTD	0.27	0.656%	+0.172%**	+0.129%	+0.211%***
Strong – Weak	0.27***	0.360%***	+0.302%***	+0.237%**	+0.534%***
		(3.68)	(3.15)	(2.35)	(5.58)
Panel B. Upper-Tail Dependence (UTD)					
1 Weak UTD	0.00	0.561%	+0.054%	+0.023%	+0.023%
2	0.01	0.526%	+0.055%	+0.007%	+0.001%
3	0.04	0.540%	+0.074%	+0.021%	+0.034%
4	0.09	0.488%	+0.070%	−0.010%	−0.006%
5 Strong UTD	0.23	0.427%	−0.037%	+0.029%	+0.011%
Strong – Weak	0.23***	−0.134%	−0.091%	+0.006%	−0.012%
		(−1.26)	(−0.99)	(+0.09)	(−0.56)

Panel C. LTD: Additional Tests

	Portfolio	Return	CAPM Alpha	CAR Alpha	FF5 Alpha
Market return > 0	Strong – Weak	0.794%***	+0.485%**	+0.106%	+0.746%***
		(6.47)	(2.41)	(0.59)	(3.74)
Market return < 0	Strong – Weak	−0.244%	+0.107%	+0.141%	+0.202%
		(−1.59)	(0.47)	(0.66)	(1.40)
High market volatility	Strong – Weak	0.428%***	+0.387%**	+0.322%*	+0.645%***
		(2.87)	(2.21)	(1.86)	(4.32)
Low market volatility	Strong – Weak	0.321%**	+0.236%*	+0.154%	+0.412%***
		(2.34)	(1.79)	(1.36)	(3.51)
CFNAI > 0	Strong – Weak	0.305%***	+0.223%**	+0.131%	+0.394%***
		(2.63)	(2.00)	(1.21)	(3.47)
CFNAI < 0	Strong – Weak	0.449%**	+0.409%**	+0.337%**	+0.663%***
		(2.60)	(2.40)	(2.33)	(3.92)
Exclude small stocks	Strong – Weak	0.343%***	+0.297%***	+0.238%**	+0.510%***
		(3.41)	(3.11)	(2.24)	(5.22)
Exclude illiquid stocks	Strong – Weak	0.339%***	+0.289%**	+0.211%*	+0.489%***
		(3.31)	(2.67)	(1.82)	(5.11)
Exclude penny stocks	Strong – Weak	0.351%***	+0.306%***	+0.227%**	+0.515%***
		(3.42)	(3.07)	(2.08)	(5.30)
2-month-ahead returns	Strong – Weak	0.694%***	+0.562%**	+0.398%*	+0.883%***
		(3.45)	(2.43)	(1.76)	(4.65)
3-month-ahead returns	Strong – Weak	0.854%*	+0.772%*	+0.593%	+1.233%***
		(1.79)	(1.80)	(1.36)	(2.98)
6-month-ahead returns	Strong – Weak	1.404%	+1.198%	+0.875%	+1.348%*
		(1.21)	(1.04)	(0.87)	(1.82)

The first column of Table 3 shows considerable cross-sectional variation in LTD: Average LTD ranges from 0.00 in the weakest-LTD quintile up to 0.27 in the strongest-LTD quintile. In the second column, we report the monthly future value-weighted average excess return over the risk-free rate of these portfolios as well as differences in average excess returns between quintile portfolio 5 (strong LTD) and quintile portfolio 1 (weak LTD) in month $t+1$. We find that stocks with strong LTD have significantly higher average future returns than stocks with weak LTD: Stocks in the quintile with the weakest (strongest) LTD earn a monthly average excess return of 0.296% (0.656%). The return spread between quintile portfolios 5 and 1 is 0.360% per month (4.32% per annum), which is statistically significant at the 1% level. These results are consistent with investors' being crash-averse and requiring a premium for holding stocks with strong LTD.

However, our findings hitherto are only univariate, and LTD is correlated with several other variables that are related to returns, such as regular beta or size (see Table 2). Thus, we also compute the monthly alphas generated by the quintile as well as the difference portfolios based on the 1-factor CAPM, the 4-factor Carhart (1997), and the 5-factor Fama and French (2015) models. Results presented in the last three columns show that alphas always increase monotonically from the weakest-LTD to the strongest-LTD quintile portfolios. The CAPM alpha (4-factor alpha, 5-factor alpha) of the difference portfolio is economically large, amounting to 0.302% (0.237%, 0.534%) per month, and is always statistically significant at least at the 5% level. Our results indicate that the positive cross-sectional relation between LTD and future returns is driven by both the outperformance of stocks with strong LTD (quintile 5) and the underperformance of stocks with weak LTD (quintile 1) relative to the Fama and French (2015) 5-factor model.

In Panel B of Table 3 we report the results of value-weighted sorts based on UTD. We find that stocks with strong UTD have lower average future returns than stocks with weak UTD. The return spread between quintile portfolios 1 and 5 is −0.134% per month, which is not statistically different from 0 at the 10% level. When computing alphas, we find that the monthly return spread of the difference portfolio further shrinks (in absolute terms) to −0.091% (for the CAPM alpha), 0.006% (for the 4-factor alpha), and −0.012% (for the 5-factor alpha), respectively, and is not significantly different from 0 in either case. A negative but (in absolute terms) weaker return premium for UTD as compared to LTD is also predicted by our theoretical model (see Appendix B). Hence, in the remainder of the article, we focus on the impact of LTD on the cross section of average future stock returns.

In Panel C of Table 3 we present the results of additional empirical tests on the relationship between LTD and future returns. In particular, we investigate the impact of LTD on future returns i) during periods of different market conditions (based on overall market returns, volatility, and economic activity) and ii) when we apply more stringent constraints on our stock sample, and iii) we expand the horizon of future returns in the asset pricing tests. As expected, the outperformance of strong-LTD stocks is mainly driven by periods of positive market returns. Additionally, our results indicate that the premium for LTD is relatively stable during periods of high/low market volatility, as well as during periods of high/low economic activity (as measured by the Chicago Fed National Activity Index, CFNAI), respectively.[19] Furthermore, the impact of LTD on future returns remains positive and statistically significant when we follow Bali, Cakici, Yan, and Zhang (2005) and use a subsample of stocks after screening out very small stocks (bottom 10% NYSE size breakpoint), illiquid stocks (bottom 10% NYSE illiquidity breakpoint), and stocks with very low nominal prices (<5 USD current stock price). Finally, we examine whether LTD not only predicts 1-month-ahead future returns but also shows longer-term predictive power. We find that the impact of LTD on future returns and alphas is always positive and typically also statistically significant for 2-month-ahead and 3-month-ahead horizons. The statistical significance diminishes (except for the Fama and French (2015) alpha) when we examine future 6-month-ahead returns, which is consistent with the limited time-series persistence of a stock's LTD (see Section II.C).

Alternative Factor Models. We now evaluate whether the return spread due to LTD is explained by alternative factor models. For this purpose, we regress the returns of the (5−1) difference portfolio (consisting of going-long stocks with strong LTD and going-short stocks with weak LTD) on various sets of asset pricing factors recently proposed in the literature. Results are presented in Table 4.

First, we include the Pastor and Stambaugh (2003) traded liquidity risk factor in regression 1. In regression 2, we replace the Pastor and Stambaugh (2003) liquidity factor with the Sadka (2006) liquidity factor that is based on the permanent (variable) component of the price impact function. In regression 3 we include the Bali et al. (2017) FMAX factor to control for investors' demand for lottery-type stocks; in regression 4 we include the Baker and Wurgler (2006) sentiment index, orthogonalized with respect to a set of macroeconomic conditions; in regression 5 we include the Frazzini and Pedersen (2013) betting-against-beta factor; and in regression 6 the Kelly and Jiang (2014) long-short tail risk factor is included.[20] In regression 7 we replace the momentum factor with the Fama–French short- and long-term reversal factors. Finally, in regression 8 we control for exposures to the Hou et al. (2015) 4-factor model consisting of the market factor, a size factor, an investment factor, and a profitability factor. In each case, we document a statistically significant and economically meaningful positive regression alpha ranging from 0.22% up to 0.53% per month, showing that alternative factor model specifications cannot explain the return spread associated with LTD.

[19]We compute market volatility as the standard deviation of the CRSP value-weighted market return over the past 24 months. We classify month t as a period of high (low) market volatility if the standard deviation is above (below) the median standard deviation over the whole sample period from 1963 to 2012. As in Allen, Bali, and Tang (2012), we characterize months with CFNAI > 0 (CFNAI < 0) as months with high (low) economic activity.

[20]The lottery demand factor is provided by Turan Bali (http://faculty.msb.edu/tgb27/fmax.xlsx), the time series of the sentiment factor is taken from http://people.stern.nyu.edu/jwurgler/, the betting-against-beta factor is obtained from Andrea Frazzini's home page (https://www.aqr.com/library/data-sets), and the tail risk factor is constructed as the return series of a portfolio of going-long stocks with high tail risk beta and going-short stocks with low tail risk beta with monthly rebalancing.

TABLE 4
Trading Strategy: Alternative Factor Models

Table 4 shows regression results of the (5−1) difference portfolio returns (consisting of going-long stocks with strong lower-tail dependence (LTD) and going-short stocks with weak LTD) on various combinations of systematic risk factors from various asset pricing models. Regression 1 includes the factors of the Carhart (1997) model (MARKETRF, SMB, HML, UMD) plus the Pastor and Stambaugh (2003) traded liquidity risk factor (PS_LIQUI). In regression 2, the Pastor and Stambaugh (2003) liquidity factor is replaced by the Sadka (2006) liquidity factor (SADKA_TF). In regressions 3–6, we include the Bali, Brown, Murray, and Tang (2017) lottery demand factor (FMAX); the Baker and Wurgler (2006) sentiment index, orthogonalized with respect to a set of macroeconomic conditions (SENT_ORTH); the Frazzini and Pedersen (2013) betting-against-beta factor (BAB); and the Kelly and Jiang (2014) long–short tail risk factor (TAIL_RISK), respectively. In regression 7, we replace the Carhart (1997) momentum factor with the Fama–French short- and long-term reversal factors (REV_SHORT and REV_LONG). Finally, in regression 8, we control for exposures to the Hou, Xue, and Zhang (2015) 4-factor model. The alpha of the strategies is shown in the second-to-last row. The sample covers all U.S. common stocks traded on the NYSE/AMEX/NASDAQ, and the sample period is from Jan. 1963 to Dec. 2012. t-statistics are in parentheses and are computed using Newey and West (1987) standard errors with 4 monthly lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Trading Strategy							
	1	2	3	4	5	6	7	8
MARKETRF	0.127***	0.108***	0.096***	0.134***	0.137***	0.087***	0.094***	0.085***
	(6.09)	(3.75)	(4.09)	(6.31)	(6.81)	(5.05)	(4.54)	(3.47)
SMB	−0.092***	−0.196***	−0.112***	−0.066**	−0.066**	−0.062**	−0.026	−0.060
	(−3.13)	(−4.86)	(−3.45)	(−2.27)	(−2.39)	(−2.28)	(−0.77)	(−1.65)
HML	−0.203***	−0.289***	−0.153***	−0.185***	−0.131***	−0.138***	−0.141***	
	(−6.33)	(−6.62)	(−4.47)	(−5.75)	(−3.85)	(−4.21)	(−5.39)	
UMD	0.214***	0.239***	0.222***	0.221***	0.242***	0.213***		
	(10.46)	(9.12)	(11.18)	(10.75)	(11.89)	(8.43)		
PS_LIQUI	0.043*							
	(1.71)							
SADKA_TF		−0.722						
		(−1.25)						
FMAX			0.078***					
			(2.80)					
SENT_ORTH				−0.003***				
				(−3.19)				
BAB					−0.128***			
					(−4.45)			
TAIL_RISK						0.356***		
						(3.89)		
REV_SHORT							−0.023	
							(−0.77)	
REV_LONG							−0.119***	
							(−2.76)	
INVEST								−0.440***
								(−7.44)
ROE								0.135***
								(3.20)
alpha	0.0022**	0.0026**	0.0029***	0.0024**	0.0030***	0.0023**	0.0045***	0.0046***
	(2.35)	(2.06)	(3.29)	(2.56)	(3.39)	(2.03)	(4.88)	(4.11)
R^2	0.303	0.361	0.303	0.312	0.317	0.389	0.158	0.178

Overall, the findings from this section suggest that it is possible to create an abnormal future return spread based on information about LTD that is not explained by common asset pricing models.[21]

[21]However, these results are only indicative because we do not take into account any trading costs and other limits of arbitrage. Both are likely to be relevant here because our trading strategy requires frequent rebalancing and we short stocks with weak LTD (which tend to be small and low-β stocks; see Table 1).

2. Bivariate Sorts

Our univariate result of higher future risk-adjusted returns of strong-LTD stocks could be driven by differences in beta,[22] differences in downside beta, or differences with respect to other related return characteristics. Thus, as a next step, we conduct double-sorts based on LTD as well as regular beta, downside beta, coskewness, cokurtosis, and the tail risk beta proposed by Kelly and Jiang (2014).

We first form quintile portfolios sorted on β. Then, within each β quintile, we sort stocks into five portfolios based on LTD. Panel A of Table 5 reports value-weighted future monthly portfolio excess returns over the risk-free rate of the $\beta \times$ LTD portfolios. Within each β quintile, we find that the return of the strong-LTD portfolio is larger than the return of the weak-LTD portfolio. The return differences are all economically large and statistically significant at least at the 5% level. The average spread in excess returns amounts to 0.404% per month and is statistically significant at the 1% level.

LTD is also related to downside beta (β^-), which is defined by Ang et al. (2006) as the stock's β conditional on the market return being below its mean. Thus, in Panel B of Table 5 we report the value-weighted future monthly excess returns of $\beta^- \times$ LTD portfolios. We find that stocks in the weak-LTD portfolios have an average (across all β^- quintiles) future excess return of 0.204% per month, whereas stocks in the strong-LTD portfolios have an average future excess return of 0.619%. The spread is significant at the 1% level. Amounting to 0.415% per month (4.98% per annum), it is also economically large. Hence, the impact of LTD on returns is not driven by β^- either.[23]

Harvey and Siddique (2000) show that lower coskewness (COSKEW) is associated with higher expected returns, and Fang and Lai (1997) and Dittmar (2002) document that higher cokurtosis (COKURT) is associated with higher expected returns. Thus, in Panel C (D) of Table 5, we show value-weighted average future excess returns of COSKEW $\times$ LTD (COKURT $\times$ LTD) portfolios. We find that controlling for coskewness in Panel C slightly reduces the impact of LTD, whereas controlling for cokurtosis in Panel D does not reduce return spreads: LTD still remains a positive and statistically significant predictor of average future returns in both cases.

Finally, Kelly and Jiang (2014) find that stocks with a strong exposure to an aggregate tail risk factor (by applying the power-law estimator of Hill (1975) to the cross section of all daily stock returns in a given month) earn higher future average returns than stocks with a low exposure. Hence, in Panel E of Table 5, we directly control for the impact of the tail risk beta when evaluating the future average returns of LTD portfolios. In line with the results of Kelly and Jiang (2014), we find that the average future returns of the strong tail risk portfolios are higher than those of the weak tail risk portfolios. More importantly for our context,

[22]Although we already control for the linear beta exposure of our portfolios by looking at the CAPM alphas, we now also analyze dependent portfolio double-sorts on LTD and regular β, which allows us to also control for a possible nonlinear impact of β.

[23]We show later that our results also cannot be explained by alternative definitions of downside beta (see Section III.D.1).

TABLE 5
Dependent Bivariate Portfolio Sorts

Table 5 reports value-weighted future average returns and risk characteristics of 25 portfolios double-sorted on lower-tail dependence (LTD) and beta (Panel A), downside beta (Panel B), coskewness (Panel C), cokurtosis (Panel D), and the tail risk beta by Kelly and Jiang (2014) (Panel E), respectively. First, we form quintile portfolios based on 1-year beta, 1-year downside beta, 1-year coskewness, 1-year cokurtosis, and 120-month tail risk beta, respectively. Then, within each quintile, we sort stocks into five quintile portfolios based on their 1-year LTD. The last column shows the average of the future excess returns of the respective LTD quintile portfolios across all beta, downside beta, coskewness, cokurtosis, and tail risk beta quintiles, respectively. The row labeled "Strong – Weak" reports the difference between the future returns of portfolio 5 and portfolio 1 in each beta, downside beta, coskewness, cokurtosis, and tail risk beta quintile, respectively, with corresponding statistical significance levels. The sample covers all U.S. common stocks traded on the NYSE/AMEX/NASDAQ, and the sample period is from Jan. 1963 to Dec. 2012. t-statistics are in parentheses and are computed using Newey and West (1987) standard errors with 4 monthly lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Beta (β) and Lower-Tail Dependence (LTD)

	Low β				High β	
Portfolio	1	2	3	4	5	Average
1 Weak LTD	0.333%	0.342%	0.419%	0.105%	−0.024%	0.235%
2	0.356%	0.310%	0.431%	0.418%	0.041%	0.311%
3	0.512%	0.289%	0.467%	0.341%	0.219%	0.366%
4	0.410%	0.461%	0.489%	0.431%	0.451%	0.446%
5 Strong LTD	0.679%	0.557%	0.711%	0.634%	0.612%	0.639%
Strong – Weak	0.346%***	0.215%**	0.291%***	0.529%***	0.637%***	0.404%***
	(3.31)	(2.25)	(3.15)	(4.54)	(4.52)	(3.62)

Panel B. Downside Beta (β^-) and Lower-Tail Dependence (LTD)

	Low β^-				High β^-	
Portfolio	1	2	3	4	5	Average
1 Weak LTD	0.312%	0.253%	0.338%	0.132%	−0.017%	0.204%
2	0.291%	0.400%	0.510%	0.345%	0.210%	0.351%
3	0.357%	0.398%	0.451%	0.410%	0.410%	0.405%
4	0.463%	0.524%	0.461%	0.567%	0.601%	0.523%
5 Strong LTD	0.520%	0.678%	0.630%	0.730%	0.537%	0.619%
Strong – Weak	0.208%*	0.426%**	0.291%**	0.598%***	0.554%***	0.415%***
	(1.82)	(4.09)	(2.52)	(4.57)	(3.58)	(3.31)

Panel C. Coskewness (COSKEW) and Lower-Tail Dependence (LTD)

	Low COSKEW				High COSKEW	
Portfolio	1	2	3	4	5	Average
1 Weak LTD	0.421%	0.489%	0.535%	0.229%	0.184%	0.372%
2	0.561%	0.310%	0.562%	0.236%	0.104%	0.355%
3	0.510%	0.451%	0.530%	0.468%	0.247%	0.441%
4	0.612%	0.561%	0.618%	0.532%	0.341%	0.533%
5 Strong LTD	0.579%	0.730%	0.772%	0.615%	0.429%	0.625%
Strong – Weak	0.159%	0.241%*	0.236%*	0.386%***	0.245%*	0.253%*
	(1.17)	(1.86)	(1.79)	(2.80)	(1.85)	(1.89)

Panel D. Cokurtosis (COKURT) and Lower-Tail Dependence (LTD)

	Low COKURT				High COKURT	
Portfolio	1	2	3	4	5	Average
1 Weak LTD	0.244%	0.249%	0.341%	0.282%	0.262%	0.276%
2	0.412%	0.453%	0.610%	0.230%	0.120%	0.365%
3	0.567%	0.561%	0.450%	0.451%	0.356%	0.477%
4	0.619%	0.600%	0.510%	0.613%	0.561%	0.581%
5 Strong LTD	0.838%	0.838%	0.801%	0.821%	0.538%	0.767%
Strong – Weak	0.594%***	0.589%**	0.460%***	0.539%**	0.276%***	0.492%***
	(4.36)	(4.54)	(3.67)	(4.88)	(2.61)	(4.02)

Panel E. Tail Risk Beta (β_{TAIL}) and Lower-Tail Dependence (LTD)

	Low β_{tail}				High β_{tail}	
Portfolio	1	2	3	4	5	Average
1 Weak LTD	0.245%	0.255%	0.227%	0.380%	0.361%	0.294%
2	0.249%	0.372%	0.323%	0.444%	0.371%	0.352%
3	0.471%	0.360%	0.441%	0.449%	0.529%	0.450%
4	0.587%	0.597%	0.617%	0.673%	0.607%	0.616%
5 Strong LTD	0.496%	0.698%	0.693%	0.653%	0.682%	0.644%
Strong – Weak	0.251%**	0.443%***	0.466%***	0.273%*	0.321%**	0.351%***
	(2.24)	(3.54)	(4.51)	(1.85)	(2.03)	(2.75)

we document that controlling for tail risk only slightly reduces the impact of LTD. The average spread in excess returns amounts to 0.351% per month and is statistically significant at the 1% level. The impact of LTD is strongest among stocks with medium levels of tail risk beta. Thus, the impact of LTD obviously is different from the impact of Kelly and Jiang's (2014) tail risk beta, suggesting that their measure captures a dimension of tail risk exposure that is different from the one captured by our more direct dependence measure.

To summarize, based on bivariate portfolio sorts, we provide strong evidence that the risk associated with LTD is related but clearly different from risks associated with regular market beta, downside beta, coskewness, cokurtosis, and tail risk. Double-sorts offer the advantage that they allow us to control for any potential nonlinear impact. However, in double-sorts, we can only control for one return characteristic at a time. Thus, we now turn to a multivariate approach that allows us to examine the joint impact of different return and other characteristics of the firm that might have an impact on the cross section of average future stock returns.

B. Multivariate Evidence

We run Fama–MacBeth (1973) regressions at the individual firm level in the period from 1963 to 2012.[24] Table 6 presents the regression results of monthly future excess returns on realized LTD and various combinations of control variables in the first five columns.

In regression 1 of Table 6, we include LTD as the only explanatory variable. It has a positive and highly statistically significant impact with a coefficient estimate of 0.0123 (statistically significant at the 1% level). In regression 2, we add the stock's UTD coefficient. It shows a significantly negative impact on returns, but the economic magnitude is again much smaller than that of the impact of LTD. In the following regressions, we expand regression model 2 and add β, as well as other firm characteristics such as SIZE, BOOK_TO_MARKET, and several other return characteristics that might have an impact on returns.[25] Specifically, in regression 3, we add coskewness (COSKEW) and the Amihud (2002) illiquidity ratio (ILLIQ) as a liquidity proxy, whereas regression 4 additionally includes previous-year returns; idiosyncratic return volatility; cokurtosis of individual returns with the market return; a stock's lottery features captured by the maximum daily return over the past year; MAX, similar to that of Bali et al. (2011), and the Kelly and Jiang (2014) tail risk beta. Results show that the impact of LTD on future returns is stable and is even slightly increasing in statistical and economic terms after the inclusion of the control variables. LTD exhibits one of the strongest influences of all variables in terms of statistical power (t-statistics of 4.85 and 4.21, respectively).

[24]This econometric procedure has the disadvantage that risk factors are estimated less precisely in comparison to using portfolios as test assets. However, Ang, Liu, and Schwarz (2017) show that creating portfolios leads to smaller standard errors of risk factor estimates but does *not* lead to smaller standard errors of cross-sectional coefficient estimates.

[25]We winsorize all realizations of our independent variables at the 1% and 99% levels to avoid outliers driving our results. Our results do not hinge on this winsorization (see Section III.D.4).

TABLE 6

Multivariate Regression Results

Table 6 presents the results of multivariate Fama–MacBeth (1973) regressions of future excess returns over the risk-free rate in month $t+1$ (columns 1–5), month $t+2$ (column 6), and month $t+3$ (column 7) on lower-tail dependence (LTD), upper-tail dependence (UTD), downside beta (β^-), upside beta (β^+), beta (β), the natural log of market capitalization (SIZE), the book-to-market ratio (BOOK_TO_MARKET), coskewness (COSKEW), the Amihud illiquidity ratio (ILLIQ), the past 12-month excess returns (PAST_RETURN), idiosyncratic volatility (IDIO_VOLA), cokurtosis (COKURT), the maximum daily return over the past 1 year (MAX), and the Kelly and Jiang (2014) tail risk beta (β_{TAIL}). All risk characteristics (LTD, UTD, β^-, β^+, β, COSKEW, IDIO_VOLA, COKURT, β_{TAIL}), as well as SIZE, BOOK_TO_MARKET, and ILLIQ, are calculated based on data until month t. The last column displays the change in annualized excess returns for a 1-standard-deviation increase in the respective independent variable based on regression 5. The independent variables are winsorized at the 1% level and at the 99% level. The sample covers all U.S. common stocks traded on the NYSE/AMEX/NASDAQ, and the sample period is from Jan. 1963 to Dec. 2012. t-statistics are reported in parentheses and are computed using Newey and West (1987) standard errors with 4 monthly lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	RETURN$_{t+1}$	RETURN$_{t+1}$	RETURN$_{t+1}$	RETURN$_{t+1}$	RETURN$_{t+1}$	RETURN$_{t+2}$	RETURN$_{t+3}$	Annualized Economic Significance Based on Regression 5
	1	2	3	4	5	6	7	
LTD	0.0123***	0.0127***	0.0170***	0.0153***	0.0142***	0.0182***	0.0162***	+2.60%
	(2.63)	(2.78)	(5.15)	(4.29)	(4.41)	(3.39)	(3.22)	
UTD		−0.00815**	0.00291	0.00223	0.00311	0.00403	0.00592	+0.22%
		(−2.14)	(1.26)	(1.03)	(1.14)	(1.41)	(1.34)	
β^-					−0.00212	−0.00302	−0.00403	−1.44%
					(−1.23)	(−1.21)	(−1.23)	
β^+					0.000344	0.000699	0.000300	+0.34%
					(0.39)	(0.75)	(0.21)	
β			−0.000373	−0.00227				
			(−0.21)	(−1.12)				
SIZE			−0.000190	−0.000478*	−0.000499*	−0.000711*	−0.00106*	−1.56%
			(−0.42)	(−1.81)	(−1.76)	(−1.75)	(−1.90)	
BOOK_TO_MARKET			0.00987***	0.0101***	0.0112***	0.0209***	0.0276***	+6.12%
			(4.90)	(5.32)	(5.67)	(5.88)	(6.01)	
COSKEW			0.0000173	0.00212	−0.00567*	−0.0145***	−0.0201***	−2.11%
			(0.01)	(1.22)	(−1.87)	(−3.50)	(−4.12)	

(continued on next page)

TABLE 6 (continued)

Multivariate Regression Results

	$RETURN_{t+1}$ 1	$RETURN_{t+1}$ 2	$RETURN_{t+1}$ 3	$RETURN_{t+1}$ 4	$RETURN_{t+1}$ 5	$RETURN_{t+2}$ 6	$RETURN_{t+3}$ 7	Annualized Economic Significance Based on Regression 5
ILLIQ			0.000567***	0.000568***	0.000502***	0.00143***	0.00176***	+4.78%
			(5.03)	(4.88)	(4.56)	(5.78)	(6.89)	
PAST_RETURN				0.00678***	0.00721***	0.0135***	0.0201***	+6.12%
				(5.67)	(6.21)	(6.12)	(6.67)	
IDIO_VOLA				0.012	0.0109	−0.00844	0.00410	+0.18%
				(0.03)	(0.21)	(−0.17)	(0.10)	
COKURT				0.00179***	0.00141**	0.00287**	0.00423**	+2.42%
				(2.87)	(2.19)	(2.90)	(3.11)	
MAX				−0.0113***	−0.0123***	−0.0298***	−0.0389***	−2.08%
				(−2.89)	(−2.78)	(−4.45)	(−5.15)	
β_{TAIL}				0.095	0.103	0.230	0.368*	+1.62%
				(0.70)	(0.63)	(1.21)	(1.87)	
Constant	0.00574***	0.00625***	−0.00192	−0.000311	−0.000289	−0.000645	0.000932	
	(2.53)	(2.72)	(−0.30)	(−0.16)	(−0.09)	(−0.07)	(0.15)	
R^2	0.004	0.006	0.054	0.072	0.071	0.083	0.089	

Several of the control variables also have a significant impact on returns that confirm findings from the existing literature: Firm size (book-to-market ratio) has a negative (positive) impact (e.g., Fama and French (1993)), illiquidity (Amihud (2002)) and cokurtosis (Fang and Lai (1997), Dittmar (2002)) have a positive impact, whereas MAX (Bali et al. (2011)) has a negative impact. We do not find a consistent statistically significant influence of coskewness (Harvey and Siddique (2000)) and idiosyncratic volatility (Ang et al. (2006), (2009)). Our results are thus in line with Bali et al. (2011), who document that the inclusion of the MAX variable drives out the impact of idiosyncratic volatility when predicting future stock returns. Moreover, our findings are similar to Bali and Cakici (2008), who show that the cross-sectional relation between idiosyncratic risk and future stock returns is sensitive to the choice of stock samples and time periods.

In regression 5 of Table 6 we replace β by β^- and β^+, and in regressions 6 and 7, we use 2-month-ahead and 3-month-ahead returns as the independent variable, respectively. In all cases, our earlier findings are confirmed: There is a very strong positive impact of LTD on average future returns, and the t-statistic for the impact of LTD is always above 3. For longer-period returns, we find slightly weaker effects that confirm similar findings from the portfolio sorts in Panel C of Table 3. This pattern again shows that LTD is time-varying and highlights the advantage of our approach to use frequently updated LTD estimates. Interestingly, including downside beta in our regressions also does not reduce the impact of LTD, showing that the measures capture distinctively different aspects of the dependence structure. As in Kelly and Jiang (2014), we report a positive association between their tail risk beta and future returns in all specifications; however, after controlling for the impact of LTD, this relationship turns out to be statistically significant only in the specification with 3-month-ahead returns as the independent variable.

The last column of Table 6 presents the economic significance based on a 1-standard-deviation change in each explanatory variable based on the results from regression 5: A 1-standard-deviation increase in LTD leads to an economically meaningful increase in future returns of 2.60% per annum. This is the fourth-largest effect in terms of economic magnitude of all dependent variables after well-known predictors such as PAST_RETURN (+6.12%), BOOK_TO_MARKET (+6.12%), and ILLIQ (+4.78%), but it is still larger than the return effects of higher-order co-moments (COSKEW: −2.11%; COKURT: +2.42%) and the tail risk beta β_{TAIL} (+1.62%).

C. Time-Varying Crash Fears of Investors

In the option pricing literature, it is sometimes argued that investors became crash-o-phobic after the experience of the 1987 crash (Rubinstein (1994), Bates (2000)).[26] Furthermore, Chen et al. (2012) argue that the risk premium for disaster risk is typically small, but it increases substantially after a disaster (because then the wealth share of pessimists rises). In a similar vein, Gennaioli et al. (2015)

[26]However, this finding is not without any doubt, as studies that find no strong "crash-fear" effect prior to 1987 typically rely on very short pre-1987 samples, due to the lack of option data availability for earlier years.

propose a theoretical model where investors overstate the fear of a future market crash when they can remember the occurrence of a black swan event.

Thus, to check whether the occurrence of a financial crisis increases the LTD premium, we split our data set into two subsamples: The "post–market crash" subsample containing the 5 years after an extreme market downturn has occurred and the "remaining years" subsample.[27] Table 7 repeats regression 5 from Table 6 for both subsamples.

TABLE 7

Time-Varying Crash Fears of Investors

Table 7 presents the results of multivariate Fama–MacBeth (1973) regressions of monthly future excess returns over the risk-free rate on lower-tail dependence (LTD) and other control variables as in regression 5 of Table 6. We provide results for two subsamples: the "Post–Market Crash" subsample containing the 5 subsequent years after an extreme market downturn has occurred and the "Remaining Years" subsample. We define "extreme market downturns" as the 10 worst market return days in our sample. Such extreme market downturns occurred in 1987, 1997, 1998, 2000, 2008, and 2011. The sample covers all U.S. common stocks traded on the NYSE/AMEX/NASDAQ, and the sample period is from Jan. 1963 to Dec. 2012. *t*-statistics are in parentheses and are computed using Newey and West (1987) standard errors with 4 monthly lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Post–Market Crash	Remaining Years
LTD	0.0241***	0.0132***
	(3.65)	(4.52)
UTD	0.00521	0.00298
	(1.60)	(1.35)
β^-	−0.00265	−0.00231
	(−1.31)	(−1.41)
β^+	0.000610	0.0000911
	(0.31)	(0.24)
SIZE	−0.00123**	−0.000300
	(−2.16)	(−0.75)
BOOK_TO_MARKET	0.0103***	0.0096***
	(5.12)	(5.76)
COSKEW	−0.00701	−0.00445
	(−1.15)	(−1.23)
ILLIQ	0.0000354	0.00071
	(0.65)	(5.78)
PAST_RETURN	0.00221	0.00721***
	(1.56)	(6.01)
IDIO_VOLA	0.156**	−0.0911
	(2.01)	(−1.02)
COKURT	0.00134	0.00147*
	(1.21)	(1.70)
MAX	−0.0234**	−0.0101**
	(−2.31)	(−2.01)
β_{TAIL}	0.124	−0.054
	(1.21)	(−0.45)
Constant	0.00522	−0.00103
	(1.02)	(−0.41)
R^2	0.054	0.077

Our findings indicate that the impact of LTD on returns is indeed much stronger in years subsequent to a market crash. The impact of LTD on returns is almost twice as high in the "post–market crash" subsample (with a coefficient for the impact of LTD of 0.0241 in contrast to a coefficient of 0.0132 for the remaining years). Overall, this result implies that investors care about the crash

[27] As in Section II.C, we define "extreme market downturns" as the 10 worst return days in our sample. These "extreme market downturns" occurred in 1987, 1997, 1998, 2000, 2008, and 2011.

sensitivity of stocks and require a high premium for taking that risk, in particular when a market crash has occurred in the recent past.

D. Robustness

In this section we summarize the results from a battery of additional robustness tests. We investigate whether our results hold when we control for downside beta defined in alternative ways (Section III.D.1), examine alternative estimation procedures of tail dependence coefficients (Section III.D.2), analyze the relationship between returns and LTD at the industry level (Section III.D.3), and summarize results from additional analyses and a battery of stability checks (Section III.D.4).

1. Alternative Downside Beta Definitions versus LTD

The results in Panel B of Table 5 show that our findings are not driven by the downside beta (β^-) as defined by Ang et al. (2006). Although the concepts of LTD and β^- seem related, this result is actually not surprising because the latter focuses on all market returns below the mean, whereas the former explicitly focuses on extreme events. However, one could argue that alternative definitions of β^- that focus more on the left tail of the market return distribution capture effects more similar to LTD. Hence, to analyze this idea more closely, we repeat our $\beta^- \times$ LTD double-sorts from Table 5 for alternative β^- definitions. Specifically, and similar to Bali et al. (2014), we calculate downside betas as betas conditional on the market return being below its 10%, 5%, 2%, and 1% quantiles, respectively (rather than being below the mean, as before and as in Ang et al. (2006)).

Moreover, Post et al. (2012) and Artavanis (2014) argue that the downside beta estimation framework of Ang et al. (2006) is not in line with economic principles and leads to violations of conditions for coherent risk measures. Thus, we also compute the alternative downside betas investigated in their articles, that is, the Hogan and Warren (1974) downside beta (β^-_{HW}), the Estrada (2004) downside beta (β^-_{EST}), and the asymmetric response beta (β^-_{AR}) of Harlow and Rao (1989). We calculate these alternative downside betas based on their original definitions (see the variable definitions in Appendix B), as well as for a more restrictive cutoff conditional on the daily market return being below its 10% quantile in the respective year. Table 8 shows the results.

We report results on the returns of the strong-minus-weak-LTD portfolios within each downside beta quintile in the first five columns, as well as the average of this difference portfolio return across all downside beta quintiles in the last column (as in the last row of Panel B in Table 5) for all alternative β^- definitions. The average monthly difference return ranges from 0.40% (for the β^- definition based on the 10% quantile) up to 0.55% (for the β^-_{EST} definition based on the 10% quantile) and is significant at the 1% level in each case.

Thus, our results on the impact of LTD not only hold after adjusting for various β^- alternatives, they frequently get stronger if we look at more restrictive β^- definitions. At first glance, this pattern might seem unexpected, as more restrictive betas (that focus more on extremely bad market returns) should be more closely related to our LTD measure. However, the reason we find even stronger results for LTD if we use alternative β^-s with low cutoffs is that they are actually not able

TABLE 8

Dependent Portfolio Sorts: Downside Beta Variants versus LTD

Table 8 reports results of value-weighted portfolios double-sorted on lower-tail dependence (LTD) and different alternative definitions of downside betas. First, we form quintile portfolios sorted on downside beta, and then, within each of those quintiles, we sort stocks into quintile portfolios based on LTD. As alternative downside beta definitions, we calculate downside betas as betas conditional on the market return being below its 10%, 5%, 2%, and 1% quantiles. Furthermore, we report results from double-sorts based on the Hogan and Warren (1974) downside beta (β^-_{HW}), the Estrada (2004) downside beta (β^-_{EST}), and the asymmetric response beta (β^-_{AR}) of Harlow and Rao (1989). We only report results on the future monthly returns of the strong-minus-weak-LTD portfolios within each downside beta quintile in the first five columns, as well as the average of this future difference portfolio return across all downside beta quintiles in the last column (as in the last row of Panel B in Table 5) for all alternative downside beta definitions. The sample covers all U.S. common stocks traded on the NYSE/AMEX/NASDAQ, and the sample period is from Jan. 1963 to Dec. 2012. t-statistics are in parentheses and are computed using Newey and West (1987) standard errors with 4 monthly lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Downside Beta	Cutoff	LTD Portfolio	Low β^- 1	2	3	4	High β^- 5	Average
β^-	$r_m < \mu_m$	Strong – Weak	0.21%* (1.82)	0.43%*** (4.09)	0.29%*** (2.52)	0.59%*** (4.57)	0.55%*** (3.58)	0.42%*** (3.31)
β^-	10% Quantile	Strong – Weak	0.47%*** (2.94)	0.17% (1.36)	0.34%*** (2.92)	0.55%*** (4.26)	0.48%*** (2.77)	0.40%*** (2.85)
β^-	5% Quantile	Strong – Weak	0.45%*** (2.78)	0.12% (1.02)	0.38%*** (2.82)	0.60%*** (4.32)	0.51%*** (3.56)	0.41%*** (2.93)
β^-	2% Quantile	Strong – Weak	0.49%*** (3.02)	0.31% (1.59)	0.39%*** (3.22)	0.51%*** (3.95)	0.55%*** (3.31)	0.45%*** (3.04)
β^-	1% Quantile	Strong – Weak	0.51%*** (3.23)	0.25% (1.40)	0.43%*** (3.76)	0.63%*** (4.98)	0.52%*** (3.57)	0.47%*** (3.57)
β^-_{HW}	$r_m < \mu_m$	Strong – Weak	0.40%*** (3.41)	0.25%** (2.10)	0.39%*** (3.98)	0.45%*** (3.56)	0.65%*** (4.16)	0.43%*** (3.50)
β^-_{HW}	10% Quantile	Strong – Weak	0.34%*** (2.95)	0.28%** (2.18)	0.48%*** (4.20)	0.49%*** (3.87)	0.65%*** (4.04)	0.45%*** (3.55)
β^-_{EST}	$r_m < \mu_m$	Strong – Weak	0.28%*** (2.91)	0.40%*** (3.57)	0.35%** (2.36)	0.61%*** (3.77)	1.07%*** (6.11)	0.54%*** (3.82)
β^-_{EST}	10% Quantile	Strong – Weak	0.25%** (2.29)	0.33%*** (2.66)	0.72%*** (4.96)	0.40%** (2.35)	1.08%*** (6.60)	0.55%*** (3.71)
β^-_{AR}	$r_m < \mu_m$	Strong – Weak	0.30%*** (2.87)	0.28%*** (2.80)	0.35%*** (3.50)	0.51%*** (4.26)	0.59%*** (4.07)	0.41%*** (3.26)
β^-_{AR}	10% Quantile	Strong – Weak	0.24%** (2.08)	0.37%*** (3.58)	0.47%*** (4.10)	0.49%*** (3.90)	0.55%*** (3.57)	0.42%*** (3.51)

to reliably capture dependence in the tails because they are estimated based on a very small number of observations (e.g., only about 12 daily return observations per year for the 5% quintile β^-) and are thus very noisy.[28]

These results also illustrate the advantage of the copula approach in estimating extreme dependence: In estimating the whole dependence structure between individual and market returns using our semi-parametric approach, we make use of all available daily return observations within a year, which allows for a relatively more precise estimation of the dependence structure. Thus, the computation of LTD as described in Section II.A is much less noisy and more informative about the true crash sensitivity of a stock.

2. Alternative Tail Dependence Estimation Procedures

We now investigate whether our results are sensitive to alternative tail dependence estimation procedures. First, instead of selecting the appropriate parametric copula by minimizing the distance between 64 different convex

[28]Correlations between the β^- alternatives and LTD actually decrease from 0.42 for the standard Ang et al. (2006) downside beta, to 0.24, 0.13, 0.04, and 0.00, respectively, for the correlation between LTD and β^- based on the 10%, 5%, 2%, and 1% quintiles.

copula combinations and the empirical copula, we ex ante choose various fixed convex copula combinations. As our ad hoc fixed copula combinations, we consider the Clayton–Gauss–Galambos copula, the Clayton–Gauss–rotated Clayton copula, the rotated Galambos–Gauss–rotated Clayton copula, the rotated Gumbel–Frank–Gumbel copula, the rotated Gumbel–FGM–Gumbel copula, and the rotated Gumbel–Frank–Joe copula. The first (latter) three are the copula combinations most (least) often selected in the estimation procedure (see Table IA.III in the Internet Appendix). We perform Fama–MacBeth (1973) regressions of excess returns on LTD (estimated based on the fixed copula combinations) as well as the full set of control variables (as in regression 5 of Table 6). Results on the coefficient estimates for the influence of LTD are displayed in the first six lines in Panel A of Table 9.

TABLE 9

Alternative Tail Dependence Estimation Procedures and Test Assets

Panel A of Table 9 shows results for the lower-tail dependence (LTD) estimate from Fama–MacBeth (1973) regressions of monthly future excess returns over the risk-free rate on LTD and the full set of controls as in regression 5 from Table 6 (included in the regression, but coefficient estimates suppressed in the table) in the first three columns. LTD coefficients are calculated based on the Clayton–Gauss–Galambos (1-A-III) copula, the Clayton–Gauss–rotated Clayton (1-A-IV) copula, the rotated Galambos–Gauss–rotated Clayton (4-A-IV) copula, the rotated Gumbel–Frank–Gumbel (2-B-II) copula, the rotated Gumbel–FGM–Gumbel (2-D-II) copula, and the rotated Gumbel–Frank–Joe (2-B-I) copula (first six rows). In the last four rows, we present results where we estimate LTD based on a convex combination of two copulas (2Cop), when we use estimated log-likelihood values instead of integrated Anderson–Darling distances when selecting the best copula combination (MLE), and when we estimate LTD based on a rolling window of 24 months and 36 months, respectively. Panel B reports results from univariate portfolio sorts based on LTD estimated from the Fama and French 49-industry portfolios. In each month, we rank industries into quintiles (1–5) and form equal-weighted portfolios based on the respective tail dependence measure. The column labeled "Return" reports the future average monthly return in excess of the 1-month T-bill rate of the portfolios. The column labeled "CAPM Alpha" ("CAR Alpha," "FF5 Alpha") reports the future average monthly alpha with regard to the Sharpe (1964) capital asset pricing model (CAPM) (Carhart (1997) 4-factor model, Fama and French (2015) 5-factor model). The row labeled "Strong – Weak" reports the difference between the returns of portfolio 5 and portfolio 1, with corresponding statistical significance levels. The sample covers all U.S. common stocks (and industries) traded on the NYSE/AMEX/NASDAQ, and the sample period is from Jan. 1963 to Dec. 2012 (dependent on the data availability of industry returns). *t*-statistics are in parentheses and are computed using Newey and West (1987) standard errors with 4 monthly lags. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Alternative Tail Dependence Estimation Procedures

Estimation Procedure	LTD (*t*-Statistic)	R^2	Economic Significance
1-A-III	0.0128*** (3.67)	0.071	+2.37%
1-A-IV	0.0112*** (2.89)	0.071	+2.09%
4-A-IV	0.0129*** (3.71)	0.071	+2.27%
2-B-II	0.0091* (1.75)	0.070	+1.84%
2-D-II	0.0111** (2.45)	0.071	+2.07%
2-B-I	0.0100** (2.17)	0.071	+1.95%
2Cop	0.0089* (1.80)	0.071	+1.79%
MLE	0.0131*** (4.02)	0.071	+2.55%
24 months	0.0110*** (3.21)	0.072	+2.08%
36 months	0.0106** (2.31)	0.070	+2.01%

(continued on next page)

TABLE 9 (continued)
Alternative Tail Dependence Estimation Procedures and Test Assets

Panel B. Results Using Fama–French 49 Industries as Test Assets

Portfolio	LTD	Return	CAPM Alpha	CAR Alpha	FF5 Alpha
1 Weak LTD	0.00	0.311%	−0.105%	−0.088%	−0.126%*
2	0.05	0.432%	+0.003%	+0.010%	−0.003%
3	0.10	0.411%	−0.021%	−0.006%	−0.051%
4	0.19	0.528%	+0.056%	+0.078%	+0.043%
5 Strong LTD	0.34	0.644%	+0.133%*	+0.124%*	+0.226%
Strong – Weak	0.34***	0.333**%	+0.238%*	+0.212%*	+0.352%**
		(2.41)	(1.82)	(1.77)	(2.36)

Second, we present results for LTD estimated using a convex combination of only two copulas (2Cop); one that allows for asymptotic dependence in the lower tail, C_{LTD}; and one copula that allows for asymptotic dependence in the upper tail, C_{UTD}:

$$C_{\text{2Cop}}(u_1,u_2,\Theta) \quad = \quad w_1 \times C_{\text{LTD}}(u_1,u_2;\theta_1)+(1-w_1)\times C_{\text{UTD}}(u_1,u_2;\theta_2),$$

with $0 \leq w_1 \leq 1$.[29]

Third, we show results for LTD when we use estimated log-likelihood values instead of integrated Anderson–Darling distances when selecting the best copula combination. Finally, we report results where we estimate LTD based on a 24-month and 36-month estimation horizon (instead of our standard 12-month horizon), respectively. Results are shown in the last three rows in Panel A of Table 9.

We find that LTD remains a significantly positive explanatory factor for the cross section of average future stocks returns in all cases and remains stable across different specifications. Nevertheless, the slightly weaker results for estimation procedures based on a fixed copula and a combination of only two copulas show that there is additional value in carefully fitting the dependence structure and that our highly flexible 3-copula approach seems to be the most appropriate in our setting. Furthermore, the fact that we find somewhat weaker results based on 2- and 3-year estimation horizons is due to the fact that LTD is time-varying and supports our approach of using relatively short estimation windows for LTD.

3. Alternative Test Assets

Our univariate portfolio sorts in Section III.A.1 were performed on the basis of individual stocks. We now investigate whether our main result of a significant relationship between LTD and future returns is stable when we analyze the Fama and French 49 industries, instead of individual stocks, as tests assets: For each month t, we sort industries into five quintile portfolios based on their LTD estimated over the previous 12 months.[30] Panel B of Table 9 reports the results of equal-weighted sorts based on LTD.

We obtain slightly weaker but still statistically and economically significant results as compared with those obtained by individual assets, but they are still

[29] As in Section II.A.2, the estimation of LTD is based on the estimated parameter Θ^* of the copula $C^*_{\text{2Cop}}(u_1,u_2,\Theta)$, which minimizes the integrated Anderson–Darling distance.

[30] To simplify the estimation procedure, we rely on the results of Section II.D.2 and choose the Clayton–Gauss–Galambos copula as our fixed convex copula combination.

statistically and economically significant: Industries with strong LTD earn significantly higher average future returns than industries with weak LTD. The monthly return spread between quintile portfolios 5 and 1 is 0.333% (4.00% per annum), which is statistically significant at the 5% level. Similarly, the CAPM alpha (4-factor alpha, 5-factor alpha) of the difference portfolio is economically meaningful, amounting to 0.238% (0.212%, 0.352%) per month, and is always statistically significant at least at the 10% level. Hence, our results are robust if we use industry portfolios instead of individual stocks as test assets.

4. Temporal Stability and Additional Robustness Tests

In this section we shortly summarize the results from a large number of additional analyses and stability checks that we conduct to analyze whether our main results from Sections III.A and III.B are stable. All results tables mentioned in this section are presented in the Internet Appendix.

First, we show that the results from value-weighted univariate sorts and multivariate regressions are stable over time (Table IA.VIII). Strong-LTD stocks have higher average future returns than weak-LTD stocks in every 10-year subperiod between 1963 and 2012 as well as in the earlier period, from 1927 to 1963. The differences are statistically significant in three out of six periods for the portfolio sorts and in five out of six periods for the multivariate regressions.

Second, we show that our main results from the Fama and MacBeth (1973) regressions are robust if we adjust raw returns based on the Fama–French 12 and 48 or Standard Industrial Classification (SIC) 2-digit, 3-digit, and 4-digit industry classifications (left side of Table IA.IX) as well as for return adjustments based on the 125 Daniel, Grinblatt, Titman, and Wermers (1997) characteristic-based benchmarks (right side of Table IA.IX). Our multivariate results also obtain if i) we do not use Newey–West standard errors in the second stage of the Fama–MacBeth (1973) regressions to determine statistical significance, ii) we do not winsorize the independent variables, iii) we perform a pooled ordinary least squares (OLS) regression with time-fixed effects and standard errors clustered by stock, and iv) we run a pooled OLS regression with time-fixed effects and standard errors clustered by industry.

Third, a possible concern for our analysis is that time-varying volatility impacts the estimation of LTD coefficients. To account for the time-varying volatility of stock returns, we fit different volatility time-series models to the daily individual stock returns and the market return. We can show that our results are stable if we account for time-varying volatility by first filtering daily return time series using an ARCH(1) model, an GARCH(1,1) model, or an EGARCH(1,1) model before using them in our LTD computation. The impact of LTD estimated from time-series residuals is very similar to the impact from LTD estimated using the actual return series (Table IA.X).

Finally, we repeat our univariate and bivariate portfolio sorts based on equal-weighted returns instead of value-weighted returns (Table IA.XI). We find that an equal-weighted portfolio formation typically leads to a stronger impact compared with a value-weighted portfolio formation. We again confirm our earlier findings of a statistically and economically important impact of LTD on average future stock returns.

IV. Conclusion

The cross section of expected stock returns reflects a premium for crash sensitivity as measured by a stock return's lower-tail dependence, LTD, with the market return. Stocks that are characterized by strong LTD earn significantly higher average future returns than stocks with weak LTD. A value-weighted (equal-weighted) portfolio consisting of stocks with the strongest LTD delivers higher average future returns of 4.3% (4.8%) per annum than a portfolio of stocks with the weakest LTD. The high average returns earned by strong-LTD stocks are not explained by alternative cross-sectional effects, including market beta, size, book-to-market ratio, momentum, liquidity, coskewness, cokurtosis, idiosyncratic volatility, downside beta, and Kelly and Jiang's (2014) tail risk beta. Because stocks with weak LTD essentially offer insurance against extreme negative portfolio returns, our results are consistent with the view that investors are willing to pay higher prices and eventually accept lower returns for such stocks.

Appendix A. Theoretical Motivation

This section motivates our empirical approach theoretically. Specifically, we show that copula-based tail dependence coefficients determine discount rates in asset pricing models. We consider a simple theoretical model for illustration in which the representative agent with utility function $u[\cdot]$ maximizes her expected utility under standard regularity conditions. Besides these regularity conditions, we do not make any assumptions about the specific form of the utility function. Thus, our model's results hold for a wide class of possible preferences (e.g., constant relative risk aversion (CRRA) preferences). We use the stochastic discount factor (SDF) implied from this simple model to show that tail-based co-moment risks determine the risk premium on risky assets. We then show that LTD and UTD are related to tail-based co-moment risks, implying that lower and upper dependence measures determine the risk premium on risky assets.

Regularity Conditions. We assume $u^{'}[\cdot]>0$, $u^{''}[\cdot]<0$, $u^{'''}[\cdot]>0$, and $u^{''''}[\cdot]<0$. Arrow (1965) and Pratt (1964) show that the representative investor's utility function exhibits nonsatiation ($u^{'}[\cdot]>0$), risk aversion ($u^{''}[\cdot]<0$), and a decreasing absolute risk aversion $\left(u^{'''}[\cdot]>0\right)$. The restriction on the third derivative of the utility function is related to the concept of prudence in Kimball (1990), (1993). Kimball (1990) shows that the concept of prudence is analogous to the precautionary-saving motive. He shows that absolute prudence must be a decreasing function of the representative investor's wealth. A decreasing absolute prudence and a concave utility restrict the sign of the kurtosis preference to $u^{''''}[\cdot]<0$. The restriction on the fourth derivative of the utility function is also defined as "temperance" by Eeckhoudt and Schlesinger (2006).

Several articles (Harvey and Siddique (2000), Dittmar (2002), Chabi-Yo (2012), Vanden (2006), among others) have shown that Kimball's concept of prudence plays a key role in determining the price of risk of higher co-moments, such as co-skewness, and higher moments, such as skewness. We will show that the same concept plays a key role in determining the price of risk of tail dependence measures.

A Simple Investor's Problem. Consider a 1-period $[t, t+1]$ economy with $t=0$. In this economy, we assume that there are n risky assets and one risk-free asset. Denote by $R_{f,t}$ the return on the risk-free asset and by R_{t+1} a vector of returns of risky assets. Without loss of generality, the representative investor has an endowed wealth of $W_t=1$ at time t.

She maximizes her expected utility

$$\text{(A-1)} \qquad \max_{\omega} E_t\left(u\left[W_{t+1}\right]\right)$$

subject to the budget constraint

$$\text{(A-2)} \qquad W_{t+1} = W_t\left(R_{f,t} + \omega'\left(R_{t+1} - R_{f,t}\right)\right),$$

where W_{t+1} is the investor's terminal wealth, and ω is a vector of portfolio weights.

Stochastic Discount Factor. The Euler equation derived from the first-order conditions of equation (A-1) is used to show that the SDF has the form

$$\text{(A-3)} \qquad M_{t+1} = \frac{u'\left[W_{t+1}^*\right]}{R_{f,t} E_t\left(u'\left[W_{t+1}^*\right]\right)},$$

where $W_{t+1}^* = W_t\left(R_{f,t} + \omega^{*'}\left(R_{t+1} - R_{f,t}\right)\right)$, and ω^* is the optimal portfolio weight with $\omega^{*'}\mathbf{1} = 1$. Here, $\mathbf{1}$ is a unity vector. Because $W_t = 1$, $W_{t+1}^*/W_t = \omega^{*'}R_{t+1}$ can be interpreted as the return on aggregate wealth. Using the market return $R_{M,t+1}$ as a proxy for the return on aggregate wealth, $R_{M,t+1} = W_{t+1}^*/W_t$.

We denote by S_{t+1} the price of the market index at time $t+1$ and express the market return as $R_{M,t+1} = S_{t+1}/S_t$. We can, therefore, express the SDF in equation (A-3) as

$$\text{(A-4)} \qquad M_{t+1} = \frac{1}{R_{f,t}} \frac{u'\left[S_{t+1}/S_t\right]}{E_t\left(u'\left[S_{t+1}/S_t\right]\right)}.$$

We now state the following lemma, which is from Carr and Madan (2001):

Lemma 1. Carr and Madan ((2001), eq. (1), p. 23): Any twice-differentiable payoff function with bounded expectation can be spanned by a continuum of on-the-money (OTM) European calls and puts. In other words, a collection of twice-differentiable functions $H[S]$ can be spanned algebraically as[31]

$$H[S] = H\left[\overline{S}\right] + \left(S - \overline{S}\right) H_S\left[\overline{S}\right] + \int_{\overline{S}}^{\infty} H_{SS}[K](S-K)^+ dK + \int_0^{\overline{S}} H_{SS}[K](K-S)^+ dK,$$

where $H_S[\cdot]$ ($H_{SS}[\cdot]$) represents the first-order (second-order) derivative of the payoff function $H[\cdot]$ evaluated at $\overline{S}$.

We exploit Lemma 1 and show in Theorem 1 that the SDF is a linear combination of the market return and a collection of payoffs on call and put options. As will be seen shortly, Theorem 1 plays a key role in showing that the tail dependence measures determine the discount rate.

Theorem 1. Assume that the first, second, third, and fourth derivatives of the utility function exist; then Lemma 1 can be used to express the SDF in equation (A-4) as

$$\text{(A-5)} \qquad \begin{aligned} M_{t+1} = {} & \frac{u'[1]}{u'[a]} \frac{1}{R_{f,t}} + \left(R_{M,t+1} - 1\right) \frac{u''[1]}{u'[a]} \frac{1}{R_{f,t}} \\ & + \int_1^{k_{\max}} \frac{u'''[k]}{u'[a]} \frac{1}{R_{f,t}} \left(R_{M,t+1} - k\right)^+ dk + \int_0^1 \frac{u'''[k]}{u'[a]} \frac{1}{R_{f,t}} \left(k - R_{M,t+1}\right)^+ dk, \end{aligned}$$

[31]Bakshi and Madan ((2000), Theorem 1, p. 212) and Bakshi, Kapadia, and Madan ((2003), Theorem 1, p. 107) use Lemma 1 to provide economic foundations for valuing derivative securities and study new insights into the economic sources of skewness.

where $k = \frac{K}{S_t}$, $k_{\max}$ is the maximum value of the gross return (whose distribution we assume to have bounded support); $a = u'^{-1}\left[E_t\left(u'[S_{t+1}/S_t]\right)\right]$; and u'^{-1} is the inverse function of u'.[32]

Proof. See the Internet Appendix.

Expected Excess Return Decomposition. For the sake of simplicity, we drop the time-subscript t and use the SDF in equation (A-5) to express the Euler equation as

$$E[MR_i] = 1. \tag{A-6}$$

For characterizations to follow, define the expected values

$$\mu_M^u[k] = E\left[(R_M - k)^+\right] \quad \text{and} \quad \mu_M^d[k] = E\left[(k - R_M)^+\right], \tag{A-7}$$

and the price of the market risk and the beta of the risky asset as

$$\lambda = -\frac{u''[1]}{u'[a]}\text{var}[R_M] \quad \text{and} \quad \beta_i = \frac{\text{cov}\left(R_i, R_M\right)}{\text{var}[R_M]}. \tag{A-8}$$

We also define the following tail-based co-moment risks

$$\delta_i^{uu}[k] = \frac{\text{cov}\left((R_i - k)^+, (R_M - k)^+\right)}{\text{var}\left((R_M - k)^+\right)}, \tag{A-9}$$

and

$$\delta_i^{ud}[k] = \frac{\text{cov}\left((R_i - k)^+, (k - R_M)^+\right)}{\text{cov}\left((k - R_M)^+, (R_M - k)^+\right)},$$

$$\delta_i^{du}[k] = \frac{\text{cov}\left((k - R_i)^+, (R_M - k)^+\right)}{\text{cov}\left((k - R_M)^+, (R_M - k)^+\right)}, \tag{A-10}$$

and

$$\delta_i^{dd}[k] = \frac{\text{cov}\left((k - R_i)^+, (k - R_M)^+\right)}{\text{var}\left((k - R_M)^+\right)},$$

and their prices of risks, respectively:

$$\lambda^{uu}[k] = -\frac{u'''[k]}{u'[a]}\text{var}\left[(R_M - k)^+\right], \quad \text{and} \quad \lambda^{ud}[k] = \frac{u'''[k]}{u'[a]}\mu_M^u[k]\mu_M^d[k], \tag{A-11}$$

$$\lambda^{du}[k] = -\frac{u'''[k]}{u'[a]}\mu_M^u[k]\mu_M^d[k], \quad \text{and} \quad \lambda^{dd}[k] = \frac{u'''[k]}{u'[a]}\text{var}\left[(k - R_M)^+\right]. \tag{A-12}$$

From equations (A-11) and (A-12), we observe that $\lambda^{uu}[k] < 0$ and $\lambda^{du}[k] < 0$, whereas $\lambda^{dd}[k] > 0$ and $\lambda^{ud}[k] > 0$; $\delta_i^{uu}[k]$ and $\delta_i^{dd}[k]$ are upper- and lower-tail-based co-moment risks, and $\delta_i^{du}[k]$ and $\delta_i^{ud}[k]$ are mixed tail-based co-moment risks. Similarly to the market beta, when asset i coincides with the market portfolio, the tail-based co-moment risks defined in equations (A-9) and (A-10) are equal to 1. We now expand the Euler equation in terms of covariance and express the expected excess return of the risky asset in terms of tail-based co-moment risks and their market prices in Theorem 2.

[32]We discuss how this theorem relates to recent equilibrium models in which the SDF is a function of nonlinear payoffs such as option payoffs (Vanden (2004)) or in which investor preferences overweight lower-tail outcomes relative to expected utility, like the generalized disappointment aversion (GDA) model of Routledge and Zin (2010) in Section C of the Internet Appendix.

Theorem 2. The expected excess return on any risky asset can be expressed as

$$\text{(A-13)} \quad E[R_i] - R_f = \lambda\beta_i + \int_1^{k_{\max}} \lambda^{uu}[k]\,\delta_i^{uu}[k]\,dk + \int_1^{k_{\max}} \lambda^{du}[k]\,\delta_i^{du}[k]\,dk + \int_0^1 \lambda^{ud}[k]\,\delta_i^{ud}[k]\,dk + \int_0^1 \lambda^{dd}[k]\,\delta_i^{dd}[k]\,dk,$$

where $\lambda > 0$, $\lambda^{uu}[\cdot] < 0$, $\lambda^{dd}[\cdot] > 0$, $\lambda^{du}[\cdot] < 0$ and $\lambda^{ud}[\cdot] > 0$.

Proof. See the Internet Appendix.

Expression (A-13) shows that beta and the tail-based co-moment risks determine the discount rate. The main implication of Theorem 2 is that $\delta_i^{uu}[k]$ and $\delta_i^{du}[k]$ are negatively related to expected excess returns, whereas $\delta_i^{ud}[k]$ and $\delta_i^{dd}[k]$ are positively related to expected excess returns.

The key here is the third derivative of the utility function u, which characterizes investor preferences for skewness. The third derivatives $u'''[k]$ may amplify or reduce the contribution of tail dependence measures on the expected excess return depending on k.[33] When our regularity conditions are satisfied, $u'''[k]$ is a decreasing function of k because $u''''[\cdot] < 0$. The magnitude of $u'''[k]$ is extremely large when k is small. In such a case, the tail-based co-moment risks have a significant impact of expected excess returns when k is small. The most interesting tail-based co-moment risks in our context are $\lim_{\varepsilon \to 0^+} \delta_i^{dd}[\varepsilon]$ and $\lim_{\varepsilon \to k_{\max}^-} \delta_i^{uu}[\varepsilon]$. We call these risk measures *limiting tail-based co-moment risks.*

Impact of the Limiting Tail-Based Co-Moment Risks on Expected Excess Returns. Under our regularity conditions, the expected excess return increases disproportionally with $\delta_i^{dd}[\varepsilon]$ in the limiting case $\varepsilon \to 0^+$. The increase in the expected excess return depends on the shape of $u'''[\varepsilon]$ when ε goes to 0. In other words, the increase is due to the fact that $u''''[\cdot] < 0$.[34] Similarly, the expected excess return decreases disproportionally with $\delta_i^{uu}[\varepsilon]$ in the limiting case $\varepsilon \to k_{\max}^-$. The proof is given in the Internet Appendix.

Does Lower-Tail Dependence Determine Discount Rates? We now show that the LTD and UTD tail dependence measures are positively related to the limiting tail-based co-moment risks. To connect the tail-based co-moment risks to the lower- and upper-tail dependence measures used in Sections II–III, we first recall that

$$\text{(A-14)} \quad \text{LTD}_i = \lim_{q \to 0^+} P\left[r_i < F_i^{-1}(q)\,|\,r_M < F_M^{-1}(q)\right],$$

$$\text{(A-15)} \quad \text{UTD}_i = \lim_{q \to 1^-} P\left[r_i > F_i^{-1}(q)\,|\,r_M > F_M^{-1}(q)\right].$$

For characterizations to follow, we define the limiting tail-based co-moment risks $\delta_i^{uu}[\varepsilon]$, $\delta_i^{ud}[\varepsilon]$, $\delta_i^{du}[\varepsilon]$, and $\delta_i^{dd}[\varepsilon]$ as the limit of $\delta_i^{\cdot\cdot}[\varepsilon]$ for ε approaching 1, 0, or $k_{\max}$, respectively (e.g., $\delta_i^{uu}[1] = \lim_{\varepsilon \to 1^+} \delta_i^{uu}[\varepsilon]$). The associated prices of risk are defined as $\lambda_i^{uu}[\varepsilon]$, $\lambda_i^{ud}[\varepsilon]$, $\lambda_i^{du}[\varepsilon]$, and $\lambda_i^{dd}[\varepsilon]$, respectively.[35] We then apply Lemma 2 (see the Internet Appendix) to the integrals in the right-hand side (RHS) of equation (A-13) and write the expected excess return of the risky asset in equation (A-16).

[33]In the special case of quadratic utility, $u'''[k] = 0$ for any k and $\lambda^{uu}[\cdot] = \lambda^{dd}[\cdot] = \lambda^{du}[\cdot] = \lambda^{ud}[\cdot] = 0$. In such a case, only the asset's beta determines the expected excess return on risky assets, and equation (A-13) reduces to the CAPM; (i.e., $E[R_i] - R_f = \lambda\beta_i$). Consequently, tail-based co-moment risks contribute to the risk premium on risky assets when the utility is not quadratic.

[34]It is important to notice that if $u''''[\cdot] = 0$, the expected excess return will not increase disproportionally in the limiting case $\varepsilon \to 0^+$.

[35]The detailed definitions for the δs and λs are shown in the Internet Appendix.

Theorem 3. A discretization of integrals in the RHS of equation (A-13) allows us to express the expected excess return as

$$\text{(A-16)} \quad E[R_i] - R_f = \lambda\beta_i + \frac{1}{2}\lambda^{dd}[0]\delta_i^{dd}[0] + \frac{1}{2}\lambda^{ud}[0]\delta_i^{ud}[0] + \frac{1}{2}(k_{\max}-1)\lambda^{uu}[k_{\max}]\delta_i^{uu}[k_{\max}] + \frac{1}{2}(k_{\max}-1)\lambda^{du}[k_{\max}]\delta_i^{du}[k_{\max}] + \frac{1}{2}(k_{\max}-1)\lambda^{du}[1]\delta_i^{du}[1] + \frac{1}{2}(k_{\max}-1)\lambda^{uu}[1]\delta_i^{uu}[1] + \frac{1}{2}\lambda^{ud}[1]\delta_i^{ud}[1] + \frac{1}{2}\lambda^{dd}[1]\delta_i^{dd}[1],$$

where $\lambda > 0$, $\lambda^{uu}[\cdot] < 0$, $\lambda^{dd}[\cdot] > 0$, $\lambda^{du}[\cdot] < 0$ and $\lambda^{ud}[\cdot] > 0$. Further,

(i) the relevant limiting tail-based co-moment risks $\delta_i^{dd}[0]$ and $\delta_i^{uu}[k_{\max}]$ are linear functions of the lower- and upper-tail dependence measures LTD_i and UTD_i, respectively;

(ii) the limiting tail-based co-moment risks $\delta_i^{dd}[0]$ and $\delta_i^{uu}[k_{\max}]$ are increasing functions of the lower- and upper-, respectively, tail dependence measures:

$$\text{(A-17)} \quad \frac{\partial\delta_i^{dd}[0]}{\partial \text{LTD}_i} > 0, \quad \text{and} \quad \frac{\partial\delta_i^{uu}[k_{\max}]}{\partial \text{UTD}_i} > 0;$$

(iii) the tail dependence measures LTD and UTD determine the expected excess return on risky assets, and

$$\text{(A-18)} \quad \frac{\partial\left(E[R_i] - R_f\right)}{\partial \text{LTD}_i} > 0 \quad \text{and} \quad \frac{\partial\left(E[R_i] - R_f\right)}{\partial \text{UTD}_i} < 0.$$

Proof. See the Internet Appendix.

Three key implications emerge from Theorem 3. First, the magnitude of the prices of risks $\lambda^{uu}[\cdot]$, $\lambda^{ud}[\cdot]$, $\lambda^{du}[\cdot]$, and $\lambda^{dd}[\cdot]$ as shown in equations (A-11) and (A-12) are related to the shape of the utility function. Second, equation (A-18) shows that LTD (UTD) is positively (negatively) related to the risk premium on risky assets. All else being equal, assets with strong LTD (UTD) have high tail-based co-moment risk and hence have higher (lower) returns on average than assets with weak or 0 LTD (UTD). Third, the magnitude of expected excess returns due to LTD is related to $\lim_{\varepsilon\to 0^+} u'''[\varepsilon]$, whereas the magnitude of expected excess returns due to UTD is related to $\lim_{\varepsilon\to k_{\max}^-} u'''[\varepsilon]$. Consequently, the impact of tail dependence on the magnitude of the risk premium depends on the concavity of the second derivative of the utility function $u''[\cdot]$. Because $u''''[\cdot] < 0$, $u'''[\varepsilon]$ is a decreasing function of ε. As ε approaches 0 from the right, $u'''[\varepsilon]$ will be large. As ε approaches $k_{\max}$ from the left, $u'''[\varepsilon]$ will be small. Thus, all else being equal, LTD has a stronger impact on the expected excess return than UTD.

Appendix B. Definitions and Data Sources of Main Variables

Appendix B briefly defines the main variables used in the empirical analysis. The data sources are the CRSP Stocks Database (CRSP), Kenneth French's Data Library (KF), and Compustat (CS). EST indicates that the variable is estimated or computed based on original variables from the respective data sources.

Returns-Based Variables

Return (return): Monthly raw excess return of a portfolio (stock) over the risk-free rate. As risk-free rate, the 1-month T-bill rate is used. *Source:* CRSP, KF, EST.

CAPM alpha, CAR alpha, FF alpha: CAPM 1-factor, Carhart (1997) 4-factor, and Fama and French (2015) 5-factor performance alpha of a portfolio over the sample period. We use monthly portfolio returns to estimate the alphas. *Source:* CRSP, KF, EST.

LTD: Lower-tail dependence coefficient of a stock. Estimated based on daily data from 1 year as detailed in Section II.A. *Source:* CRSP, EST.

UTD: Upper-tail dependence coefficient of a stock. Estimated based on daily data from 1 year as detailed in Section II.A. *Source:* CRSP, EST.

β: Factor loading on the market factor from a CAPM 1-factor regression estimated based on daily data from 1 year: $\beta = \text{COV}(r_i, r_m)/\text{VAR}(r_m)$. *Source:* CRSP, EST.

β^-: Downside beta estimated based on daily return data from 1 year as defined by Ang et al. (2006): $\beta^- = \text{COV}(r_i, r_m | r_m < \mu_m)/\text{VAR}(r_m | r_m < \mu_m)$, where μ_m is the mean of the daily market return. *Source:* CRSP, EST.

β^+: Upside beta estimated based on daily return data from 1 year as defined by Ang et al. (2006): $\beta^+ = \text{COV}(r_i, r_m | r_m > \mu_m)/\text{VAR}(r_m | r_m > \mu_m)$. *Source:* CRSP, EST.

β^-_{HW}: Downside beta estimated based on daily return data from 1 year as defined by Hogan and Warren (1974): $\beta^-_{\text{HW}} = E(r_i \times r_m | r_m < \mu_m)/E(r_m^2 | r_m < \mu_m)$. *Source:* CRSP, EST.

β^-_{EST}: Downside beta estimated based on daily return data from 1 year as defined by Estrada (2004): $\beta^-_{\text{EST}} = \sum_{t=1}^{T} (\min[0, (r_{it} - \mu_m)] \times \min[0, (r_{mt} - \mu_m)]) / \sum_{t=1}^{T} (\min[0, (r_{mt} - \mu_m)])^2$. *Source:* CRSP, EST.

β^-_{AR}: Downside beta estimated based on daily return data from 1 year as defined in Harlow and Rao (1989): $\beta^-_{\text{AR}} = E(Xr_i) - E(X)E(r_i)/E(X^2) - E(X)^2$ with $X = (r_m \times 1_{r_m \leq \mu_m} + E(r_m | r_m > \mu_m) \times 1_{r_m > \mu_m})$. *Source:* CRSP, EST.

ILLIQ: The Amihud (2002) illiquidity ratio, defined as follows: $\text{ILLIQ}_{i,t} = 1/\text{DAYS}_t^i \cdot \sum_{d=1}^{\text{DAYS}} |r_{i,d}|/\text{VOL}_{i,d}$, where $\text{VOL}_{i,d}$ is security i's trading volume in dollars on day d, and DAYS_t^i is the number of trading days in year t. *Source:* CRSP, EST.

IDIO_VOLA: A stock's idiosyncratic volatility, defined as the standard deviation of the CAPM residuals of its daily returns. *Source:* CRSP, EST.

COSKEW: The co-skewness of a stock's daily returns with the market: $\text{COSKEW} = E[(r_i - \mu_i)(r_m - \mu_m)^2]/\sqrt{\text{VAR}(r_i)}\text{VAR}(r_m)$. *Source:* CRSP, EST.

COKURT: The co-kurtosis of a stock's daily returns with the market: $\text{COKURT} = E[(r_i - \mu_i)(r_m - \mu_m)^3]/\sqrt{\text{VAR}(r_i)}\text{VAR}(r_m)^{3/2}$. *Source:* CRSP, EST.

MAX: The maximum daily return over the last year or month, respectively. *Source:* CRSP.

β_{TAIL}: The tail risk beta by Kelly and Jiang (2014), computed as the 120-month sensitivity of a stock's return to the aggregate tail risk factor. The aggregate tail risk factor is computed by applying the tail risk estimator of Hill (1975) to the cross section of all daily stock returns in a given month. *Source:* CRSP, EST.

Other Firm Characteristics

SIZE: The natural logarithm of a firm's equity market capitalization in million USD. *Source:* CS.

BOOK_TO_MARKET: 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). *Source:* CS.

LEVERAGE: A firm's leverage, computed as a company's book debt level (AT − CEQ) divided by total assets (AT). *Source:* CS.

CASH_FLOW_VOLA: Standard deviation of a company's quarterly cash flows estimated over the past 5 years. *Source:* CS.

DISTRESS_RISK: Distress risk of a company; estimated by a company's Altman (1968) Z-score. *Source:* CS.

R&D_SPENDING: A firm's R&D spending, defined as the R&D expenses (XRD) divided by total assets (AT). *Source:* CS.

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