Extreme Dependence Structures and the Cross-Section of Expected Stock Returns

Stefan Ruenzi and Florian Weigert *

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

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

*Stefan Ruenzi is from the Chair of International Finance at the University of Mannheim, Address: L9, 1-2, 68131 Mannheim, Germany, Telephone: ++49-621-181-1640, e-mail: *ruenzi@bwl.uni-mannheim.de*. Florian Weigert is from the Chair of International Finance and CDSB at the University of Mannheim, Address: L9, 1-2, 68131 Mannheim, Germany, Telephone: ++49-621-181-1625, e-mail: *weigert@bwl.uni-mannheim.de*. The authors thank Andres Almazan, Allaudeen Hameed, Maria Kasch, Alexandra Niessen-Ruenzi, Sheridan Titman, and seminar participants at the University of Mannheim and the University of Texas at Austin for their helpful comments. All errors are our own.

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We examine whether investors get a compensation for holding stocks with a strong sensitivity to extreme market downside movements. We use copulas to measure such lower tail dependence. Standard asset pricing models are unable to capture these extreme dependencies because they rely on the linear correlation as their sole dependence measure. We show that extreme dependence structures in the form of lower tail dependence are indeed important drivers of the cross-sectional variation of expected stock returns. Stocks with strong lower tail dependence have high average returns. This effect cannot be explained by traditional risk factors and is different from the impact of coskewness or downside beta. Our findings are consistent with results from the empirical option pricing literature that out-of-the-money index puts exhibit high implied volatility. They support the notion that stock market investors are crash averse and that this eventually leads to higher equilibrium returns of crash-prone stocks.

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1 Introduction

There is strong empirical support for the notion that investors are crash-averse. The option pricing literature documents that deep out-of-the-money index puts, i.e. instruments that offer protection against extreme market downturns, have a high implied volatility, i.e. they are relatively expensive.[1] Garleanu, Pedersen, and Poteshman (2009) show that this effect is driven by high demand for out of the money puts, which drives up their price.[2] This strong demand is typically interpreted as investors being crash-averse or showing signs of 'crash-o-phobia' (Rubinstein (1994)). Surprisingly, the potential impact of crash-aversion has not caught much attention in the empirical asset pricing literature on common stocks. Our study addresses this issue by investigating the impact of individual stock crash-sensitivity on the cross-section of returns.

We capture the crash-sensitivity of a stock based on copula methods. We examine the influence of extreme dependence between individual stocks and the market on the cross section of asset returns. 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 CAPM, a stock whose return has a high linear correlation with the market return must earn a higher return than securities that are less correlated with the market to induce risk averse investors to hold the security. In the context of bivariate normal distributions, the linear correlation is the appropriate dependence concept. However, the linear correlation is not able to characterize the full dependence structure of non-normally distributed random variables such as realized stock returns (Embrechts, McNeil, and Straumann (2002)). Particularly, it is not able to capture clustering in the tails of the bivariate return distribution between individual securities and the market.

We examine whether extreme dependence structures, and in particular clustering in the lower left tail (also called lower tail dependence, LTD), in the joint distribution of individual stock returns and the market can explain the cross-section of expected stock returns.[3] All else being equal, securities that exhibit a high degree of lower tail dependence are unattractive assets to hold for crash-averse investors; they tend to realize their lowest payoffs exactly

[1] See, e.g., Rubinstein (1994), Jackwerth and Rubinstein (1996), Aït-Sahalia and Lo (2000), Bates (2000), Jackwerth (2000), and Rosenberg and Engle (2002).

[2] Bollen and Whaley (2004) also show that buying pressure for index puts increases their price. Grossman and Zhou (1996) suggest an equilibrium model where a group of investors buys portfolio insurance. This can explain the high prices of out-of-the-money put options, too.

[3] This 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).

when the market also realizes its lowest payoff, i.e. when investors' wealth is very low (given one accepts the market as a proxy for investor wealth). Adding stocks with weak or no lower tail dependence essentially is an insurance against extreme negative portfolio returns (similar to buying out-of-the-money index puts) as these stocks do not realize their worst returns when the markets realizes its worst return. Consequently, investors who are sensitive to extreme downside losses will require a return premium for holding stocks with strong lower tail dependence.

The impact of crash aversion has to be distinguished from downside risk aversion and the corresponding impact of downside beta documented in Ang, Chen, and Xing (2006) as well as from the impact of coskewness documented in Harvey and Siddique (2000) and other higher moments.[4] Downside beta focuses on individual securities' exposure to market returns conditional on below average market returns with no particular emphasis on extreme events. A stock's coskewness is essentially the covariance of its return with the squared market return and does not take into account asymmetries between down and up markets (Ang, Chen, and Xing (2006)). In contrast, lower tail dependence captures the dependence in the extreme left tail of return distributions, i.e. it only focuses on extreme downside events and how individual securities behave during the worst market return realizations.

Based on daily return data for all US stocks from 1963 to 2009 we calculate tail dependence coefficients for each stock and year. To do so, we first determine the convex combination of basic parametric copulas that explains the empirical bivariate distribution of individual security and market returns best.[5] Then, we compute the respective tail dependence coefficients. As expected, we find that average lower tail dependence peaks around the 1987 crash as well as in the years of the recent financial crises 2008 and 2009.

More importantly, we then relate the individual tail dependence coefficients to contemporaneous returns. By relating tail dependence coefficients to contemporaneous returns on a yearly basis we follow Lewellen and Nagel (2006) who suggest to use short, non-overlapping periods and daily data in asset pricing exercises when risk exposures might be time varying. Our empirical results using portfolio sorts and Fama and MacBeth (1973) regressions on the individual firm level show a strong positive impact of unconditional lower tail dependence on average returns. A portfolio consisting of the 20% stocks with the strongest lower tail dependence delivers a contemporaneous return which is 17.44% p.a. higher than that of a portfolio consisting of the 20% stocks with the weakest lower tail dependence. In contrast, low-LTD stocks have significantly higher returns that high-LTD stocks in crises periods, i.e.

[4]Other papers that examine downside risk and related concepts based on conditional second and higher moments of the bivariate distributions include Kraus and Litzenberger (1976), Friend and Westerfield (1980), Smith (2007), Fang and Lai (1997), Dittmar (2002).

[5]The combination chosen most frequently is the Rotated Joe/F-G-M/Joe-copula.

they offer some protection against extreme market downturns.

We also show that risks associated with tail dependence can neither be captured by coskewness (Harvey and Siddique (2000)), cokurtosis (Fang and Lai (1997)), downside beta (Ang, Chen, and Xing (2006)), or idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang (2006)). Adding lower tail dependence as an explanatory variable even drives out the impact of downside beta in a multivariate setting. This suggests that crash aversion has an additional impact on the cross section of returns which can be distinguished from the impact of the related concept of downside aversion. We also control for the standard list of firm characteristics that can impact returns including size (Banz (1981)), book-to-market (Basu (1983)), and momentum (Jegadeesh and Titman (1993)) in our multivariate analysis. Our results based on Fama-MacBeth (1973) regressions show that an increase of one standard deviation in lower tail dependence is associated with an average return premium of 5.15% p.a.

We conduct several robustness tests to confirm the stability of our results. We show that our results are very similar if we do not calibrate the optimal copula structure for each stock and year. Just estimating tail dependence coefficients based on fixed copula combinations that were most frequently chosen for all stocks deliver very similar results. This might be useful for future research, because selecting the right copula combination is computationally costly. Additionally, we examine the impact of upper tail dependence and find that it has a negative impact on contemporaneous returns. However, the impact of upper tail dependence is significantly smaller (in absolute terms) than the impact of lower tail dependence and is not robust.

Finally, we analyze the persistence of stocks' tail dependence coefficients with the market and check whether past lower tail dependence can predict future returns. We find that during our sample period from 1963 through 2009 an investible trading strategy with monthly rebalancing consisting of buying a portfolio of stocks with the strongest past lower tail dependence and selling a portfolio of stocks with the weakest past lower tail dependence over the previous twelve months delivers a significant abnormal return of 4.06% p.a. before trading costs. This result holds after controlling for the Fama and French (1993) factors, momentum and systematic liquidity.

Overall, the main contribution of our study is twofold: (1) We document that extreme dependence matters for stock returns by (2) applying copula methods to capture the dependence structure between individual stock and market returns in an asset pricing exercise for the first time. Thus, our study is related to three strands of literature. First, our paper relates to the literature on asset pricing with downside risk. In his pioneering work Markowitz (1959) suggests to use the semi-variance as a measure of risk. 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), Harvey and Siddique (2000), and Smith (2007) document that investors dislike negative coskewness of stock returns with the market return. Fang and Lai (1997) and Dittmar (2002) show that stocks with high cokurtosis earn high average returns. More recently, Ang, Chen, and Xing (2006) compute downside betas over periods when the excess market return is below the mean and document that stocks with high downside betas have high average returns, too.

Second, we contribute to the literature on downside risk aversion and crash aversion of investors. Downside risk aversion is already discussed in Roy (1952) who argues that investors display 'safety-first' preferences and dislike downside losses more than they like upside gains.[6] Kahneman and Tversky (1979) argue that individuals evaluate outcomes relative to reference points and show that individuals strongly prefer avoiding losses to acquiring gains.[7] Although aversion to losses, i.e. downside risk, is discussed extensively, only few papers investigate the effect of loss- or disappointment aversion of investors on expected asset returns. Shumway (1997) develops and tests an asset pricing model with loss averse investors that demand an additional risk premium for risk associated with negative market returns.[8] In a similar vein, Ang, Chen, and Xing (2006) propose a equilibrium model based on Gul (1992)'s disappointment preferences in which investors demand an additional risk premium for holding stocks with high downside beta. Their empirical investigation shows that stocks with higher downside beta earn higher returns. Our paper focuses on crash aversion which differs from downside aversion in that crash averse investors would demand an additional compensation for stocks that are crash-prone, i.e. stocks that have particularly bad returns exactly when the market crashes. Surprisingly, extreme downside or crash-aversion has caught little attention in the asset pricing literature on common stocks. The impact of tail risk on individual asset returns is examined in Kelly (2009) and Bali, Demirtas, and Levy (2009). Kelly (2009) predicts aggregate tail risk based on individual extreme events by applying Hill (1975) tail risk estimator. He also documents that stocks that deliver high payoffs when aggregate tail risk is high earn low abnormal returns. Bali, Demirtas, and Levy (2009) find that different measures of downside risk are positively related to portfolio returns.

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

[6]Safety first investors are also at the heart of the analysis in Baumol (1963), Levy and Sarnat (1972), and Arzac and Bawa (1977).

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

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

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

The rest of this paper is organized as follows. Section 2 gives an overview of extreme value theory and presents the estimation procedure for tail dependence coefficients. Section 3 demonstrates that stocks with strong lower tail dependence contemporaneously have high average returns. In Section 4, we examine the persistence of tail dependence, try to find predictive variables for it, and evaluate a trading strategy based on lower tail dependence. Section 5 performs robustness checks. Section 6 concludes and the Appendix provides some technical details on the tail dependence coefficient estimation procedure.

2 Copulas and Tail Dependence Coefficients

As copula concepts are not yet regularly used in standard asset pricing applications, we will first give a short intuitive introduction into the concept and describe how we can compute measures of extreme or tail dependence based on copulas.[9]

2.1 Copulas

Most of the standard empirical asset pricing literature focuses on risk factors based on linear correlation coefficients. However, this measure of stochastic dependence is typically not able to completely characterize the dependence structure of non-normally distributed random variables (Embrechts, McNeil, and Straumann (2002)). It is now widely recognized that

[9] A more precise technical but still accessible treatment of copula concepts is contained in Nelsen (2006). Previous finance applications are discussed in Cherubini, Luciano, and Vecchiato (2004).

many financial time series, including stocks, are non-normally distributed.[10] 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 fails to capture the dependence structure in the extreme lower left and upper right tail. As an example, consider the following illustrations of 2000 simulated bivariate realizations based on different dependence structures between (X_1, X_2) in Figure 1.

[Insert Figure 1 about here]

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. For comparison, in Panel A we first show an example where we did not allow for clustering in either tail of the distribution. In that case, the linear correlation can be a sufficient statistic to describe the dependence structure. However, in reality many bivariate distributions (e.g., between individual stocks and the market return) exhibit clustering in one or both tails. Panels B to D show examples of no increased dependence in the upper right tail, in the lower left tail, and symmetric increased dependence in both tails. Still, all of these bivariate distributions are characterized by a linear correlation coefficient of 0.8. This documents that it is not always possible to describe the dependence structure by linear correlation alone. Copulas offer an elegant way to describe the complete dependence structure between random variables.[11]

Every bivariate distribution function of two random variables X_1 and X_2 (e.g. an individual asset return and the market return) implicitly contains both a description of the marginal distribution functions $F_1(x_1)$ and $F_2(x_2)$ and their dependence structure. The copula approach allows us to isolate the description of the dependence structure from the univariate marginal distributions of the bivariate distribution. Sklar (1959) shows that all bivariate distribution functions $F(x_1, x_2)$ can be completely described based on the univariate distributions and a copula C: $[0, 1]^2 \rightarrow [0, 1]$. Sklar's Theorem explicitly states that all bivariate distributions contain copulas and bivariate distributions can be constructed by combining the univariate marginal distributions using copulas (McNeil, Frey, and Embrechts (2005)):

Theorem 1 (Sklar 1959). *Let F be a bivariate distribution function with margins F_1 and*

[10] For some early evidence, see Fama (1965). A discussion of properties of empirical asset returns can be found in Cont (2001).

[11] The realizations plotted in Figure 1 are based on simulations of different popular copula functions. The statistical models used to simulate these realizations are the Gauss-copula (Panel A), the Gumbel-copula (Panel B), the Clayton-copula (Panel C), and the Student t-copula (Panel D).

F_2. Then there exists a copula $C : [0,1]^2 \mapsto [0,1]$ such that, for all x_1, x_2 in $\overline{\mathbb{R}} = [-\infty, \infty]$,

$$F(x_1, x_2) = C(F_1(x_1), F_2(x_2)). \tag{1}$$

If the margins are continuous, then C is unique. Conversely, if C is a copula and F_1 and F_2 are univariate distribution functions, then the function F defined in (1) is a bivariate distribution function with margins F_1 and F_2.

There are many different parametric copulas that can model different tail dependence structures. In this study we will use combinations of simple basic parametric copulas that allow for 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). By allowing any possible convex combination between one copula from each class we allow for maximum flexibility in modeling dependence structures (see Section 2.2).

Copulas will be helpful in estimating coefficients of upper and lower tail dependence (Sibuya (1960)). In contrast to the linear correlation, the coefficients of tail dependence are measures of pairwise dependence that only depend on the copula (see, among others, Nelsen (2006) or McNeil, Frey, and Embrechts (2005)) of a pair of random variables X_1 and X_2. They provide measures of extremal dependence, i.e. measures of the strength of dependence in the tails of a bivariate distribution.

2.2 Computation of Tail Dependence Coefficients

Intuitively, the lower (upper) tail dependence coefficient between two variables reflects the probability that a realization of one random variable is in the extreme lower (upper) tail of its distribution conditional on the realization of the other random variable also being in the extreme lower (upper) tail of its distribution. Formally, lower tail dependence LTD is defined as

$$\text{LTD} := \text{LTD}(X_1, X_2) = \lim_{u \to 0+} P(X_2 \leq F_2^{-1}(u) | X_1 \leq F_1^{-1}(u)), \tag{2}$$

where $u \in (0,1)$ is the argument of the distribution function, i.e. $\lim_{u \to 0+}$ indicates the limit if we approach the left-tail of the distribution from above. Analogously, we can define the upper tail dependence coefficient UTD as:

$$\text{UTD} := \text{UTD}(X_1, X_2) = \lim_{u \to 1-} P(X_2 > F_2^{-1}(u) | X_1 > F_1^{-1}(u)). \tag{3}$$

If LTD (UTD) is equal to zero, the two variables are asymptotically independent in the lower (upper) tail. Simple expressions for LTD and UTD in terms of the copula C of the bivariate distribution can be derived based on

$$\text{LTD} = \lim_{u \to 0+} \frac{C(u,u)}{u} \tag{4}$$

and

$$\text{UTD} = \lim_{u \to 1-} \frac{1 - 2u + C(u,u)}{1-u}, \tag{5}$$

if F_1 and F_2 are continuous (McNeil, Frey, and Embrechts (2005)). The coefficients of tail dependence have closed form solutions for many parametric copulas. Table 1 shows the formulas for the computation of LTD and UTD of the basic copula families used in this study.

[Insert Table 1 about here]

These basic copulas do not allow us to model upper and lower tail dependence simultaneously. However, flexible copula structures can be obtained by constructing convex combinations of these basic copulas.[12] Tawn (1988) shows that a copula is a convex set and every convex combination of existing copula functions is again a copula. Thus, if $C_1(u_1,u_2)$, $C_2(u_1,u_2)$, ..., $C_n(u_1,u_2)$ are bivariate copula functions, then

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

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

To allow for the maximum of flexibility possible, we consider all 64 possible convex combinations of the afore-mentioned basic copulas that each consist of one copula that allows for asymptotic dependence in the lower tail, C_{LTD}, one copula which is asymptotically independent, C_{NTD}, and one copula that allows for asymptotic dependence in the upper tail, C_{UTD}:

$$\begin{aligned} C(u_1,u_2,\Theta) = {} & w_1 \cdot C_{\text{LTD}}(u_1,u_2;\theta_1) \\ & + w_2 \cdot C_{\text{NTD}}(u_1,u_2;\theta_2) + (1 - w_1 - w_2) \cdot C_{\text{UTD}}(u_1,u_2;\theta_3), \end{aligned} \tag{6}$$

[12] These convex combinations are similar to other copulas like the BB1 to BB7 copulas suggested in Joe (1997), but offer more flexibility. Particularly, as our convex combinations contain one copula which is asymptotically independent, we argue that this is an extremely flexible and efficient way to model dependence structures.

where Θ denotes the set of the basic copula parameters θ_i, $i = 1, 2, 3$ and the weights w_1 and w_2. Our estimation approach for the upper and lower tail dependence coefficients follows a three-step procedure. First, based on daily return data for the market and each stock and each year, we estimate a set of copula parameters Θ_j for $j = 1, \ldots, 64$ different copulas $C_j(\cdot, \cdot; \Theta_j)$ between an individual stock return r_i and the market return r_m.[13] Each of these convex combinations requires the estimation of five parameters: one parameter θ_i ($i = 1, 2, 3$) for each of the three basic copulas and two parameters for the weights w_1 and w_2. The copula parameters Θ_j are estimated via the canonical maximum likelihood procedure of Genest, Ghoudi, and Rivest (1995).

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 distance.[14] The result of this step is summarized in Table 2, in which we present the absolute and percentage frequency by which each of the possible 64 combinations is picked. All combinations are picked regularly and no specific copula clearly dominates. The three copula combinations that are most often selected are the Rotated-Joe/F-G-M/Joe-copula (3.29%), the Rotated-Galambos/F-G-M/Joe-copula (3.08%), and the Gumbel/F-G-M /Joe-copula (2.65%).

[Insert Table 2 about here]

Third, we compute the tail dependence coefficients LTD and UTD implied by the estimated parameters Θ^* of the selected copula $C^*(\cdot, \cdot; \Theta^*)$ based on the respective formulas for LTD and UTD from Table 1. The lower and upper tail dependence coefficient of the convex combination are calculated as the weighted sum of the LTD and UTD coefficients from the individual copulas, respectively, where the weights from (6) are used, i.e. $\text{LTD}^* = w_1^* \cdot \text{LTD}(\theta_1^*)$ and $\text{UTD}^* = (1 - w_1^* - w_2^*) \cdot \text{UTD}(\theta_3^*)$. As this procedure is repeated for each stock and year, we end up with a panel of tail dependence coefficients $\text{LTD}_{i,t}^*$ and $\text{UTD}_{i,t}^*$ at the year-firm level. For a more technical and detailed description of the estimation and selection method, we refer the reader to the Appendix.

2.3 Data and the Evolution of Aggregate Tail Dependence

Our sample consists of all common stocks (CRSP share codes 10 and 11) from CRSP trading on the NYSE/AMEX between January 1, 1963 through December 31, 2009. Copulas

[13] 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.

[14] Results are very similar if we select the copula based on the Kolmogorov-Smirnov distance or the estimated log-likelihood value. For a detailed description of the selection procedure, see the Appendix.

as well as tail dependence coefficients are estimated for each firm and each year separately. To estimate the yearly tail dependence coefficients we use daily data for all days on which the stock's price at the end of the previous trading day was at least \$2. We retain all stocks that have at least 100 valid daily return observations per year. Overall, there are $96,676$ firm-year observations. The number of firms in each year over our sample period ranges from $1,489$ to $2,440$.

To get a first idea about the characteristics of tail dependence, we investigate the time series of aggregate LTD and aggregate UTD. We define aggregate LTD of the market, $\text{LTD}_{m,t}$, as the yearly cross-sectional, equally-weighted, average of $\text{LTD}_{i,t}$ over all stocks i in our sample. Analogously, we define aggregate UTD of the market, $\text{UTD}_{m,t}$, as the yearly cross-sectional, equally-weighted, average of $\text{UTD}_{i,t}$. In Figure 2, we plot the time series of $\text{LTD}_{m,t}$ and $\text{UTD}_{m,t}$.

[Insert Figure 2 about here]

There is no particular time trend in $\text{LTD}_{m,t}$ and $\text{UTD}_{m,t}$.[15] The time series of $\text{LTD}_{m,t}$ and $\text{UTD}_{m,t}$ are only weakly correlated with a linear correlation coefficient of 0.003. However, the graph does exhibit occasional spikes in $\text{LTD}_{m,t}$ that roughly correspond to worldwide financial crises. The highest value in $\text{LTD}_{m,t}$ corresponds to 1987, the year of Black Monday with the largest one-day percentage decline in US stock market history. Another spike in market LTD occurs during the years 2007 through 2009, the years of the recent worldwide financial crisis. This suggests that $\text{LTD}_{m,t}$ - similar as return correlations - increases in times of financial crises.

Figure 2 also shows that in most of the years of our sample $\text{LTD}_{m,t}$ exceeds $\text{UTD}_{m,t}$. We report differences of $\text{LTD}_{m,t}$ and $\text{UTD}_{m,t}$ for the whole sample and for 5-year subsamples from 1963 to 2009 in Table 3.

[Insert Table 3 about here]

Over the whole sample period, $\text{LTD}_{m,t}$ is on average 0.177 which is significantly higher than the average $\text{UTD}_{m,t}$ of 0.142. This also holds true for each five year subperiod we consider. The general tendency for stronger asymptotic dependence in the left tail than in the right tail of the distributions is also consistent with the well documented finding that return correlations generally increase in down markets.[16]

[15]Performing two augmented Dickey-Fuller tests reject the null hypothesis that $\text{LTD}_{m,t}$ contains a unit root with a p-value smaller that 2% and that $\text{UTD}_{m,t}$ contains a unit root with a p-value smaller than 1%.

[16]See, e.g. Ang and Chen (2002). Increased extreme dependence between international markets in bear markets is also documented in Longin and Solnik (2001) and Poon, Rockinger, and Tawn (2004).

To get a first impression of the characteristics of firms with strong tail dependence, in Table 3 we also look at the differences in LTD (UTD) between large and small firms. In every 5-year subsample we sort firms into five size quintiles and investigate the difference in LTD (UTD) between the large firm- and the small firm quintile. We find that LTD (UTD) is significantly higher for large firms than for small firms. This makes intuitive sense, as a market crash will typically first mainly be reflected in the returns of large blue-chip stocks.

Correlations among yearly individual security upper and lower tail dependence coefficients and other security characteristics are displayed in Table 4.[17]

[Insert Table 4 about here]

The correlation between UTD and LTD is relatively moderate at 0.09. The low correlation shows that firms with strong tail dependence in one tail of the distribution do not necessarily exhibit strong tail dependence in the other tail, too. This finding also justifies our flexible modeling approach for tail dependence that allows for asymmetric tail dependence in the upper and lower tail. Lower tail dependence is closely related to downside beta with a correlation coefficient of 0.46 and to beta with a correlation coefficient of 0.34. There is also a positive (negative) correlation between LTD and size as well as LTD and cokurtosis (coskewness). Upper tail dependence is closely related to upside beta, regular beta, and size. We also observe positive correlations between UTD and coskewness as well as UTD and cokurtosis. We will make sure to carefully take into account the impact of these correlations in our later analysis.

3 Extreme Dependence and Realized Returns

We start our empirical investigation by looking at the contemporaneous relationship between extreme dependence and returns using univariate sorts (Section 3.1). In Section 3.2, we examine double-sorts to disentangle the reward for LTD from the impact of market beta, downside beta (as in Ang, Chen, and Xing (2006)), and coskewness (as in Harvey and Siddique (2000)), respectively. In Section 3.3 we conduct Fama and MacBeth (1973) regressions to control for various other potential determinants of returns. Finally, in Section 3.4, we investigate whether we get similar results if we use a simplification of the estimation procedure for tail dependence coefficients.[18]

In the main part of our empirical analysis in this section we relate realized tail dependence coefficients to portfolio and individual security returns over the same period. This procedure,

[17] The exact procedure for the calculation of the other variables is described in Sections 3.2 and 3.3.

[18] Further robustness tests are deferred to Section 5.

that closely follows papers like Ang, Chen, and Xing (2006) and Lewellen and Nagel (2006), implicitly assumes that realized returns are on average a good proxy for expected returns and is mainly motivated by the fact that several studies document that risk exposures (like regular beta) are time-varying (see, e.g., Fama and French (1992), and Ang and Chen (2007)). It is likely that extreme dependence is also time-varying and past extreme dependence might thus not be a good predictor of future extreme dependence.[19] As advocated by Lewellen and Nagel (2006), we thus use daily return data for non-overlapping intervals of one year, from t to $t+1$. Over each annual period t, we calculate a sto ck i's LTD- and UTD-coefficients (as well as other risk measures like regular beta or downside beta).[20] Using an annual horizon trades off two concerns: First, we need a sufficiently large number of observations to get reliable estimates for our tail dependence coefficients. Second, by investigating contemporaneous relationships over relatively short horizons we are able to account for time-varying extreme dependence.

3.1 Univariate Portfolio Sorts

To examine whether stocks with strong lower tail dependence earn a premium, we first look at simple univariate portfolio sorts. At the beginning of year t we sort stocks into five quintiles based on their realized LTD in the same year. Panel A of Table 5 reports the annual equally-weighted average excess return over the risk free rate for these quintile portfolios. We also report t-statistics of differences in average excess returns between quintile portfolio 5 (high LTD) and quintile portfolio 1 (low LTD).

[Insert Table 5 about here]

We find that stocks with high LTD have significantly higher average returns than stocks with low LTD. Stocks in the quintile with the lowest (highest) LTD earn an annual average excess return of 1.73% p.a. (19.17% p.a). The spread in average excess returns between quintile portfolio 1 and 5 is 17.44% p.a., which is statistically significant at the 1% level. While only univariate in nature, these results are consistent with agents being crash-averse and avoiding stocks which show a high dependence structure with the market when the market crashes. Clearly, this is only a first indication and there are of course many other variables that are correlated with tail dependence and that might be responsible for our findings (see Table 4).

[19] A more detailed examination of predictive variables for tail dependence is presented in Section 4.1.

[20] The estimation procedure of the LTD- and UTD-coefficients for each stock is performed according to Section 2.2 and the Appendix.

In Panel A, we also report the average LTD- and UTD-coefficients, the average contemporaneous β, downside β of Ang, Chen, and Xing (2006), and coskewness (all estimated based on daily data), the average size, and the average book-to-market value of the stocks in each quintile portfolio. We compute size as the log of market capitalizations and the book-to-market ratio as the fraction of book value (obtained from Compustat) and market capitalization at the beginning of year t. Results for average LTD coefficients show that there is a significant cross-sectional dispersion in LTD across quintiles. Average LTD in the lowest quintile is 0.01, while it rises to 0.29 for the highest quintile. We also document a positive relationship between LTD and UTD, with UTD being lowest (highest) in the lowest (highest) LTD quintile. Furthermore, there is a strong relationship between LTD and β, downside β, and coskewness. The average (downside) beta in the lowest LTD quintile is (0.43) 0.56 and rises monotonically up to (1.54) 1.19 in the highest LTD quintile. Similarly, average coskewness in the lowest LTD quintile is 0.00 and decreases monotonically down to -0.17 in the highest LTD quintile. Thus, the return pattern we document could be driven by beta, downside beta or coskewness: High LTD stocks may earn high returns because they have high betas, high downside betas, or negative coskewness. There also seems to be a negative relationship between LTD and size or book to market. This indicates that the premium for high LTD is not related to the size-premium of Banz (1981) and the value-premium of Basu (1983).

Panel B of Table 5 shows the relationship between realized average excess returns and UTD. Stocks in the quintile with the lowest (highest) UTD have an average excess return of 11.09% p.a. (7.54% p.a.). The average return difference between quintile portfolios 1 and 5 is -3.55% p.a. This effect is much smaller than the impact of LTD from Panel A and the pattern of average excess returns and UTD throughout the different portfolios is not monotonic. These results suggest that investors might have preferences for stocks with extreme dependence in the upper tail; While this result is related to an argument made by Shumway (1997) that an asset that is highly correlated with the market when the market moves upwards should not be considered riskier, this argument does not explain why these stocks actually provide lower returns. However, the preference of investors for stocks with strong UTD seems much weaker than the preference to avoid extreme downside losses. The UTD portfolios show a positive relationship with LTD, beta, upside beta, coskewness, and size, as well as a negative relationship with book-to-market.

In summary, results from Table 5 suggest that extreme dependence determines the cross-section of stock returns. Stocks with high LTD (UTD) earn high (low) average contemporaneous returns. This is consistent with the view that stocks with low LTD offer protection against extremely low returns in crises periods, while stocks with high LTD perform particularly bad. As a consistency check, we now specifically focus on crises periods to check whether stocks with low LTD really earn higher returns than high LTD stocks in these special periods. We analyze portfolio returns on the most relevant financial crises days in our sample period. We examine "Black Monday" (October 19, 1987), the Asian Crisis (October 27, 1997), the burst of the dot-com bubble (April 14, 2000), and the recent Lehman crises (October 15, 2008). Results are presented in Table 6.

[Insert Table 6 about here]

As expected (and opposite to what we find during normal periods), the high LTD portfolio strongly underperforms the low LTD portfolio in each case. The differences are economically large. The daily return of the low LTD portfolio is by 4.4% up to 9.2% higher than that of the high LTD portfolio on these specific days. To assess the statistical significance, we also analyze all days on which the excess return of the market over the riskfree rate was less than -5% together. Results are presented in the last column of Table 6 and show that the low LTD portfolio outperforms the high LTD portfolio by nearly 5%. The effect is statistically significant at the 1%-level. To graphically illustrate this finding, in Figure 3 we also plot the average daily excess returns over the market of the five LTD portfolios for days on which the market return minus the riskfree rate is less than -2%.[21]

[Insert Figure 3 about here]

We again find that the low LTD portfolios strongly outperform the high LTD portfolios on days of strong negative market returns. Taken together with the results in Table 6, these findings show that low LTD stocks can serve as an insurance for loss-averse investors and might explain why they earn lower returns than high LTD stocks in normal times as documented above.

3.2 Bivariate Portfolio Sorts

As mentioned above, our result of higher average returns of high LTD stocks that we obtain in the univariate sorts could be driven by differences in regular beta, downside/upside beta, or coskewness across the different tail dependence quintiles. This is also suggested by the results from the correlation Table 4, where (un-) conditional betas and coskewness are the variables most strongly correlated with our tail dependence coefficients. Thus, we now conduct double sorts based on tail dependence and these variables.

[21] We choose 2% instead of 5% (as in Table 6) to make sure we have enough observations on which we can base the graph.

3.2.1 Tail Dependence vs. Beta

We perform dependent portfolio double-sorts on beta and LTD. We first form quintile portfolios sorted on beta. Then, within each beta quintile, we sort stocks into five portfolios based on LTD. Similar as above, both LTD and beta are computed over the same one-year horizon for which we examine returns.

[Insert Table 7 about here]

Table 7 reports equally-weighted average portfolio excess returns over the risk free rate. In Panel A we show the results of the 5×5 beta and LTD portfolios. In all beta quintiles we document a monotonic increase in average excess returns. The return difference between the lowest LTD quintile and the highest LTD quintile within all beta quintiles is economically large and statistically significant at the one-percent level. It ranges from 6.51% p.a. up to 21.36% p.a. with an increasing relation between beta and the magnitude of the impact of LTD on returns. The average spread in excess returns amounts to 11.96% p.a. Hence, regular beta risk cannot account for the reward earned by holding stocks with high LTD.

Next, in Panel B of Table 7, we also report average excess returns of the 25 beta $\times$ UTD portfolios. Stocks in the lowest (highest) UTD quintile earn an average excess return of 11.99% p.a. (6.26% p.a.). The average difference in average excess returns between the fifth and the first quintile of UTD is -5.73% p.a., which is statistically significant at the 1% level. Similar as in the univariate case, the effects are weaker than for LTD. The difference between high and low UTD stocks is not significant and economically small for stocks in the lowest beta quintile.

3.2.2 Tail Dependence vs. Downside/Upside Beta

Besides regular beta, we can also expect that tail dependence is related to betas which are conditioned on returns being high or low. Bawa and Lindenberg (1977) and Ang, Chen, and Xing (2006) define downside beta as

$$\beta^- = \frac{\mathrm{COV}(r_i, r_m | r_m < \mu_m)}{\mathrm{VAR}(r_m | r_m < \mu_m)}, \tag{7}$$

where r_i (r_m) is security i's (the market's) excess return, and μ_m is the average market excess return. Similar as above, in a first step we form quintile portfolios sorted on β^-. Then, within each β^- quintile, we sort stocks into five portfolios based on LTD. Panel A of Table 8 reports equally-weighted average excess returns of the 25 downside beta $\times$ LTD portfolios.

[Insert Table 8 about here]

Quintile 1 (5) has an average excess return of 4.25% p.a. (15.29% p.a.), which translates into an average return spread of 11.04% p.a. This spread is significant at the 1% level. The spread is also economically large (ranging from 8.42% p.a. to 18.77% p.a.) and highly statistically significant within every β^- quintile. Hence, the impact of LTD on returns is not driven by downside beta. The strongest effect of LTD on returns is found in the highest β^- quintile.

Furthermore, we find that the equally-weighted returns of the low β^- portfolios tend to be smaller than those of the high β^- portfolios. This confirms the results from Ang, Chen, and Xing (2006) and shows that β^- and LTD are two distinct factors. Interestingly though, the relationship between β^- and returns is not monotonic in all cases.

A strong positive correlation also exists between UTD and upside beta (see Table 4). Thus, we form quintile portfolios sorted on upside beta, defined as

$$\beta^+ = \frac{\mathrm{COV}(r_i, r_m | r_m > \mu_m)}{\mathrm{VAR}(r_m | r_m > \mu_m)}. \tag{8}$$

Then, within each β^+ quintile, we sort stocks into five equally-weighted portfolios based on UTD. Panel B of Table 8 shows average excess returns of the 25 upside beta $\times$ UTD portfolios. We find that the difference in average excess returns between the fifth and the first quintile is -7.06% p.a., which is significant at the 1% level. Thus, upside beta does not drive the lower returns of high UTD stocks.

3.2.3 Tail Dependence vs. Coskewness

The return premium for stocks with high LTD could be driven by low coskewness (see Table 4 and Table 5), defined as

$$\text{coskew} = \frac{E[(r_i - \mu_i)(r_m - \mu_m)^2]}{\sqrt{\mathrm{VAR}(r_i)}\mathrm{VAR}(r_m)}, \tag{9}$$

where r_i (r_m) is security i's (the market's) excess return, and μ_i (μ_m) is stock i's (the average market) excess return. The findings of Harvey and Siddique (2000) show that lower coskewness is associated with higher expected returns. To explicitly control for the effect of coskewness, in a first step we form quintile portfolios sorted on coskew. Then, within each coskew quintile, we sort stocks into five portfolios based on LTD. Panel A of Table 9 shows equally-weighted average excess returns of the 25 coskew $\times$ LTD portfolios.

[Insert Table 9 about here]

In all coskew quintiles we document a monotonic increase in average returns. The return difference between the lowest LTD quintile and the highest LTD quintile ranges from 11.49% p.a. to 15.26% p.a. with an average spread of 14.37% p.a. This spread again is highly significant at the 1% level, which indicates that coskewness risk cannot account for the reward earned by holding stocks with high LTD.

Finally, within each coskew quintile, we also sort stocks into five equally-weighted portfolios based on UTD. Panel B of Table 9 documents the excess returns of the 25 coskew × UTD portfolios. On average, we find that the difference in average excess returns between the fifth and the first quintile is −2.51% p.a., which is economically small relative to the spreads documented for LTD and only marginally significant at the 10% level. This suggests that most of the return discount stocks with strong UTD experience is due to their higher coskewness.

To summarize, based on double sorts we provide strong evidence that the risk associated with LTD is different from market beta, downside beta, and coskewness. Double sorts offer the advantage that they also allow us to detect potential non-linearities. However, in double sorts we can only control for one characteristic of the stocks 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 stock returns.

3.3 Fama-MacBeth Regressions

To confirm whether there is a premium for high LTD in the cross section of expected stock returns, we now run Fama and MacBeth (1973) regressions of excess returns on firm characteristics on the individual firm level in the period from 1963 - 2009 using non-overlapping data.[22] Panel A of Table 10 presents the regression results of excess returns on realized extreme dependence and various combinations of regular, downside, and upside beta.

[Insert Table 10 about here]

Regression (1) shows that in line with the normal CAPM the regular market beta carries a significant positive coefficient. In Regression (2), we regress excess returns on their respective downside- and upside betas. We find that the downside beta is highly significant, while the

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

upside beta is not significantly different from zero. This is broadly consistent with the analysis and results in Ang, Chen, and Xing (2006) who find that downside beta is an important determinant of the cross-section of stock returns while upside beta has much less of an impact. More important in our context, Regression (3) tests the importance of LTD and UTD when explaining the cross-section of expected stock returns. Both LTD and UTD are significant at the 1% level and carry the expected signs. The magnitude of LTD is more than twice as large as that of UTD. In Regression (4) we expand the model by including market beta again. The insertion of beta reduces the magnitude of the LTD-coefficient from 0.622 to 0.432; however, it clearly remains significant at the 1% level. Finally, Regression (5) reports the results of a joint regression of excess returns on beta, LTD, UTD, downside- and upside beta. Again, LTD and UTD remain highly significant explanatory variables. On the contrary, downside- and upside beta completely lose their explanatory power when we account for LTD and UTD in our regression.

The impact of LTD is also economically significant. A one standard deviation (i.e. 0.114) increase of LTD leads to an increase in expected returns of approximately 5.10% p.a. The impact of UTD is weaker: a one standard deviation (i.e. 0.094) increase in UTD leads to a decrease in expected returns of -2.99% p.a. These numbers are also consistent with our previous findings: the economic magnitude of the impact of LTD is much stronger (almost twice as large) than the impact of UTD. Our results indicate that investors earn a significant premium for bearing extreme downside risk which is not captured by beta or downside beta.

We will now expand our multivariate regression model and add various other firm characteristics including size, book-to-market, momentum, idiosyncratic volatility, coskewness, and cokurtosis.[23] We capture momentum effects (Jegadeesh and Titman (1993)) by including the past 1-year excess return of the firm. Idiosyncratic volatility is calculated as the standard deviation of CAPM-residuals of daily firm returns in year t. Ang, Hodrick, Xing, and Zhang (2006) and Ang, Hodrick, Xing, and Zhang (2009) find that idiosyncratic volatility has a negative impact on returns. Cokurtosis is defined as

$$\text{cokurt} = \frac{E[(r_i - \mu_i)(r_m - \mu_m)^3]}{\sqrt{\text{VAR}(r_i)}\text{VAR}(r_m)^{3/2}}, \tag{10}$$

where r_i (r_m) is security i's (the market's) excess return, and μ_i (μ_m) is stock i's (the average market) excess return during the period. The findings of Fang and Lai (1997) and Dittmar (2002) predict a positive impact of cokurtosis on expected returns. Results are presented in Panel B of Table 10.

[23]Size and book-to-market are computed as before. As book-to-market ratios can get very large if prices are low, we winsorize all realizations of our independent variables at the 1% and 99% levels in order to avoid outliers driving our results. Our results do not hinge on this winsorization (see Section 5).

Regression (1) includes a restricted set of explanatory variables. It confirms a standard set of cross-sectional return patterns: Market beta (+), size (-), book-to-market (+) and coskewness (-) are significant explanatory variables for the cross-section of stock returns. In regression (2) we add our measures of extreme dependence. Results show that the premium for LTD is robust to controlling for size, book-to-market, and coskewness. The coefficient remains very stable; the economic significance of LTD even increases when controlling for size, book-to-market, and coskewness. In regressions (3) to (5), we expand the set of independent variables by including past returns, idiosyncratic volatility, cokurtosis, as well as downside- and upside beta. We find that past returns, idiosyncratic volatility, and upside and downside beta are only weakly significant or insignificant explanatory variables for the cross-section of stock returns, while LTD exhibits the strongest influence of all variables (t-statistic of 9.65). The last column illustrates the economic significance of our results. Based on Regression (5), we show the change in contemporaneous returns p.a. if the respective independent variable changes by one standard deviation from its mean. For a one standard deviation increase in LTD, annual returns increase by 5.12%. This is the third largest (after beta and size) impact of all the variables included. Hence, even when controlling for a standard list of firm characteristics, the importance of LTD as a determinant for the cross-section of stock returns is not reduced. Generally, LTD, beta, and size seem to be the most important and consistently priced factors for the cross-section of stock returns with stable coefficients within all specifications.

3.4 Simplifying Tail Dependence Coefficient Estimation

The copula selection procedure described in Section 2.2 and the Appendix is computationally costly.[24] We now investigate whether this estimation procedure could be simplified. Instead of selecting the appropriate parametric copula by minimizing the distance between 64 different convex copula combination and the empirical copula, we choose 6 different convex copula combinations as the fixed dependence structure for stock i in year t. Hence, the LTD- and UTD-coefficients are based solely on the estimates of the fixed copula dependence structure. As our fixed copula combinations, we choose the Rotated Joe/FGM/Joe (2-D-I)-, the Rotated Galambos/FGM/Joe (3-D-I)-, the Rotated Gumbel/FGM/Joe (4-D-I)-, the Rotated Gumbel/Frank/Gumbel (2-B-II)-, the Rotated Galambos/Frank/Gumbel (4-B-II)-, and the Rotated Galambos/Frank/Galambos (4-B-III)-copula out of Table 2. We choose the copula combinations (2-D-I), (3-D-I), and (4-D-I) because they were the copulas most often selected

[24]The selection of the optimal copula combination and the estimation of the tail dependence coefficients on a grid cluster takes about 20 seconds per stock and year. This amounts to an entrire estimation time of 537 hours.

in the estimation procedure in Table 2. In contrast, copula combinations (2-B-II), (4-B-II), and (4-B-III) were the copulas least often selected in the estimation procedure. We perform Fama-Macbeth (1973) regression results of excess returns on LTD and UTD (estimated with different copula combinations) as well as the full set of control variables (as in Regression (5) in Panel B of Table 10). The results are displayed in Table 11.

[Insert Tables 11 about here]

The main message of Table 11 is that LTD is a highly significant explanatory factor for the cross-section of expected stocks returns independent of the specified convex copula combination. Dependent on the selected combination, a one standard deviation increase of LTD leads to an increase in expected returns of around 5.48% p.a. to 6.84% p.a. Again, the impact of UTD is much weaker: a one standard deviation increase in UTD leads to a decrease in expected returns of between −1.67% p.a. and −3.61% p.a. The magnitude of the coefficients and the significance levels of the control variables remain stable across the different specifications. Hence, we assure that our results are not driven by the tail dependence coefficient estimation procedure. The estimation procedure, which is computationally intensive, can be dramatically simplified by just picking a reasonable copula combination (like one of those in Table 1). This might be a helpful result for researchers working on the impact of tail dependence in similar settings.

4 Predicting Future Extreme Dependence

The previous section documents that unconditional tail dependence can explain the cross section of contemporaneous returns. We now examine whether tail dependence can be predicted. This would be necessary for an investor who wants to get exposure to tail dependence risk, e.g. because she is not crash-averse and wants to earn the risk premium documented above. We first examine how stable tail dependence is over time and whether we can find other variables that help us to predict extreme dependence (Section 4.1). Then, while not the focus of our paper, we want to check whether a profitable trading strategy could be implemented solely based on past information about future tail dependence (Section 4.2).

4.1 Persistence and Further Predictors of Extreme Dependence

We first examine whether individual stock extreme dependence is time-varying. To do so, we compute the average LTD of the stocks in the quintile portfolios over time. Firms are sorted into quintiles based on their realized LTD in year $t = 1$. Panel A of Figure 4 displays the evolution of the average equal weighted LTD of these portfolios over the following four years $t = 2$ to $t = 5$.

[Insert Figure 4 about here]

Visual inspection clearly shows that the stocks in the high LTD portfolio also have higher LTD than the stocks from the low LTD portfolio in the following years. However, the spread associated with LTD (UTD) quickly shrinks considerably. Panel B shows a similar pattern for the persistence in UTD. The patterns documented indicate that there is some predictability in extreme dependence, but the sharply decreasing spreads suggest that many stocks are exposed to time-varying tail risk.[25]

We now turn to a quantitative analysis of the variables that might help us to predict extreme dependence. We perform Fama and MacBeth (1973) regressions of our extreme dependence measures in year t on various firm characteristics and risk factors that are known in year $t-1$. Finding firm characteristics and risk factors that are cross-sectionally correlated with future extreme dependence can help us to predict future extreme dependence and eventually returns. In Panel A of Table 12, we explore the past determinants of LTD. Regressions (1) – (9) use one independent variable at a time, while Regression (10) uses all variables simultaneously.

[Insert Table 12 about here]

Regression 1 of Table 12 documents that past LTD does predict future LTD over the next year with significance at the 1% level. This result confirms the visual impression from Figure 4. However, the coefficient is far from one (0.248) and lower than the autocorrelation of for example market beta (0.620). In Regressions (2) – (9), we investigate the predictive power of other past firm characteristics and risk factors for future LTD. The lagged realizations of UTD, beta, size, returns, and cokurtosis are all positively related to future LTD, while lagged book-to-market and lagged idiosyncratic volatility have a negative impact on future LTD. Regression (10) shows that results are generally similar if we include all variables in one regression. However, in the multivariate setting, UTD is not a significant predictor of future LTD and book-to-market changes the sign of its coefficient.

We also investigate the past determinants of UTD in Panel B of Table 12. Again, Regressions (1) – (9) use one independent variable at a time, while Regression (10) uses all variables simultaneously.

[25]This latter finding also justifies our previous approach of relating returns to contemporaneous tail dependence realizations over relatively short horizons (as suggested for time-varying risk exposures in Lewellen and Nagel (2006)).

In Regression (1) of Panel B, we document that past UTD does predict future UTD over the next year with significance at the 1% level. However, the coefficient of (0.200) is even lower than the autocorrelation of LTD (0.248). Regressions (2) − (9) show that in a univariate setting past beta, size, past return, past coskewness, and past cokurtosis have a positive impact on UTD. Book-to-market, and past idiosyncratic volatility are negative predictors of UTD. Finally, Regression (10) documents that the results remain stable if we include all independent variables in a multivariate setting. Again, we find that the opposite past extreme dependence structure (in this case past LTD) is not a significant predictor of future UTD if we include all past variables at the same time.

The significant predictors of future extreme dependence can help in developing trading strategies that have a certain exposure on extreme dependence risk (see Section 4.2).

4.2 Past Extreme Dependence Risk and Future Returns

We now examine whether it is possible to generate abnormal returns based on prior information about past extreme dependence. In particular, an investor who is not crash-averse might try to get LTD-exposure to earn the risk premium documented in Section 3.

Our trading idea is to go long in stocks with strong past LTD and to go short in stocks with weak past LTD with monthly rebalancing. Specifically, we sort stocks into five quintile portfolios at time t based on their past LTD realizations over the previous twelve months. Then, we examine equally-weighted returns of these portfolios over the next month and calculate the return difference between the highest and the lowest LTD portfolio. The sample period is from January 1963 to December 2009, with our first year risk measurement period ending in December 1963 for the portfolio formation in January 1964.

Our empirical setup requires the estimation of LTD-coefficients for each stock for 552 overlapping 12 month periods. Thus, to reduce the computational effort, we rely on the results from Section 3.4 and simplify the estimation procedure for LTD in selecting the Rotated Joe/FGM/Joe (2-D-I)-copula as our fixed copula convex combination for all stocks and periods.

Table 13 reports the monthly equally-weighted average excess return over the risk free rate for all quintile portfolios based on past LTD. We also report t-statistics of differences in average excess returns between quintile portfolio 5 (high LTD) and quintile portfolio 1 (low LTD).

[Insert Table 13 about here]

Our findings show that stocks in the highest past LTD quintile earn an average equally-weighted excess return over the risk free rate of 0.788% per month, while the stocks in the lowest past LTD quintile earn 0.450% per month. Thus, our trading strategy of investing in high LTD stocks and shorting low LTD stocks delivers an economically significant future return of 0.338% per month, which translates into an average return premium of 4.06% p.a. The spread in average excess returns between quintile portfolio 5 and 1 is statistically significant at the 1% level.[26]

In Table 13, we also report the average past LTD, past market beta, size and book-to-market of each quintile portfolio. As documented in Table 5, there exists a strong positive relationship between LTD and β as well as size, whereas LTD is negatively related to book-to-market. This indicates that the premium for high LTD is unlikely to be attributable to the size-premium of Banz (1981) or the value-premium of Basu (1983). However, the results could be driven by regular market beta: High past LTD stocks may earn high future returns because they have high realized regular beta during the evaluation period.

To check whether beta-exposure drives our finding, we regress the time series of the monthly difference of excess returns between LTD quintile portfolio 5 and LTD quintile portfolio 1 on the monthly excess market return. Table 14 reports the regression results.

[Insert Table 14 about here]

Regression (1) documents that a part of the premium of our trading strategy is indeed due to high sensitivity to current market beta. However, the market factor cannot explain all of the return premium. The estimates for the regression constant in the last row show that the trading strategy delivers a monthly alpha of 0.216% after controlling for market beta. This alpha remains significant on the 5% significance level. When taking into account the size factor (SMB) and the book-to-market factor (HML) in Regression (2), the alpha of our strategy increases to 0.383% per month. The returns of our trading strategy load significantly negatively on both factors. In Regression (3), we also control for the momentum factor. The momentum factor is not a significant factor and we still obtain an monthly alpha of 0.351% per month when investing in high LTD stocks and go short in low LTD stocks. Additionally, we also control for Pastor and Stambough (2003)'s traded liquidity risk factor in Regression (4). The monthly alpha of our trading strategy is 0.323% and remains significant at the 1% significance level.[27] Finally, in Regression (5) we run exactly the same model, but estimate the LTD coefficients that we use for sorting firms into portfolios based on a moving window of 5 years instead of 12 months of daily data. The monthly alpha is slightly reduced to 0.283% but is still significant at the 1% significance level.

[26]In unreported tests, we also investigate a trading strategy based on UTD. We find no significant return spreads based on such a strategy.

[27]In unreported tests, we replace the Pastor and Stambough (2003) liquidity factor by the Sadka (2006) liquidity factor that is based on the permanent (variable) component of the price impact function and get very similar results.

These results suggest that it is possible to also create a profitable trading strategy based on extreme dependence exposure. However, these results are only indicative, as we do not take into account any trading costs and other limits of arbitrage. Limits of arbitrage are likely to be relevant here, because we short stocks with low LTD which tend to be small and low beta stocks. Furthermore, this strategy would of course only be profitable on a risk-adjusted basis for investors that do not require a risk premium for bearing extreme dependence risk that is higher than the documented return difference.

5 Robustness Checks

In this section we conduct a battery of robustness tests to analyze whether our main results from Section 3 are stable. We examine the influence of the weighting scheme in the portfolio sorts (Section 5.1), the temporal stability of our results (Section 5.2), and variations of the regression technique employed in the multivariate tests (Section 5.3).[28]

5.1 Weighting Scheme

So far, our sorts and double sorts focus on equal weighted portfolios and results thus could be influenced by overweighting the importance of small stocks.[29] Therefore, we now examine annual value-weighted average excess returns of univariate sorts by LTD and UTD as well as bivariate sorts on beta and LTD (UTD) in Table 15.

[Insert Table 15 about here]

Univariate results for LTD are presented in Panel A. Consistent with our previous results, we find that stocks in the quintile with the lowest (highest) LTD earn an annual average excess return of -0.53% p.a. (9.83% p.a.). The spread in average excess returns between quintile portfolio 1 and 5 is 10.36% p.a., which is statistically significant at the 1% level. In Panel B we document that stocks in the quintile with the lowest (highest) UTD earn an equal weighted annual average excess return of 6.67% p.a. (4.44% p.a.). The spread of -2.23% p.a. between the extreme quintiles is only marginally significant at the 10% level.

As mentioned above, the results from the univariate sorts could be driven by the difference in regular beta. Thus, we also conduct value-weighted double sorts based on tail dependence

[28] Besides the robustness tests described here, we also use weekly data instead of daily data and a longer estimation horizon to determine our tail dependence coefficients. Our results (not reported) are similar if we use a longer estimation horizon of 2 years, 3 years, or 5 years instead of 12 months.

[29] Similar concerns can also be raised with respect to the regression results because the regression evidence presented in Tables 10 to 11 is essentially also based on equal weighting, because each observations enters the cross-sectional Fama-MacBeth (1973) regressions with the same weight.

coefficients and beta similar as in Table 7. In Panel C of Table 15 we perform value-weighted double-sorts on beta and LTD. As with equally-weighted portfolios, we document an increase in average excess returns in each beta quintile. The return spread between high and low LTD stocks ranges from 2.45% p.a. for the lowest beta quintile up to 17.39% p.a. in the highest beta quintile. The return spread within all beta quintiles except for the lowest beta quintile are significant at the 1% level. Stocks in the quintile with the lowest (highest) LTD earn an annual average excess return over all beta quintiles of 2.51% p.a. (9.87% p.a.). The average spread excess returns between quintile portfolio 1 and 5 is 7.36% p.a, which is statisticalwly significant at the 1% level.

In Panel D of Table 15 we perform value-weighted double-sorts on beta and UTD. We document a decrease in average excess returns in each beta quintile. The average return spread between quintile portfolio 1 and 5 is −2.88% p.a., which is only marginally significant at the 10% level. In three beta quintiles we cannot document a significant decrease in average excess returns at all. The impact of UTD on returns is not stable.

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

5.2 Temporal Stability

In this section, we explore the temporal stability of our main result. As a first check, we reproduce the results of the univariate sorts from Table 5 for the first half of our sample 1963 to 1986 and for the second half of our sample 1987 to 2009 separately. Thus, we can check whether the results differ prior to the crash of 1987 and after. In the option pricing literature it is sometimes argued that investors became crash-o-phobic after the experience of the 1987 crash (Rubinstein (1994)). If investors were not crash-averse prior to 1987, we should not see any compensation for LTD in the earlier subperiod. Results are presented in Table 16.

[Insert Table 16 about here]

Results in Panel A show a return spread between stocks with strong LTD and stocks with weak LTD of 18.34% p.a. in the period 1963 to 1986. Results for the later superiod are presented in Panel B and show that the return spread is of similar magnitude at 16.48% p.a. In both cases, the magnitude of the spread is similar to that from the complete sample and significant at the 1% level. This shows that investors on the stock market got compensated for bearing stocks with strong LTD also prior to 1987.[30]

Additionally, we also look at the results from our multivariate regressions with the full set of explanatory variables for 8-year subperiods. Results of the respective Fama and MacBeth (1973) regressions are presented in Panel C of Table 16. Even within these relatively short subsamples, we always find a coefficient for the impact of LTD which is of similar magnitude than in the full sample. It ranges from 0.328 in the second 8-year period of our sample up to 0.568 in the fourth 8-year subperiod. It is significant at the 10% level in the first subperiod, significant at the 5% level in the last subperiod and significant at the 1% level in all other subperiods. Besides size, LTD is the most consistently priced factor in our sample. This confirms that the strong positive cross sectional impact of LTD on stock returns is remarkably stable over time.

5.3 Regression Methods

Our previous regression evidence relies on Fama and MacBeth (1973) regressions with winsorized variables. We now perform several variations of this basic regression approach on the full set of independent variables (extreme dependencies, betas, firm characteristics, and risk characteristics) for the full time period from 1963 – 2009. Results are presented in Table 17.

[Insert Table 17 about here]

Regression (1) performs a Fama-Macbeth-Regression, but we do not winsorize the independent variables. In Regression (2) we perform a pooled OLS-regression with time-fixed effects and standard errors clustered by single stocks. Regression (3) is identical, but we cluster standard errors by industry. Regression (4) performs a panel data regression with firm fixed effects. Finally, in Regression (5) we regress excess returns on the independent variables via a random-effect panel data regression.

We document that within all different regression setups, LTD is a highly significant explanatory factor for the cross-section of expected stocks returns. The point estimate for the influence of LTD is about 0.45 and very similar across regressions. Hence, our results are not driven by the specific regression technique or by a certain dependence structure of the error terms.

[30] Consistent with these results, Bates (2000) documents that out-of-the-money put options were also relatively expensive during certain periods prior to 1987. This suggests that investors on the options market also were crash averse not only after 1987 (or evaluated the probability of a crash occuring as high).

6 Conclusion

The cross-section of expected stock returns reflects a premium for risk associated with lower tail dependence. Stocks that are characterized by strong lower tail dependence earn significantly higher average returns than stocks with weak LTD. We find that the contemporaneous high average returns earned by stocks with high LTD are not explained by a list of cross-sectional effects, including market beta, size, book-to-market, momentum, coskewness, cokurtosis, idiosyncratic volatiltiy, or downside beta. Controlling for these and other cross-sectional effects, we find that an increase of one standard deviation in LTD is associated with an expected return premium of 5.15% p.a. Our findings also suggest that most of the impact of the downside beta of Ang, Chen, and Xing (2006) seems to be driven by extreme dependence in the lower tail of the bivariate distribution of individual security and market returns.

We also find that stocks with weak LTD outperform stocks with strong LTD in crises periods. As stocks with weak LTD thus essentially offer an 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 stocks with low LTD. While this conjecture that the higher returns of stocks with strong LTD is a reflection of higher equilibrium returns in the presence of crash averse investors is consistent with findings from the empirical literature on option prices (e.g. Rubinstein (1994)), the theoretical literature on crash aversion is scarce and offers promising possibilities for future theoretical work.[31]

We also document some predictability of extreme dependence based on past extreme dependence as well as some other predictive variables including past beta and size. We can form an investable trading strategy based on past extreme dependence structures that earns an excess return over the risk free rate before trading costs of 0.338% per month, which translates into an average return premium of 4.06% p.a. over the sample period from $1963-2009$. The Carhart (1997) four factor alpha of the strategy amounts to 4.21% p.a.

The fact that investors earn a premium for bearing extreme dependence risk can have serious implications: If financial institutions do not have to bear the expected costs of a severe market downturn (e.g. because they expect to be bailed out in a severe crises), they might be inclined to invest in exactly those securities that are characterized by strong lower tail dependence with the market in order to earn the associated extreme dependence premium we document in this study.[32] Such incentives would make those institutions even

[31]Promising approaches in this direction are offered in papers on the equilibrium effect of portfolio insurance like Grossman and Zhou (1996). However, this literature typically just adds an external restriction on the lower bound of terminal portfolio wealth, i.e. these models are typically agnostic about the motivation for portfolio insurance and crash-aversi on is in that sense an assumption rather than a result.

[32]Some suggestive evidence along these lines is again provided in the empirical option market literature.

more vulnerable. Whether current regulatory proposals based on downside risk concepts like Value-at-Risk sufficiently address these effects is an open question.

Garleanu, Pedersen, and Poteshman (2009) documents that dealers on aggregate hold short positions in out-of-the-money puts - that also offer protection against downturns - while end-users (defined as customers of brokers), seem to hold long positions, i.e. they insure against extreme downside risk.

A Appendix: Estimating Tail Dependence Coefficients

The estimation of LTD- and UTD-coefficients can either be based on the entire set of observations or on extremal data. In the univariate setting the extreme value distributions can be expressed in parametric form (see Fisher and Tippett (1928)) and parametric extreme value theory (EVT) is the natural choice for inferences on extreme values. To the contrary, bivariate extreme value distributions [as in this paper] cannot be characterized by a fully parametric model in general, which leads to more complicated estimation techniques. Our estimation approach relies on the entire set of observations and follows a three-step procedure.

A.1 Estimation of the Copula Parameters

We consider $j = 1, \ldots, 64$ convex combinations of copulas $C_j(\cdot, \cdot; \Theta_j)$ that each consist of one copula that allows for asymptotic dependence in the lower tail, C_{LTD}, one copula which is asymptotically independent, C_{NTD}, and one copula that allows for asymptotic dependence in the upper tail, C_{UTD} [as in (6)]. 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. We estimate the marginal distributions F_i and F_m of an individual stock return r_i and the market return r_m non-parametrically by their scaled empirical distribution functions

$$\widehat{F}_i = \frac{1}{n+1} \sum_{k=1}^{n} \mathbb{1}_{r_i \leq x} \quad \text{and} \quad \widehat{F}_m = \frac{1}{n+1} \sum_{k=1}^{n} \mathbb{1}_{r_m \leq x}. \tag{11}$$

The estimation of F_i and F_m by their empirical counterparts avoids an incorrect specification of the marginal distributions. It remains to estimate the set of copula parameters Θ_j. Since we assume a parametric form of the copula functions, the parameters Θ_j can be estimated via the maximum likelihood estimator

$$\widehat{\Theta}_j = \operatorname{argmax}_{\Theta_j} L_j(\Theta_j) \quad \text{with} \quad L_j(\Theta_j) = \sum_{k=1}^{n} \log\left(c_j(\widehat{F}_{i,k}, \widehat{F}_{m,k}; \Theta_j)\right), \tag{12}$$

where $L_j(\Theta_j)$ denotes the log-likelihood function and $c_j(\cdot, \cdot; \Theta_j)$ the copula densitiy. Assuming that $\{r_{i,k}, r_{m,k}\}_{k=1}^{n}$ is an i.i.d. random sample, Genest, Ghoudi, and Rivest (1995) and Shih and Louis (1995) show that $\widehat{\Theta}$ is a consistent and asymptotic normal estimate of the set of copula parameters Θ under regular conditions.[33]

[33] We are aware that daily return data violate the assumption of an i.i.d. random sample. An alternative

A.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 (1979) and Deheuvels (1981) to evaluate the fit of different parametric copula families.

Let $\{R_{i,k}, R_{m,k}\}_{k=1}^{n}$ denote the rank statistic of $\{r_{i,k}, r_{m,k}\}_{k=1}^{n}$. Deheuvels (1979) and Deheuvels (1981) introduce the empirical copula $\widehat{C}_{(T)}$ on the lattice

$$L = \left[\left(\frac{t_1}{T}, \frac{t_2}{T}\right), t_k = 1, \ldots, n, k = 1, 2\right]$$

by the following equation:

$$\widehat{C}_{(T)}\left(\frac{t_1}{T}, \frac{t_2}{T}\right) = \frac{1}{T}\sum_{i=1}^{n} \mathbb{1}_{R_{1,i}\leq t_1} \cdot \mathbb{1}_{R_{2,i}\leq t_2}. \tag{13}$$

Following the Theorem of Sklar (1959), the bivariate empirical distribution function $\widehat{F}$ corrresponding to F is uniquely defined by the empirical marginal distributions $\widehat{F}_1$ and $\widehat{F}_2$ and the values of the empirical copula $\widehat{C}_{(T)}$ on the lattice L.

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

$$D_{j,IAD} = \sum_{t_1=1}^{T}\sum_{t_2=1}^{T} \frac{\left(\widehat{C}_{(T)}\left(\frac{t_1}{T}, \frac{t_2}{T}\right) - C_j\left(\frac{t_1}{T}, \frac{t_2}{T}; \widehat{\Theta}_j\right)\right)^2}{C_j\left(\frac{t_1}{T}, \frac{t_2}{T}; \widehat{\Theta}_j\right) \cdot \left(1 - C_j\left(\frac{t_1}{T}, \frac{t_2}{T}; \widehat{\Theta}_j\right)\right)}. \tag{14}$$

Hence, we calculate the distance between the predicted value of the parametric copulas $C_j(\cdot,\cdot;\widehat{\Theta}_j)$ and the empirical $\widehat{C}_{(T)}$ copula on 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 $C^*(\cdot,\cdot;\Theta^*)$ that minimzes $D_{j,IAD}$. In unreported robustness checks, we also apply the Kolmogorov-Smirnov distances $D_{j,KS}$ between the parametric copulas $C_j(\cdot,\cdot;\widehat{\Theta}_j)$ and the empirical copula $\widehat{C}_{(T)}$, i.e.

approach to the problem of non-i.i.d. data due to serial correlation in the first and the second moment of the time series would be to specify an ARMA-GARCH model for the univariate processes and analyze the dependence structure of the residuals. We decide not to filter our data, due to the fact that filtering will also change the data's dependence structure.

$$D_{j,KS} = \max_{1 \leq t_k \leq T} |\widehat{C}_{(T)}\left(\frac{t_1}{T}, \frac{t_2}{T}\right) - C_j\left(\frac{t_1}{T}, \frac{t_2}{T}; \widehat{\Theta}_j\right)| \quad \text{for} \quad k = 1, 2. \tag{15}$$

and log-likelihood values to select the appropriate dependence structure. Independent of the selected evaluation measure ($D_{j,IAD}$, $D_{j,KS}$, or log-likelihood values), we obtain very similar results for the selected parametric copula.

A.3 Calculation of the Tail Dependence Coefficient

We compute the tail dependence coefficients implied by the estimated parameters Θ^* of the selected copula $C^*(\cdot, \cdot; \Theta^*)$. The calculation of LTD and UTD is straightforward if the copula in question has a closed form (such as copulas 1-4, A-D, and I-IV in Table 1) and is based on formulas (4) and (5). The lower and upper tail dependence coefficient of the convex combination are calculated as the weighted sum of the LTD and UTD coefficients from the individual copulas, respectively, where the weights from (6) are used, i.e. $\text{LTD}^* = w_1^* \cdot \text{LTD}(\theta_1^*)$ and $\text{UTD}^* = (1 - w_1^* - w_2^*) \cdot \text{UTD}(\theta_3^*)$.

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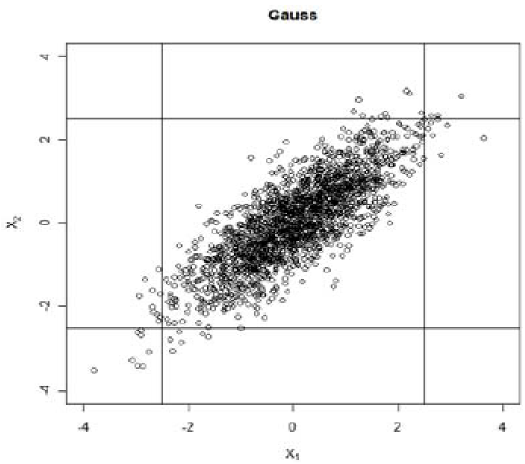
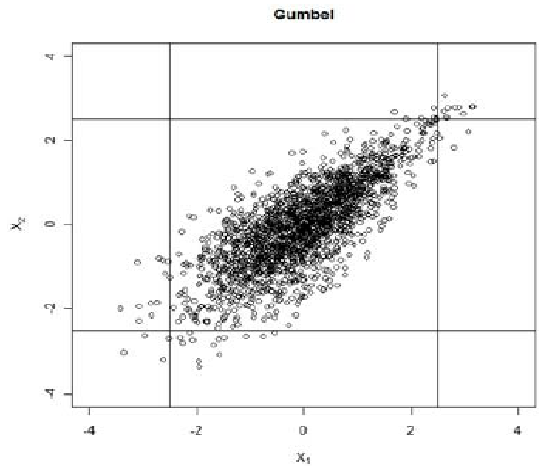
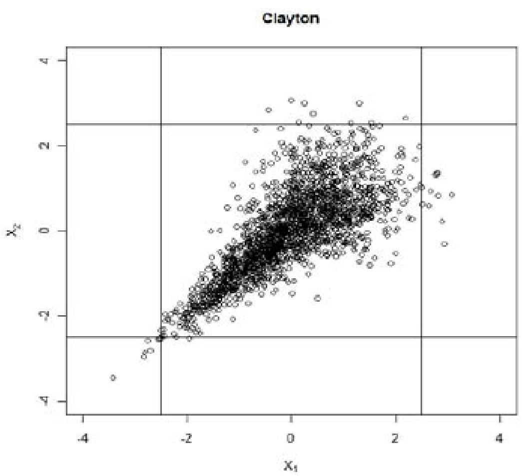
Figure 1: Different Copula Dependence Structures



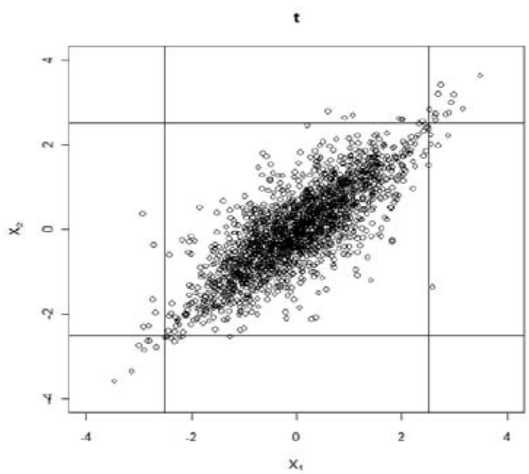
(a) Panel A: Gauss-copula structure



(b) Panel B: Gumbel-copula structure



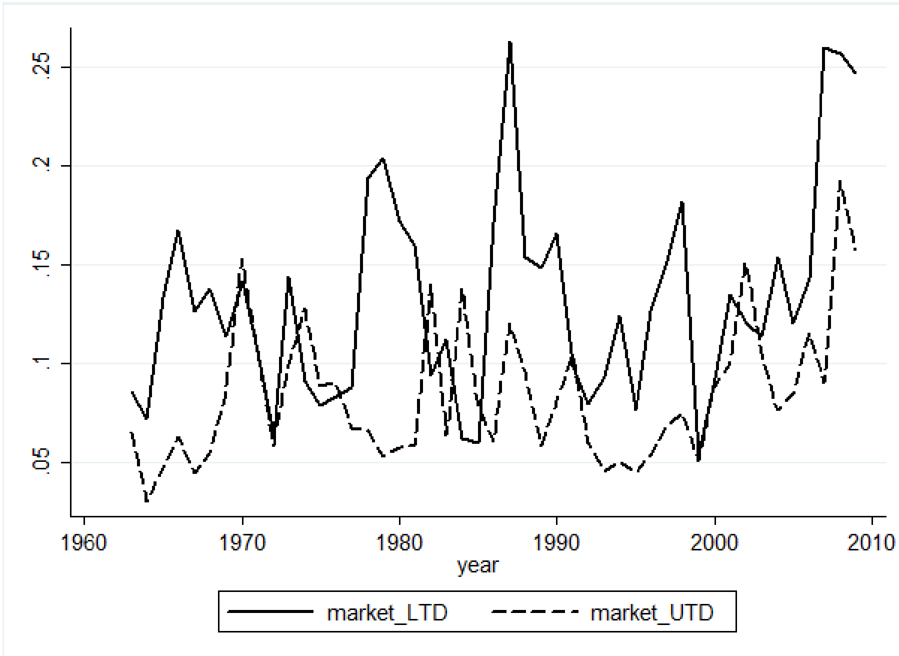
(c) Panel C: Clayton-copula structure



(d) Panel D: Student t-copula structure

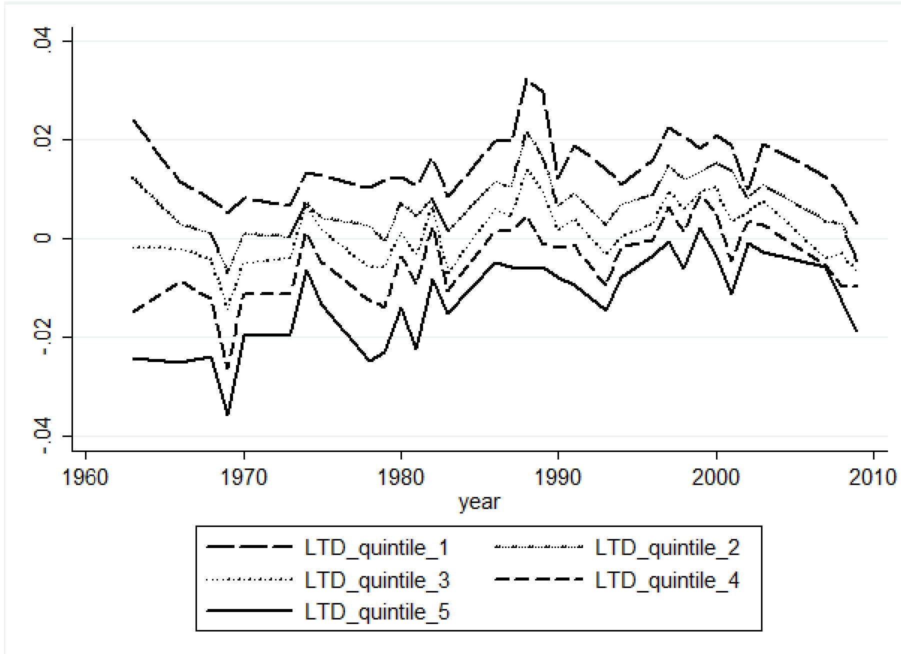
This figure displays 2000 random variates from four bivariate distributions with standard normal marginal distributions and the Gauss-copula (Panel A), the Gumbel-copula (Panel B), the Clayton-copula (Panel C), and the Student t-copula (Panel D). In each panel the parameters are chosen to provide a linear correlation of 0.8.

Figure 2: Aggregate Tail Dependence over Time



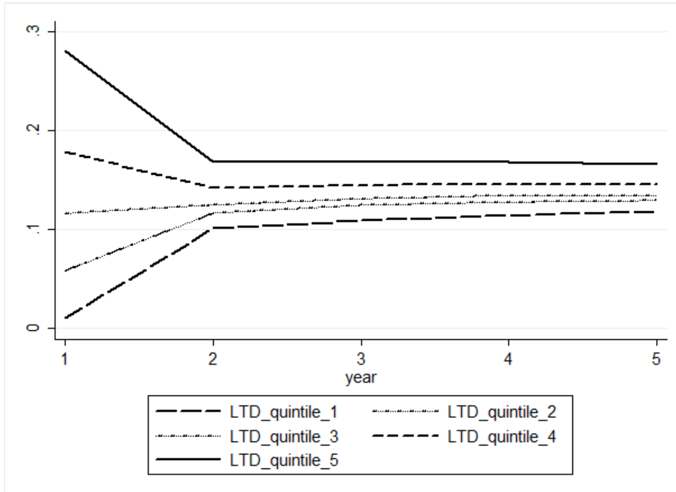
This figure displays the evolution of market LTD (UTD) over time. Market LTD (UTD) is defined as the yearly cross-sectional, equal-weighted, average of the individual lower tail dependence coefficients, $\text{LTD}_{i,t}$ (upper tail dependence coefficients, $\text{UTD}_{i,t}$) over all stocks i in our sample. The sample period is from January 1963 to December 2009.

Figure 3: LTD Portfolios on Days With Strong Negative Returns

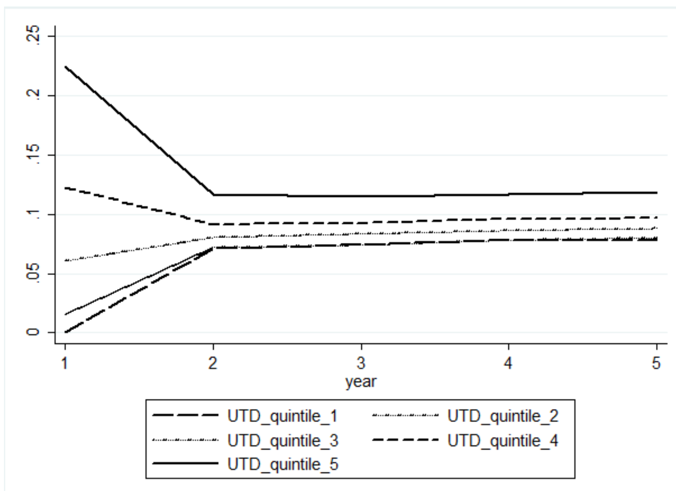


This figure plots the average daily excess returns over the market of five LTD portfolios for days on which the market return minus the riskfree rate is less than -2%. Firms are sorted into quintiles based on their realized yearly LTD. The sample period is from January 1963 to December 2009.

Figure 4: Persistence of Tail Dependence



(a) Panel A: Evolution of LTD portfolios over time



(b) Panel B: Evolution of UTD portfolios over time

This figure displays the evolution of the average equal-weighted tail dependence of five quintile portfolios. Firms are sorted into quintiles based on their realized LTD (UTD) in year $t = 1$. Then, the equal-weighted average of lower tail dependence, LTD (upper tail dependence, UTD) of these portfolios is computed again in the following four years. Panel A displays the evolution of the LTD portfolios, Panel B displays the evolution of the UTD portfolios. The sample period is from January 1963 to December 2009.

Table 1: Bivariate Copula Functions with Tail Dependence Coefficients

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

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

Table 2: Frequency and Relative Percentage of Copula Selection

Copula	Freq	Perc	Copula	Freq	Perc	Copula	Freq	Perc	Copula	Freq	Perc
(1-A-I)	1,448	1.50	(2-A-I)	1,557	1.61	(3-A-I)	1,756	1.81	(4-A-I)	1,337	1.38
(1-A-II)	1,323	1.37	(2-A-II)	949	0.98	(3-A-II)	1,299	1.34	(4-A-II)	888	0.92
(1-A-III)	1,544	1.60	(2-A-III)	1,150	1.19	(3-A-III)	1,566	1.62	(4-A-III)	890	0.92
(1-A-IV)	1,596	1.65	(2-A-IV)	1,843	1.90	(3-A-IV)	1,679	1.74	(4-A-IV)	1,294	1.34
(1-B-I)	1,586	1.64	(2-B-I)	1,046	1.08	(3-B-I)	1,509	1.56	(4-B-I)	1,265	1.31
(1-B-II)	1,163	1.20	(2-B-II)	524	0.54	(3-B-II)	940	0.97	(4-B-II)	661	0.68
(1-B-III)	1,631	1.69	(2-B-III)	1,019	1.05	(3-B-III)	1,360	1.41	(4-B-III)	808	0.83
(1-B-IV)	1,486	1.54	(2-B-IV)	1,407	1.45	(3-B-IV)	1,287	1.33	(4-B-IV)	1,206	1.25
(1-C-I)	1,800	1.86	(2-C-I)	1,555	1.61	(3-C-I)	2,309	2.39	(4-C-I)	1,802	1.86
(1-C-II)	1,400	1.45	(2-C-II)	803	0.83	(3-C-II)	1,184	1.22	(4-C-II)	1,019	1.05
(1-C-III)	1,618	1.67	(2-C-III)	1,221	1.26	(3-C-III)	1,558	1.61	(4-C-III)	831	0.86
(1-C-IV)	1,359	1.40	(2-C-IV)	1,565	1.62	(3-C-IV)	1,361	1.41	(4-C-IV)	1,300	1.34
(1-D-I)	2,452	2.53	**(2-D-I)**	**2,569**	**2.65**	**(3-D-I)**	**3,180**	**3.29**	**(4-D-I)**	**2,985**	**3.08**
(1-D-II)	1,666	1.72	(2-D-II)	1,144	1.18	(3-D-II)	1,498	1.55	(4-D-II)	1,281	1.32
(1-D-III)	2,092	2.16	(2-D-III)	1,468	1.52	(3-D-III)	2,173	2.25	(4-D-III)	1,633	1.69
(1-D-IV)	2,130	2.20	(2-D-IV)	2,477	2.56	(3-D-IV)	2,020	2.09	(4-D-IV)	2,297	2.37

This table reports the absolute and percentage frequency of the selected parametric copula combinations. The appropriate dependence structure is selected by minimizing the distance between the parametric copulas and the empirical copula via the Integrated Anderson-Darling distance. The estimation of the lower tail dependence coefficients and upper tail dependence coefficients is based on the parametric copula that minimizes the distance to the empirical copula. In columns 1, 4, 7, and 10 we indicate the label of the respective copula combination based on the basic copula labels from Table 1. The three copulas that are most often selected are: (2-D-I) - Rotated Joe/FGM/Joe-copula, (3-D-I) - Rotated Galambos/FGM/Joe-copula, and (4-D-I) - Rotated Gumbel/FGM/Joe-copula. These copulas are marked in bold.

Table 3: Aggregate Tail Dependence Over Time

Time Period	Obs	market LTD	market UTD	Diff	LTD large	LTD small	Diff	UTD large	UTD small	Diff
1963 – 1968	12,021	0.122	0.051	0.071***	0.146	0.073	0.073***	0.077	0.029	0.048***
1969 – 1974	13,939	0.109	0.105	0.004***	0.123	0.081	0.042***	0.142	0.071	0.071***
1975 – 1979	11,275	0.129	0.073	0.056***	0.153	0.078	0.079***	0.112	0.052	0.060***
1980 – 1984	10,599	0.121	0.091	0.030***	0.135	0.086	0.049**	0.155	0.051	0.104**
1985 – 1989	9,726	0.159	0.083	0.076***	0.261	0.084	0.177***	0.140	0.048	0.092***
1990 – 1994	9,640	0.112	0.067	0.045***	0.161	0.067	0.094***	0.119	0.036	0.083***
1995 – 1999	11,415	0.120	0.059	0.061***	0.182	0.065	0.127***	0.110	0.028	0.082***
2000 – 2004	9,483	0.122	0.104	0.018***	0.166	0.065	0.101***	0.168	0.034	0.134***
2005 – 2009	8,669	0.203	0.126	0.077***	0.254	0.099	0.155***	0.155	0.055	0.100***
1963 – 2009	96,767	0.177	0.142	0.035***	0.176	0.078	0.098***	0.131	0.045	0.086***

This table reports equal-weighted means and differences of aggregate lower and upper tail dependence, market LTD and market UTD, within 5-year subsamples and over the whole sample period from January 1963 to December 2009. We define market LTD as the yearly cross-sectional, value-weighted, average of individual lower tail dependence, $LTD_{i,t}$, over all stocks i in our sample. Analogously, we define market UTD as the yearly cross-sectional, value-weighted, average of individual upper tail dependence, $UTD_{i,t}$, over all stocks i in our sample.

Table 4: Correlations

	beta	LTD	UTD	down beta	up beta	size	bookmarket	past return	idio vola	coskew	cokurt
beta	1.00	-	-	-	-	-	-	-	-	-	-
LTD	0.34	1.00	-	-	-	-	-	-	-	-	-
UTD	0.28	0.09	1.00	-	-	-	-	-	-	-	-
downside beta	0.78	0.46	0.04	1.00	-	-	-	-	-	-	-
upside beta	0.79	0.17	0.46	0.49	1.00	-	-	-	-	-	-
size	0.05	0.23	0.28	−0.08	−0.04	1.00	-	-	-	-	-
book-to-market	−0.05	−0.04	−0.07	−0.01	−0.04	−0.22	1.00	-	-	-	-
past return	0.11	0.06	−0.05	0.13	0.06	0.02	0.13	1.00	-	-	-
idiosyncratic vola	0.30	−0.04	−0.07	0.33	0.17	−0.40	0.00	−0.06	1.00	-	-
coskewness	0.07	−0.35	0.19	−0.09	0.20	−0.04	0.00	−0.07	0.03	1.00	-
cokurtosis	0.15	0.35	0.19	0.11	0.15	0.15	−0.04	−0.01	−0.04	−0.78	1.00

This table displays linear correlations between the independent variables used in this study. As independent variables we use beta, lower tail dependence (LTD), upper tail dependence (UTD), downside beta, upside beta, size (computed as the log of market capitalization), book-to-market value, past returns, idiosyncratic volatility, coskewness, and cokurtosis. A detailed description of the computation of these variables is given in the main text. The sample period for all independent variables is from January 1963 to December 2009.

Table 5: Univariate Equal-weighted Portfolio Sorts: Tail Dependence and Returns

Panel A: Lower Tail Dependence (LTD)

Portfolio	Return	LTD	UTD	down beta	coskew	beta	size	bookmarket
1 Low LTD	1.73%	0.01	0.06	0.43	0.00	0.56	11.35	0.98
2	7.01%	0.06	0.08	0.77	−0.05	0.73	11.79	0.92
3	8.99%	0.12	0.09	0.96	−0.09	0.82	12.01	0.90
4	12.76%	0.18	0.10	1.18	−0.12	0.95	12.36	0.86
5 High LTD	19.17%	0.29	0.09	1.54	−0.17	1.19	12.97	0.82
5 High - Low	17.44%***	0.28***	0.03***	1.11***	−0.17***	0.63***	1.62***	−0.16***

Panel B: Upper Tail Dependence (UTD)

Portfolio	Return	UTD	LTD	up beta	coskew	beta	size	bookmarket
1 Low UTD	11.09%	0.00	0.11	0.34	−0.15	0.69	11.59	0.95
2	11.15%	0.01	0.12	0.41	−0.13	0.69	11.52	0.96
3	10.27%	0.06	0.14	0.72	−0.09	0.82	11.93	0.92
4	9.69%	0.12	0.15	0.98	−0.06	0.93	12.31	0.88
5 High UTD	7.54%	0.23	0.14	1.35	−0.01	1.11	13.10	0.79
5 High - Low	−3.55%***	0.23***	0.03***	1.01***	0.14***	0.42***	1.51***	−0.16***

This table reports equal-weighted average returns and risk characteristics of stocks sorted by realized LTD (Panel A) and UTD (Panel B). Each year we rank stocks into quintiles (1-5) and form equal-weighted portfolios at the beginning of each annual period. The column labelled 'Return' reports the average return in excess of the one-month T-bill rate over the next year. The other columns report average risk- and firm characteristics measured contemporaneously with returns. The row labelled 'High-Low' reports the difference between the returns of portfolio 5 and portfolio 1 with corresponding statistic significance level. The sample period is from January 1963 to December 2009. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 6: Excess Returns of LTD-Portfolios during Financial Crises

Portfolio	Black Monday	Asia Crisis	Dot-Com Bubble Burst	Lehman Crisis	Daily Excess Market Returns $< -5\%$
1 Low LTD	−9.5%	−2.4%	−1.7%	−5.9%	−4.4%
2	−13.3%	−4.4%	−3.1%	−6.9%	−6.0%
3	−15.7%	−5.7%	−4.3%	−9.4%	−7.3%
4	−16.3%	−6.3%	−5.9%	−11.2%	−8.4%
5 High LTD	−18.7%	−6.8%	−7.3%	−11.8%	−9.2%
5 High - Low	−9.2%	−4.4%	−5.6%	−5.9%	−4.8%***

This table reports equal-weighted daily excess returns returns of stocks sorted by realized LTD. Each year we rank stocks into quintiles (1-5) and form equal-weighted portfolios at the beginning of each annual period. We investigate daily excess returns of these portfolios during "Black Monday" (October 19, 1987), the Asian Crisis (October 27, 1997), the burst of the dot-com bubble (April 14, 2000), and the recent Lehman crises (October 15, 2008). The last column reports daily excess returns of the portfolios when the daily excess market return dropped more than 5%. The row labelled 'High-Low' reports the difference between the returns of portfolio 5 and portfolio 1 with corresponding statistic significance level (only last column). ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 7: Dependent Equal-weighted Portfolio Sorts: Beta vs. Tail Dependence

Panel A: Beta (β) and Lower Tail Dependence (LTD)

Portfolio	1 Low β	2	3	4	5 High β	Average
1 Low LTD	1.46%	2.95%	3.47%	4.04%	6.35%	3.66%
2	3.78%	6.32%	6.75%	11.19%	12.83%	8.17%
3	4.24%	8.17%	8.64%	12.70%	17.84%	10.32%
4	4.91%	8.47%	11.89%	13.45%	21.74%	12.09%
5 High LTD	7.97%	11.80%	13.85%	16.76%	27.71%	15.62%
High-Low	6.51%***	8.85%***	10.38%***	12.72%***	21.36%***	11.96%***

Panel B: Beta (β) and Upper Tail Dependence (UTD)

Portfolio	1 Low β	2	3	4	5 High β	Average
1 Low UTD	5.37%	9.07%	10.46%	14.82%	20.22%	11.99%
2	3.18%	8.23%	11.56%	14.98%	22.67%	12.12%
3	4.31%	8.71%	8.28%	12.04%	18.39%	10.35%
4	3.66%	6.12%	8.78%	9.91%	14.50%	8.59%
5 High UTD	3.38%	5.06%	5.53%	6.53%	10.80%	6.26%
High-Low	−1.99%	−4.01%***	−4.93%***	−8.29%***	−9.42%***	−5.73%***

This table reports equal-weighted average returns of 25 portfolios sorted by realized beta and realized LTD and UTD, respectively. First, we form quintile portfolios sorted on beta. Then, within each beta quintile, we sort stocks into five equal-weighted portfolios based on LTD (UTD). Panel A displays the results of the 25 beta - LTD sorts, Panel B shows the results of the 25 beta - UTD sorts. The row labelled 'High-Low' reports the difference between the returns of portfolio 5 and portfolio 1 in each beta quintile with corresponding statistic significance level. The sample period is from January 1963 to December 2009. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 8: Dependent Equal-weighted Portfolio Sorts: Downside/Upside Beta vs. Tail Dependence

Panel A: Downside Beta (β^-) and Lower Tail Dependence (LTD)

Portfolio	1 Low β^-	2	3	4	5 High β^-	Average
1 Low LTD	0.48%	3.35%	3.18%	5.76%	8.49%	4.25%
2	1.42%	5.86%	7.44%	10.52%	14.28%	7.90%
3	4.10%	7.46%	9.26%	11.89%	17.91%	10.12%
4	5.75%	7.94%	12.27%	14.07%	20.81%	12.17%
5 High LTD	8.90%	9.98%	12.79%	17.54%	27.26%	15.29%
High-Low	8.42%***	6.63%***	9.61%***	11.78%***	18.77%***	11.04%***

Panel B: Upside Beta (β^+) and Upper Tail Dependence (UTD)

Portfolio	1 Low β^+	2	3	4	5 High β^+	Average
1 Low UTD	8.85%	11.03%	13.24%	14.98%	15.36%	12.69%
2	8.84%	9.31%	11.87%	13.93%	17.13%	12.22%
3	7.61%	10.66%	9.22%	11.04%	14.67%	10.64%
4	6.81%	6.77%	9.20%	9.33%	10.15%	8.45%
5 High UTD	2.31%	5.16%	6.55%	6.00%	8.12%	5.63%
High-Low	−6.54%***	−5.87%***	−6.69%***	−8.98%***	−7.24%***	−7.06%***

This table reports equal-weighted average returns of 25 portfolios sorted by realized downside (upside) beta and realized LTD (UTD). In Panel A, we form quintile portfolios sorted on downside beta. Then, within each downside beta quintile, we sort stocks into five equal-weighted portfolios based on LTD. In Panel B, we form quintile portfolios sorted on upside beta. Then, within each upside beta quintile, we sort stocks into five equal-weighted portfolios based on UTD. The row labelled 'High-Low' reports the difference between the returns of portfolio 5 and portfolio 1 in each downside (upside) beta quintile with corresponding statistic significance level. The sample period is from January 1963 to December 2009. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 9: Dependent Equal-weighted Portfolio Sorts: Coskewness vs. Tail Dependence

Panel A: Coskewness (coskew) and Lower Tail Dependence (LTD)

Portfolio	1 Low coskew	2	3	4	5 High coskew	Average
1 Low LTD	6.67%	4.90%	3.21%	0.83%	0.95%	3.31%
2	9.07%	9.39%	7.57%	5.90%	3.77%	7.14%
3	11.78%	11.17%	9.11%	7.23%	6.14%	9.09%
4	15.86%	14.76%	12.36%	11.92%	7.77%	12.53%
5 High LTD	21.64%	19.78%	18.44%	16.09%	12.44%	17.68%
High-Low	14.97%***	14.88%***	15.23%***	15.26%***	11.49%***	14.37%***

Panel B: Coskewness (coskew) and Upper Tail Dependence (UTD)

Portfolio	1 Low coskew	2	3	4	5 High coskew	Average
1 Low UTD	13.58%	13.41%	10.82%	7.97%	6.64%	10.48%
2	14.89%	9.85%	11.51%	8.28%	6.85%	10.28%
3	15.18%	13.22%	9.91%	9.02%	6.52%	10.77%
4	12.17%	12.69%	10.50%	8.53%	6.18%	10.01%
5 High UTD	10.66%	9.02%	8.11%	7.85%	4.25%	7.98%
High-Low	−2.92%*	−4.39%***	−2.71%*	−0.12%	−2.39%*	−2.51%*

This table reports equal-weighted average return and risk characteristics of 25 portfolios sorted by realized coskewness and realized LTD (UTD). First, we form quintile portfolios sorted on coskewness. Then, within each coskewness quintile, we sort stocks into five equal-weighted portfolios based on LTD (UTD). The row labelled 'High-Low' reports the difference between the returns of portfolio 5 and portfolio 1 in each coskewness quintile with corresponding statistic significance level. The sample period is from January 1963 to December 2009. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 10: Fama-Macbeth (FMB) Regressions

Panel A: FMB with Betas and Tail Dependence

Regression	(1)	(2)	(3)	(4)	(5)
Dep. Var.	return	return	return	return	return
beta	0.0881***			0.0625**	0.0678**
	(3.70)			(2.27)	(2.43)
down beta		0.0604***			-0.0127
		(3.28)			(-0.91)
up beta		0.00434			0.00567
		(0.56)			(0.48)
LTD			0.622***	0.432***	0.447***
			(9.80)	(7.67)	(6.01)
UTD			-0.237***	-0.340***	-0.318***
			(-4.00)	(-3.58)	(-5.24)
constant	0.0250	0.0334	0.0401	0.00964	0.0104
	(1.22)	(1.60)	(1.29)	(0.42)	(0.47)
R^2	0.035	0.039	0.028	0.056	0.065

Table 10: continued

Panel B: FMB with Full Set of Controls

Regression Dep. Var.	(1) return	(2) return	(3) return	(4) return	(5) return	Economic Significance
beta	0.102***	0.0718**	0.132***	0.121***	0.160***	+8.94%
	(3.68)	(2.61)	(5.73)	(4.94)	(4.87)	
size	-0.0180**	-0.0229***	-0.0487***	-0.0500***	-0.0507***	-8.74%
	(-2.68)	(-3.56)	(-8.27)	(-8.26)	(-8.18)	
bookmarket	0.0400***	0.0367***	0.0363***	0.0359***	0.0368***	2.68%
	(4.42)	(4.18)	(4.00)	(3.98)	(4.12)	
coskew	-0.114**	0.135***	0.104**	0.0853*	0.154**	4.73%
	(-2.61)	(2.74)	(2.24)	(1.69)	(2.62)	
LTD		0.572***	0.447***	0.429***	0.449***	5.12%
		(11.23)	(10.03)	(9.76)	(9.65)	
UTD		-0.262***	-0.299***	-0.310***	-0.290***	-2.73%
		(-4.72)	(-6.89)	(-7.07)	(-6.05)	
past return			-0.0254	-0.0247	-0.0260	-1.15%
			(-1.28)	(-1.25)	(-1.30)	
idio vola			-4.043**	-3.753**	-3.419**	-3.77%
			(-2.43)	(-2.33)	(-2.05)	
cokurt				0.0204*	0.0243*	+4.49%
				(1.70)	(1.85)	
down beta					-0.0129	-0.94%
					(-0.95)	
up beta					-0.0397**	-3.06%
					(-2.36)	
constant	0.181*	0.230**	0.657***	0.663***	0.657***	
	(2.01)	(2.61)	(7.49)	(7.59)	(7.55)	
R^2	0.085	0.101	0.146	0.149	0.165	-

This table displays the results of Fama-MacBeth (1973) regressions of 1-year excess returns over the risk free rate on tail dependence coefficients, LTD and UTD, and beta, downside beta, and upside beta (Panel A). All risk characteristics are calculated contemporaneously to the yearly excess return. In Panel B, firm characteristics are included additionally. The log of market capitalizations (size), book-to-market ratios (bookmarket), and past 12-month excess returns (past return), all computed at the beginning of each period, are included. The independent variables are winsorized at the 1% level and at the 99% level. The last column displays the change in annualized returns for a one standard deviation increase in the respective independence variable based on the regression in Column (5). The sample period is from January 1963 to December 2009. t statistics are in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 11: Fama-Macbeth Regressions with Fixed Copula Combinations

	Copula (2-D-I)	Copula (3-D-I)	Copula (4-D-I)	Copula (2-B-II)	Copula (4-B-II)	Copula (4-B-III)
Dep. Var.	return	return	return	return	return	return
beta	0.151***	0.125***	0.137***	0.147***	0.138***	0.136***
	(4.13)	(3.68)	(4.14)	(4.49)	(4.17)	(4.06)
LTD	0.600***	0.514***	0.510***	0.572***	0.481***	0.506***
	(9.51)	(7.38)	(7.61)	(10.20)	(9.48)	(8.98)
UTD	-0.375***	-0.384***	-0.370***	-0.178***	-0.250***	-0.241***
	(-6.71)	(-5.45)	(-6.26)	(-3.15)	(-4.03)	(-4.30)
size	-0.0516***	-0.0462***	-0.0523***	-0.0502***	-0.0435***	-0.0443***
	(-7.86)	(-7.30)	(-8.29)	(-8.44)	(-7.27)	(-7.28)
bookmarket	0.0328***	0.0382***	0.0359***	0.0363***	0.0385***	0.0383***
	(3.66)	(4.17)	(3.81)	(3.82)	(4.13)	(4.10)
past return	-0.0196	-0.0272	-0.0297	-0.0294	-0.0273	-0.0271
	(-0.93)	(-1.26)	(-1.39)	(-1.39)	(-1.26)	(-1.25)
idio vola	-3.962**	-3.167**	-3.152*	-3.196*	-3.343**	-3.272**
	(-2.47)	(-2.17)	(-1.79)	(-1.80)	(-2.26)	(-2.20)
coskew	0.213***	0.248***	0.244***	0.252***	0.240***	0.237***
	(3.29)	(3.98)	(4.37)	(4.48)	(3.78)	(3.74)
cokurt	0.0187	-0.00385	0.0149	0.0143	0.00516	0.00793
	(1.37)	(-0.26)	(1.40)	(1.34)	(0.33)	(0.51)
down beta	-0.0250	-0.00913	-0.00646	-0.00229	-0.00154	-0.00426
	(-1.37)	(-0.55)	(-0.51)	(-0.19)	(-0.10)	(-0.27)
up beta	-0.0272*	-0.0301*	-0.0478**	-0.0562***	-0.0390**	-0.0386**
	(-1.86)	(-1.92)	(-2.53)	(-2.92)	(-2.40)	(-2.38)
constant	0.684***	0.611***	0.682***	0.649***	0.575***	0.585***
	(7.60)	(7.16)	(7.94)	(7.79)	(6.97)	(7.02)
R^2	0.165	0.166	0.162	0.160	0.163	0.163

This table displays the results of Fama-MacBeth (1973) regressions of 1-year excess returns on the full set of firm- and risk characteristics. The tail dependence coefficients, LTD and UTD, are estimated with fixed copula cominations. The applied copula combination for the estimation is displayed in the top column. All risk characteristics (tail dependence coefficients, beta, downside beta, upside beta, coskewness, and cokurtosis) are calculated contemporaneously to the yearly excess return. The firm characteristics are log of market capitalizations (size), book-to-market ratios (bookmarket), and past 12-month excess returns (past return), all computed at the beginning of each period. The independent variables are winsorized at the 1% level and at the 99% level. The sample period is from January 1963 to December 2009. t statistics are in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 12: Prediction of Tail Dependence

Panel A: Prediction of Lower Tail Dependence (LTD)

	(1) LTD	(2) LTD	(3) LTD	(4) LTD	(5) LTD	(6) LTD	(7) LTD	(8) LTD	(9) LTD	(10) LTD
past LTD	0.248***									0.0516***
	(12.56)									(6.37)
past UTD		0.169***								-0.00988
		(10.10)								(-1.32)
past beta			0.0610***							0.0340***
			(11.86)							(8.36)
size				0.0173***						0.0105***
				(12.13)						(8.08)
bookmarket					-0.0129***					0.00519***
					(-6.48)					(3.00)
past return						0.0333***				0.0141***
						(6.91)				(4.13)
past idio vola							-0.905***			-0.325*
							(-3.32)			(-1.96)
past coskew								-0.0196		-0.0115
								(-1.13)		(-1.25)
past cokurt									0.0424***	0.00663**
									(10.78)	(2.33)
constant	0.0987***	0.120***	0.0841***	-0.0814***	0.146***	0.130***	0.163***	0.117***	0.0764***	-0.0414**
	(16.00)	(16.01)	(14.62)	(-5.27)	(17.01)	(17.21)	(14.89)	(16.25)	(14.14)	(-2.58)
R^2	0.071	0.026	0.094	0.112	0.011	0.026	0.025	0.032	0.112	0.158

Table 12: continued

Panel B: Prediction of Upper Tail Dependence (UTD)

	(1) UTD	(2) UTD	(3) UTD	(4) UTD	(5) UTD	(6) UTD	(7) UTD	(8) UTD	(9) UTD	(10) UTD
past UTD	0.200***									0.0347***
	(15.61)									(4.20)
past LTD		0.137***								-0.00483
		(13.21)								(-0.90)
past beta			0.0398***							0.0219***
			(12.16)							(5.60)
size				0.0161***						0.0114***
				(16.60)						(11.39)
bookmarket					-0.0158***					-0.000854
					(-9.83)					(-0.82)
past return						0.0110***				0.000365
						(4.47)				(0.19)
past idio vola							-1.687***			-0.727***
							(-11.75)			(-6.59)
past coskew								0.0346***		0.0109**
								(2.92)		(2.14)
past cokurt									0.0377***	0.00973***
									(10.30)	(3.99)
constant	0.0687***	0.0670***	0.0534***	-0.113***	0.0993***	0.0858***	0.130***	0.0775***	0.0384***	-0.0659***
	(14.39)	(14.11)	(14.21)	(-10.98)	(17.38)	(15.36)	(17.44)	(14.28)	(12.39)	(-5.29)
R^2	0.044	0.030	0.052	0.121	0.014	0.007	0.036	0.022	0.097	0.145

This table displays the results of Fama-MacBeth (1973) regressions of tail dependence coefficients at year t on past firm- and risk characteristics for lower tail dependence (Panel A) and upper tail dependence (Panel B). The risk characteristics (tail dependence coefficients, beta, downside beta, upside beta, coskewness, and cokurtosis) and firm characteristics (size, bool-to-market ratios, and past 12-month excess returns) are all computed at year $t-1$. All independent variables are cut off at the 1% level and at the 99%. The sample period is from January 1963 to December 2009. t statistics are in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 13: Past Lower Tail Dependence and Future Returns

Portfolio	Monthly Return	past LTD	past beta	size	bookmarket
1 Low LTD	0.450%	0.025	0.543	11.11	1.04
2	0.595%	0.094	0.716	11.71	0.95
3	0.663%	0.154	0.831	12.10	0.91
4	0.746%	0.216	0.965	12.60	0.84
5 High LTD	0.788%	0.315	1.193	13.35	0.78
5 High - Low	0.338%***	0.290***	0.650***	2.24***	-0.26***

This table lists equal-weighted average returns and risk characteristics of stocks sorted by past lower tail dependence (LTD). Each month we rank stocks into quintiles (1-5) and form equal-weighted portfolios based on past 1-year LTD. The column labelled 'Return' reports the average return in excess of the one-month T-bill rate over the following month. The other columns report average realized risk characteristics measured contemporaneously with returns. The row labelled 'High-Low' reports the difference between the returns of portfolio 5 and portfolio 1 with corresponding statistic significance level. The sample period is from January 1963 to December 2009. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 14: Trading Strategy Based on Lower Tail Dependence: Factor Models

	(1)	(2)	(3)	(4)	(5)
marketrf	0.292***	0.323***	0.330***	0.302***	0.374***
	(13.10)	(15.17)	(15.21)	(13.94)	(15.26)
smb		-0.351***	-0.351***	-0.370***	-0.576***
		(-11.91)	(-11.93)	(-12.86)	(-17.62)
hml		-0.209***	-0.197***	-0.249***	-0.253***
		(-6.52)	(-6.02)	(-7.52)	(-6.67)
mom			0.0334	0.0693***	-0.115***
			(1.60)	(3.19)	(-6.69)
ps liqui				-0.0000381	0.0114
				(-1.24)	(0.38)
constant	0.00216**	0.00383***	0.00351***	0.00323***	0.00283***
	(2.14)	(4.22)	(3.79)	(3.40)	(2.68)
R^2	0.238	0.413	0.416	0.441	0.540

This table lists OLS-regression results of a trading strategy based on the difference of high past LTD (quintile 5) and low past LTD (quintile 1) on the Fama-French factors (marketrf, smb and hml), momentum (mom) and the liquidity risk factor (ps liqui) of Pastor and Stambough (2003). In Regressions (1) – (4) the LTD coefficients are estimated based on a moving window of 12 months, in Regression (5) we estimate the LTD coefficients based on a moving window of 5 years. Portfolios are rebalanced monthly. The sample period is from January 1963 to December 2009. t statistics are in parentheses. t statistics are in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 15: Value-weighted Portfolio Sorts

Panel A: Lower Tail Dependence (LTD)

Portfolio	Return	LTD	UTD	down beta	coskew	beta	size	b-m
1 Low LTD	−0.53%	0.01	0.10	0.61	0.04	0.79	14.84	0.63
2	2.36%	0.06	0.13	0.79	−0.00	0.89	15.12	0.61
3	3.91%	0.12	0.15	0.90	−0.06	0.91	15.11	0.61
4	5.91%	0.18	0.16	0.99	−0.09	0.95	15.26	0.61
5 High LTD	9.83%	0.31	0.14	1.25	−0.13	1.11	15.71	0.57
5 High - Low	10.36%***	0.30***	0.04***	0.64***	−0.17***	0.32***	0.87***	−0.06**

Panel B: Upper Tail Dependence (UTD)

Portfolio	Return	UTD	LTD	up beta	coskew	beta	size	b-m
1 Low UTD	6.67%	0.00	0.14	0.67	−0.14	0.87	14.88	0.63
2	7.54%	0.02	0.18	0.61	−0.15	0.83	14.72	0.63
3	6.05%	0.06	0.19	0.82	−0.12	0.92	15.08	0.62
4	6.04%	0.12	0.20	0.95	−0.09	0.96	15.18	0.60
5 High UTD	4.44%	0.25	0.18	1.22	−0.02	1.07	15.86	0.56
5 High - Low	−2.23%*	0.25***	0.04***	0.55***	0.12***	0.20***	0.98***	−0.07***

Table 15: continued

Panel C: Beta (β) and Lower Tail Dependence (LTD)

Portfolio	1 Low β	2	3	4	5 High β	Average
1 Low LTD	4.52%	2.18%	5.86%	−0.00%	−0.00%	2.51%
2	2.46%	3.84%	3.93%	4.86%	3.84%	3.79%
3	4.50%	5.56%	4.10%	4.60%	7.36%	5.22%
4	5.24%	6.63%	7.15%	5.81%	9.63%	6.89%
5 High LTD	6.97%	6.87%	8.24%	9.88%	17.39%	9.87%
High-Low	2.45%	4.69%***	2.38%***	9.88%***	17.39%***	7.36%***

Panel D: Beta (β) and Upper Tail Dependence (UTD)

Portfolio	1 Low β	2	3	4	5 High β	Average
1 Low UTD	6.19%	6.81%	5.80%	10.00%	10.29%	7.84%
2	6.68%	5.50%	8.31%	8.66%	12.72%	8.37%
3	6.30%	5.60%	5.75%	7.37%	11.78%	7.36%
4	4.68%	5.06%	5.31%	6.07%	5.74%	5.37%
5 High UTD	4.68%	5.83%	4.24%	4.06%	5.99%	4.96%
High-Low	−1.51%	−0.98%	−1.66%	−5.94%***	−4.30%**	−2.88%*

Panel A and Panel B of this table show value-weighted average returns and risk characteristics of stocks sorted by realized LTD (Panel A) and UTD (Panel B). Each year we rank stocks into quintiles (1-5) and form value-weighted portfolios at the beginning of each annual period. The column labelled 'Return' reports the average return in excess of the one-month T-bill rate over the next year. The other columns report average risk characteristics measured contemporaneously with returns. Panel C and Panel D report value-weighted average returns of 25 portfolios sorted by realized beta and realized LTD and UTD, respectively. First, we form quintile portfolios sorted on beta. Then, within each beta quintile, we sort stocks into five equal-weighted portfolios based on LTD (UTD). Panel C displays the results of the 25 beta - LTD sorts, Panel D shows the results of the 25 beta - UTD sorts. In all panels, the row labelled 'High-Low' reports the difference between the returns of portfolio 5 and portfolio 1 with corresponding statistic significance level. The sample period is from January 1963 to December 2009. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 16: Temporal Stability: Portfolio Sorts and Fama-MacBeth (1973) Regressions

Panel A: Lower Tail Dependence from January 1963 **to December** 1986

Portfolio	Return	LTD	UTD	down beta	coskew	beta	size	b-m
1 Low LTD	2.41%	0.01	0.07	0.46	0.04	0.60	10.59	1.13
2	7.46%	0.05	0.08	0.83	0.02	0.78	10.98	1.05
3	8.93%	0.11	0.08	1.02	-0.01	0.85	11.05	1.03
4	13.79%	0.17	0.09	1.28	-0.03	1.00	11.26	1.00
5 High LTD	20.75%	0.27	0.08	1.73	-0.06	1.30	11.73	0.99
5 High - Low	18.34%***	0.26***	0.01***	1.27***	-0.12***	0.70***	1.14***	-0.14***

Panel B: Lower Tail Dependence from January 1987 **to December** 2009

Portfolio	Return	LTD	UTD	down beta	coskew	beta	size	b-m
1 Low UTD	1.03%	0.01	0.06	0.40	-0.04	0.51	12.13	0.84
2	6.55%	0.07	0.08	0.71	-0.12	0.67	12.64	0.79
3	9.06%	0.13	0.10	0.90	-0.17	0.78	13.00	0.78
4	11.68%	0.20	0.11	1.08	-0.22	0.90	13.51	0.71
5 High UTD	17.51%	0.31	0.10	1.34	-0.29	1.08	14.27	0.66
5 High - Low	16.48%***	0.30***	0.04***	0.94***	-0.25***	0.57***	2.14***	-0.18***

Table 16: continued

Panel C: FMB Regressions for 8-yr Subperiods

	(1963-1970) return	(1971-1978) return	(1979-1986) return	(1987-1994) return	(1995-2002) return	(2003-2009) return
beta	0.0880	0.0863	0.224**	0.216**	0.237*	0.0917
	(1.61)	(1.25)	(3.27)	(3.10)	(2.15)	(0.93)
LTD	0.376*	0.328***	0.560***	0.568***	0.477***	0.365**
	(2.14)	(4.55)	(7.95)	(3.86)	(5.10)	(3.36)
UTD	-0.315	-0.318***	-0.334***	-0.129	-0.318**	-0.338***
	(-1.27)	(-5.51)	(-4.86)	(-1.53)	(-2.54)	(-5.02)
size	-0.0254**	-0.0576**	-0.0669***	-0.0644**	-0.0528***	-0.0314***
	(-3.40)	(-3.20)	(-3.80)	(-3.43)	(-4.45)	(-3.85)
bookmarket	0.0185	0.0617**	0.0304	0.0457*	0.0429***	0.0166
	(0.53)	(2.51)	(1.58)	(2.02)	(3.87)	(0.95)
past return	-0.0585	-0.000864	0.00633	-0.00572	-0.0169	-0.0927
	(-1.55)	(-0.02)	(0.16)	(-0.18)	(-0.65)	(-0.91)
idio vola	4.891	-4.426	-6.975	-5.875**	-6.248**	-0.472
	(0.59)	(-1.67)	(-1.73)	(-3.12)	(-3.20)	(-0.16)
coskew	-0.125	0.108	0.333***	0.198**	0.162	0.219
	(-0.89)	(0.63)	(4.10)	(2.37)	(0.82)	(1.58)
cokurt	-0.0509	0.100**	0.0206	0.0272	0.0280	0.00950
	(-1.55)	(2.44)	(0.83)	(1.02)	(1.27)	(0.36)
down beta	0.0163	0.00312	-0.0302	-0.0122	-0.0381	-0.0129
	(0.42)	(0.16)	(-1.26)	(-0.48)	(-0.71)	(-0.37)
up beta	0.0262	-0.0290	-0.0878***	-0.0558	-0.0479	-0.0347
	(0.72)	(-1.21)	(-3.69)	(-1.51)	(-0.73)	(-0.72)
constant	0.207	0.632*	0.902***	0.869***	0.777***	0.477**
	(1.66)	(2.29)	(3.70)	(4.04)	(4.75)	(3.57)
R^2	0.257	0.178	0.158	0.129	0.109	0.104

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: continued

Panel A and Panel B of this table list equal-weighted average returns and risk characteristics of stocks sorted by realized LTD in different time periods. Panel A covers the sample period from January 1963 to December 1986. Panel B covers the sample period from January 1987 to December 2009. Each year we rank stocks into quintiles (1-5) and form equal-weighted portfolios at the beginning of each annual period. The column labelled 'Return' reports the average return in excess of the one-month T-bill rate over the next year. The other columns report average risk characteristics measured contemporaneously with returns. The row labelled 'High-Low' reports the difference between the returns of portfolio 5 and portfolio 1 with corresponding statistic significance level. Panel C table displays the results of Fama-MacBeth (1973) regressions of 1-year excess returns on firm characteristics and realized risk characteristics for 8-year subsamples. The firm characteristics are log of market capitalizations (size), book-to-market ratios (bookmarket), and past 12-month excess returns (past return), all computed at the beginning of each period. The realized risk characteristics are beta, LTD, UTD, coskewness, idiosyncratic volatility, cokurtosis, downside beta, and upside beta. These risk characteristics are calculated contemporaneously to the yearly excess return. All independent variables are cut off at the 1% level and at the 99%. The respective sample periods are displayed in the first row. t statistics are in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 17: Different Regression Methods

	(1) return	(2) return	(3) return	(4) return	(5) return
beta	0.154***	0.157***	0.157***	0.200***	0.189***
	(4.69)	(12.55)	(10.57)	(21.44)	(20.96)
LTD	0.456***	0.462***	0.462***	0.429***	0.454***
	(9.53)	(20.45)	(14.44)	(19.43)	(20.86)
UTD	-0.283***	-0.290***	-0.290***	-0.272***	-0.290***
	(-5.81)	(-13.08)	(-11.05)	(-11.39)	(-12.29)
size	-0.0512***	-0.0524***	-0.0524***	-0.226***	-0.118***
	(-8.07)	(-30.88)	(-14.68)	(-66.27)	(-50.58)
bookmarket	0.0217***	0.0625***	0.0625***	0.0761***	0.106***
	(3.19)	(13.94)	(9.14)	(16.48)	(26.53)
past return	-0.0181	-0.0213***	-0.0213***	-0.0350***	-0.0587***
	(-1.06)	(-3.62)	(-3.30)	(-7.13)	(-12.60)
idio vola	-3.284**	-5.669***	-5.669***	-8.119***	-8.357***
	(-2.11)	(-11.80)	(-8.00)	(-23.82)	(-26.82)
coskew	0.180***	0.0954***	0.0954***	0.108***	0.0976***
	(2.83)	(5.91)	(4.53)	(6.84)	(6.30)
cokurt	0.0227	0.00815***	0.00815***	0.00642***	0.00560***
	(1.58)	(3.21)	(2.66)	(2.98)	(2.66)
down beta	-0.0108	-0.00495	-0.00495	-0.00739	-0.00652
	(-0.84)	(-0.61)	(-0.60)	(-1.33)	(-1.20)
up beta	-0.0421**	-0.0316***	-0.0316***	-0.0359***	-0.0319***
	(-2.37)	(-3.61)	(-2.67)	(-6.54)	(-5.95)
constant	0.675***	0.697***	0.697***	2.623***	1.918***
	(7.60)	(26.40)	(12.92)	(57.77)	(49.68)
Method	fmb	ols	ols	panel	panel
Windsorized	no	yes	yes	yes	yes
Year Effects		yes	yes	yes	yes
Firm Effects		no	no	fixed	random
Clustered SE		firm	industry	no	no
R^2	0.152	0.217	0.217	0.285	0.285

This table reports the results of various regression techniques of excess returns on firm- and risk characteristics. The independent variables are the same as in Table 10. Regression (1) performs a Fama-Macbeth-Regression, but we do not winsorize the independent variables. In Regression (2) we perform a pooled OLS-regression with time-fixed effects and standard errors clustered by single stocks. Regression (3) is identical, but we cluster standard errors by industry. Regression (4) performs a panel data regression with firm fixed effects. In Regression (5) we regress excess returns on the independent variables via a random-effect panel data regression. The sample period is from January 1963 to December 2009.