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Research Article

The Risk of Individual Stocks' Tail Dependence with the Market and Its Effect on Stock Returns

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Traditional beta is only a linear measure of overall market risk and places equal emphasis on upside and downside risks, but actually the latter is always much stronger probably due to the trading mechanism like short-sale constraints. Therefore, this paper employs the nonlinear measure, tail dependence, to measure the extreme downside risks that individual stocks crash together with the whole market and investigates whether such tail dependence risks will affect stock returns. Our empirical evidence based on Shanghai A shares confirms that most stocks display nonnegligible tail dependence with the whole market, and, more importantly, such tail dependence risks can indeed provide additional information beyond beta and other factors for asset pricing. In cross-sectional regression, it is proved that this tail dependence does help to explain monthly returns on Shanghai A shares, whereas the time-series regression further indicates that mimicking portfolio returns for tail dependence can capture strong common variation of Shanghai A stock returns.

1. Introduction

Based on the classical Capital Asset Pricing Model (CAPM) developed by Sharpe [1], Lintner [2], and Black [3], it is the comovements of individual stocks with the whole markets that determine stocks' expected returns. The stock prices, especially, depend on market betas, which are defined as the covariance of the stock and market returns divided by the variance of market returns. As a linear measure, beta provides an overall description of market risk and cannot distinguish upside from downside risk. However, it is well-documented that the degree of downside market risk is usually stronger than upside market risk's; see Longin and Solnik [4] and Ang and Chen [5]. As advocated by Hong and Stein [6], due to the short-sale constraints existing in many stock markets, the trade of bearish investors who want to sell stocks short is always prohibited and hence the adverse information held by these investors could not be released to the market. If such adverse information is pent-up for a long time, it may accumulate to a very large amount. As long as such adverse information is finally flushing out to the market, it would provoke a heavy crash and bring the extreme downside risk which is much stronger than the upside counterpart.

Therefore, in this paper, we want to turn our focus onto this extreme downside market risk. We employ tail dependence, which is a flexible measure of extreme comovements and can be easily calculated using the sound Copula theory, to capture the risk that individual stocks crash together with the whole market and further explore the effect of such tail dependence risk on stock returns. The main purpose of our investigation is to compare the role of this new tail dependence in the asset pricing framework with that of classical beta. Such a comparison is motivated by two aspects. The first motivation is from the institutional perspective. As suggested by the theory of Hong and Stein [6], the extreme downside risk generated by short-sale constraints is stronger than upside risk and thus demands greater compensation, so we expect that the tail dependence risk defined in our paper would play a more significant role than linear beta in affecting the stock returns. The second motivation is from the statistical perspective: beta is a linear measure which describes the overall degree of dependence, whereas tail dependence is a nonlinear measure of extreme comovements. Intuitively, tail dependence can measure the probability that both the returns of individual stocks and the market returns are extremely negative (or extremely positive). Beta is calculated based on all the observations but tail dependence only looks at the tails of the distribution, and thus those stocks sharing the same betas might have different tail dependence with the market; see Hu [7]. We believe that the tail dependence should provide additional important information beyond beta for asset valuations.

Before 2010[1], China's stock market was one of the few markets completely prohibiting the short selling of stocks and lacking other financial derivatives like stock index futures which can be sold short; see Comerton-Forde and Rydge [8] and Bris et al. [9]. According to our discussion above, such a specific feature would make heavy extreme downside market risk a strong feature of the Chinese stock market. Considering this, we choose to carry out our empirical analysis based on the data of Shanghai A shares. Besides, there are also many other special features in Shanghai's stock market. For example, the fact that many firms in China have far lower free float may make the size effect weaker or even disappear, and, because of the dubious accounting practice, the ability of book-to-market variables to explain stock returns might become questionable too. These unique features in Shanghai's stock market are quite different from those in mature stock markets, so this study can also allow us to diagnose whether those factors which proved to be useful in explaining the stock returns on mature markets would be important factors in pricing Chinese stocks, in addition to verifying the existence of tail dependence and examining its effects on stock returns.

As early as 1970s, Bawa and Lindenberg [10] proposed that the CAPM should be extended by taking into account the asymmetry of downside and upside market risks. And, recently, a study which is very close to ours, Ang et al. [11], defined a "downside beta" to measure the downside market risk and confirmed that the stock returns are significantly affected by downside betas. The downside beta in their paper was calculated as the covariation of individual stocks and the market when the market return falls below its average. But, differently, our focus is the *extreme* downside market risk during market crisis (i.e., the market returns are extremely negative, not just below the average). Such extreme downside market risks cannot be captured by just using downside beta, so we employ the tail dependence to measure the extreme comovements of individual stocks and the market. Besides, by introducing the sound Copula theory[2] into the calculation of tail dependence, we are able to provide a more explicit representation of the dependence structure between individual stocks and the market and capture their tail behaviours without the discretionary choice of a threshold to define "downside beta" as in Ang et al. [11]. Huang et al. [12] also defined a measure of extreme downside risk and explored its effects on expected stock returns, but it is also different than our extreme downside *market* risk in as much as individual stocks crash down with the whole market, measured by the tail dependence between individual stocks and the market. Huang's measure of extreme downside risk is constructed by the left tail index, only based on the information of each stock's marginal distribution[3].

Our empirical evidence based on A shares of Shanghai's stock market confirms that remarkable tail dependence with the whole market does exist for most stocks in this market. More importantly, we find that this tail dependence plays a nonnegligible role in explaining the cross-sectional stock returns in Shanghai's stock market; the stocks with stronger tail dependence tend to have higher average monthly returns. Even after controlling the effects of linear beta and other factors, the tail dependence still shows significant relation with stock returns. In contrast, the coefficients of linear beta are consistently insignificant in our cross-sectional regressions. Furthermore, we also employ the time-series regression approach of Black et al. [13] to analyze the role of tail dependence in asset pricing, and the results suggest that a portfolio constructed as proxy for risk factor related to tail dependence can capture strong common variations in returns of Shanghai A shares. Therefore, we advocate that the tail dependence of individual stocks with the market may contain additional information beyond linear beta and other factors; thus tail dependence risk should be taken into account in asset pricing.

Our investigation can provide two contributions to the existing literature. Firstly, we define a "tail dependence" index to represent a new dimension for market risk, "extreme downside market risk," that is, the risk of individual stocks crashing together with the whole market. More importantly, we recommend by providing supportive evidence that this "tail dependence" index has the potential to be a new pricing factor for stock returns. Secondly, our analysis may provide a possible explanation for the inconspicuous relation of betas with stock returns in previous studies like Fama and French [14] and Easley et al. [15]. These studies found that the cross section of returns on common stocks shows little relation to the market betas, but our results show that although no significant relation with stock returns could be found for betas, tail dependence will significantly affect stock returns. The insignificant relation of beta with stock returns found before is probably only due to the fact that beta is an overall measure for market risk. We insist that the pricing ability of market risk should not be doubted, and thus the extreme downside market risk measured by tail dependence is still a necessary factor for explaining stock returns.

The rest of this paper is organized as follows: Section 2 first introduces the calculation of tail dependence based on Copula theory and explains its difference with linear market beta; Section 3 then provides a brief description of the data used, and some important preliminaries on methodology; Section 4 outlines the empirical analysis for the existence of tail dependence and its effects in asset pricing; finally, we conclude our main results in Section 5.

2. Methodology

2.1. Tail Dependence and Copula Theory. As discussed above, in the stock markets like China's, a large amount of adverse information may be sidelined due to the existence of short-sale constraints first and then flushing out during market crashes. As a result, a majority of stocks tend to crash down with the whole market and hence the extreme downside market risk exists for most stocks. In our paper, we employ the measure of tail dependence to describe such a risk of individual stocks' crashing together with the market, which cannot be measured by classical betas or even downside beta.

Tail dependence is a nonlinear measure of extreme comovements and thus could be a perfect candidate to describe the relations between individual stocks and the market during crisis. For two variables X and Y with the cumulative distribution functions (CDFs) of F and G, respectively, their tail dependence can be defined as follows:

$$\begin{aligned}\lambda_U &= \lim_{u\to 1} P\left\{Y > G^{-1}(u) \mid X > F^{-1}(u)\right\},\\ \lambda_L &= \lim_{u\to 0} P\left\{Y < G^{-1}(u) \mid X < F^{-1}(u)\right\},\end{aligned} \tag{1}$$

where λ_U and λ_L represent upper and lower tail dependences, respectively. Loosely said, the bivariate tail dependence looks at the concordance in the tail, that is, the relation between the extreme values of X and Y. Geometrically, it measures the dependence in the upper-right or lower-left quadrant tail of a bivariate distribution. The value of tail dependence is essentially calculated as a limit, so we can avoid the discretionary choice of a threshold as in the definition of downside beta. Besides, the tail dependence can be very easily calculated using the sound Copula functions.

Copula is a function that incorporates marginal distributions into a joint distribution. Defined precisely, it is a joint distribution function of standard uniform random variables with a probability integral transformation applied to marginals. For more details, see Nelsen [16] and Cherubini et al. [17]. The linkage between the joint distribution and its marginal is demonstrated by Sklar's theorem. Let $X = (X_1, \ldots, X_n)$ be a vector of n univariate variables with the marginal distributions denoted by $F_1, \ldots, F_n$; Sklar's theorem states that there exists a Copula function C which could link the joint n-dimensional distribution function F to its marginals as follows:

$$F(x_1, \ldots, x_n) = C(F_1(x_1), \ldots, F_n(x_n)). \tag{2}$$

This relation can be expressed in terms of densities by deriving both sides of (2), and we get

$$\begin{aligned}f(x_1, \ldots, x_n) &= c(F_1(x_1), \ldots, F_n(x_n)) \times f_1(x_1)\\ &\quad \times \cdots \times f_n(x_n),\end{aligned} \tag{3}$$

where f represents the joint density function and f_i the marginal density function. And the Copula density function is defined by $c(u_1, \ldots, u_n) = \partial C(u_1, \ldots, u_n)/\partial u_1, \ldots, \partial u_n$. Hence, the joint density can be defined as the product of the Copula density and the univariate marginal densities[4].

Therefore, the information of marginal distributions is contained in $F_i(x_i)$, while the information of dependence structure is completely captured by Copula functions. Copula can capture the nonlinear dependence structure and allows the dependence degree in the tails to be different from that in the middle of distribution. One important feature of Copula functions is that it can always be easily related to the tail dependence we focus on in this paper; there exists a formula relating Copula functions to tail dependence as follows [18]:

$$\begin{aligned}\lambda_U &= \lim_{u\to 1} P\left\{Y > G^{-1}(u) \mid X > F^{-1}(u)\right\} = \lim_{u\to 1}\frac{P\left\{X > F^{-1}(u), Y > G^{-1}(u)\right\}}{P\left\{X > F^{-1}(u)\right\}}\\ &= \lim_{u\to 1}\frac{1 - P\left\{X < F^{-1}(u)\right\} - P\left\{Y < G^{-1}(u)\right\} + P\left\{X < F^{-1}(u), Y < G^{-1}(u)\right\}}{1 - P\left\{X < F^{-1}(u)\right\}} = \lim_{u\to 1}\frac{1 - 2u + C(u,u)}{1-u},\end{aligned} \tag{4}$$

$$\lambda_L = \lim_{u\to 0} P\left\{Y < G^{-1}(u) \mid X < F^{-1}(u)\right\} = \lim_{u\to 0}\frac{P\left\{X < F^{-1}(u), Y < G^{-1}(u)\right\}}{P\left\{X < F^{-1}(u)\right\}} = \lim_{u\to 0}\frac{C(u,u)}{u}. \tag{5}$$

If the formula in (4) exists finitely, C is said to have upper tail dependence if $\lambda_U \in (0, 1]$, no upper tail dependence if $\lambda_U = 0$. The value λ_U, called the "upper tail dependence coefficient," represents the limit of the conditional probability that the distribution function of X exceeds the threshold u, given that the corresponding function for Y does, when u tends to one, and analogously for the lower tail dependence coefficient λ_L. Through this formula, we can introduce the sound Copula theory into the calculation of tail dependence between individual stocks and the market. Especially for some well-known parametric families of Copula functions, their parameters could be directly related to tail dependence; see Table 1.

Just as shown by Table 1, various Copulas can represent different patterns of dependence structure and thus have different features of tail dependence. In previous studies four stylized Copulas are most widely used: Gaussian Copula is always used as a benchmark and no tail dependence exists, Student's T Copula has symmetric tail dependence in both lower and upper tails, and Clayton and Gumbel Copulas

Table 1: Parameters and tail dependence coefficients of various Copulas.

	Parameters	Lower tail dependence coefficients	Upper tail dependence coefficients
Gaussian	ρ	—	—
T	ρ, ν	$2T_{\nu+1}(-\sqrt{\nu+1}(\sqrt{1-\rho}/\sqrt{1+\rho}))$	$2T_{\nu+1}(-\sqrt{\nu+1}(\sqrt{1-\rho}/\sqrt{1+\rho}))$
Clayton	α	$2^{-1/\alpha}$	—
Gumbel	θ	—	$2-2^{1/\theta}$

have only lower and upper tail dependence, respectively. As our focus in this paper is on the *extreme downside* market risk, we choose to employ the Clayton Copula to model the dependence structure between individual stocks and the whole market and calculate their lower tail dependence, that is, the propensity of individual stocks crashing together with the market. The formula of the Clayton Copula function is given as follows:

$$C_{\text{Cla}}(u,v) = \max\left\{\left(u^{-\alpha}+v^{-\alpha}-1\right)^{-1/\alpha}, 0\right\}, \quad \alpha \in (-1,0) \cup (0,+\infty). \tag{6}$$

Applying formulas (4) and (5), we can easily derive that the Clayton Copula has no upper tail dependence but has lower tail dependence for $\alpha > 0$, and the tail dependence coefficient can be calculated by

$$\lambda_L = 2^{-1/\alpha}. \tag{7}$$

In this paper, the marginal distributions of individual stocks' returns and the market returns are estimated as empirical distributions to ensure robustness and due to the scarcity of data, and, next, we calculate the MLE estimates of the parameter α[5]. Then, the (lower) tail dependence between individual stocks and the market can be obtained through (7).

2.2. Beta versus Tail Dependence. Beta or correlation could only tell us the overall strength of the linear relation, but Copula function can provide a detailed picture of the dependence structure and, more importantly, can show us different manners of dependence in tails. Next, we will employ two symmetric Copula functions, Gaussian and Student's T Copulas, to explain an intuition that the variables sharing the same linear relationship may depict different features in tail dependence. In Figure 1, the difference between linear and nonlinear relations can be easily observed.

The two densities in Figure 1(a) show that, for the two Student's T Copulas with the same correlation coefficients of 0.5 but different degree of freedom parameters, the levels of dependence in tails are obviously different. Smaller degree of freedom ($\nu = 2.5$), especially, brings stronger tail dependence. There might be two more particular cases. As shown by the first density in Figure 1(b) even the correlation of two variables calculated using all the observations of the whole distribution is small ($\rho = 0.1$); the extreme comovements in tails of these two variables could be very strong; that is, two variables with no significant linear relation may have strong tail dependence. On the other hand, if the dependence structure between two variables is described by the Gaussian Copula (see the last density in Figure 1), we cannot find any obvious tail dependence although they have a moderate correlation, so two variables with significant linear relation may be independent in the tails.

As discussed above, Copula functions could describe the nonlinear dependence beyond linear correlation. Similarly, tail dependence is also different from the linear beta and contains additional information for the asset valuation. Actually, the classical beta in CAPM theory is related to linear covariance, while the tail dependence coefficients (TDCs) are a nonlinear measurement focusing on the extreme comovements in the tails of distributions. Hence, the tail dependence of individual stocks with the market should provide a different perspective to understand the market risk, and it is thus necessary to examine whether such tail dependence also affects stock returns or even plays a more significant role than linear beta in asset pricing.

3. Data and Preliminaries

In Chinese stock markets, there are two share types. A shares are restricted to domestic investors (only became available in 2005 for some Qualified Foreign Institutional investors), while B shares were restricted to foreign investors until early 2001 and then opened to domestic investors. Since B-share markets are very illiquid and much smaller than the A-share markets with less than 10% of the total numbers of stocks outstanding, in this paper we focus on the A-share stocks traded on Shanghai Stock Exchange, which is bigger than Shenzhen Stock Exchange with most of the larger predominantly state-owned companies listed [20, 21]. Our price files are from DataStream while the files of the trading and financial statement data are generated from the China Stock Market & Accounting Research (CSMAR), which is the most reliable and widely used security database in China. Our sample period is 1997–2008, because the price limit of 10% came into effect towards the end of 1996.

Two approaches are employed in our study. One is the portfolio analysis, widely used in the literature like Ang and Chen [5]. We construct portfolios ranked by tail dependence and other factors and then analyze the characteristics of the returns of the constructed portfolios. The other one is regression analysis, including the cross-sectional regression of Fama and MacBeth [19] as well as the time-series regression of Black et al. [13]. Since we want to examine whether the tail dependence will still significantly affect stock returns even after controlling the effect of other factors which have been proved by previous studies to be important for asset pricing, we involve the following factors in our analysis. First, we follow Fama and French's [14] suggestion to analyze the roles

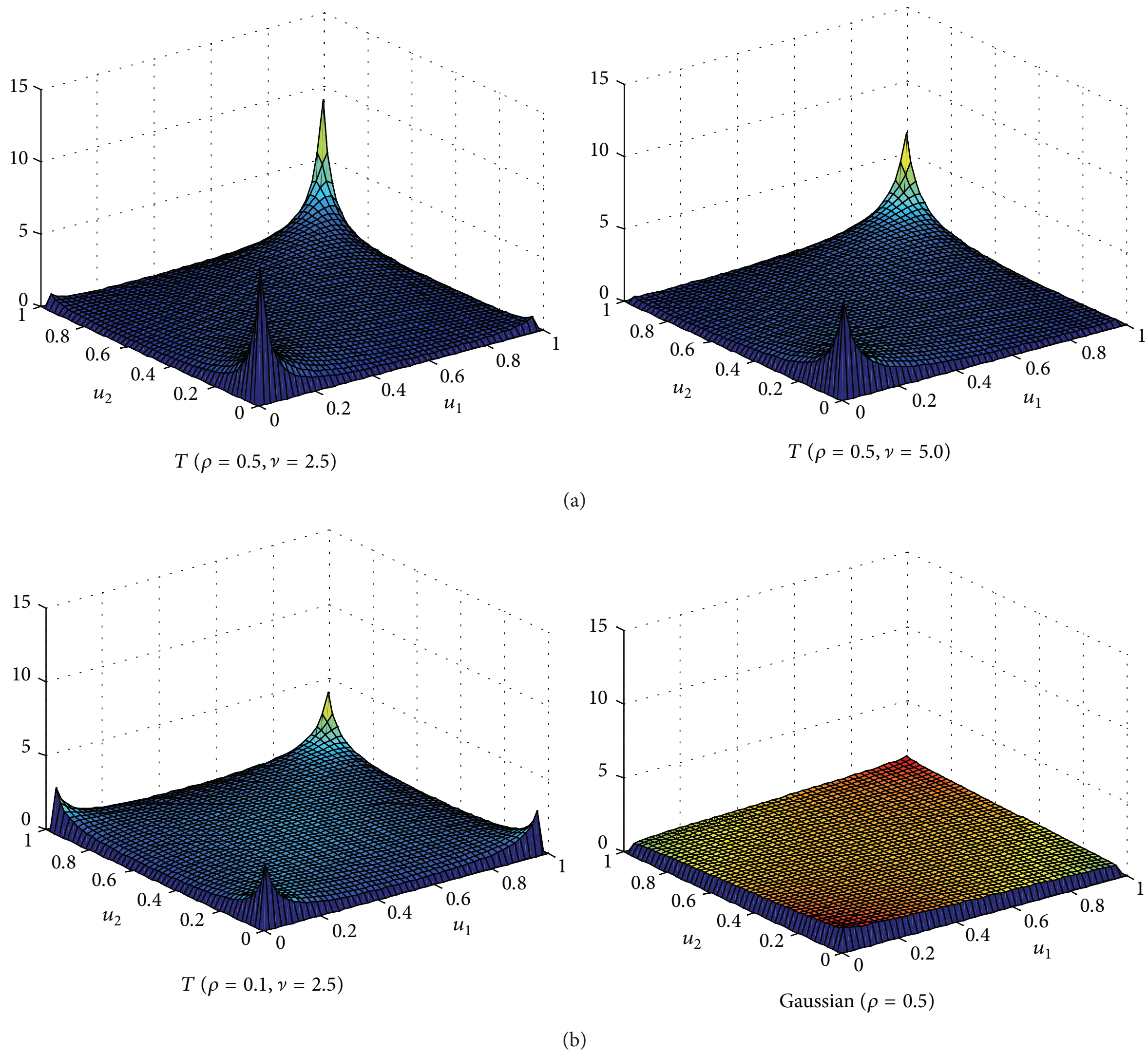


FIGURE 1: Four detailed pictures of Copula density functions. To visualize their joint probability distributions and dependence structures between variables, this figure shows the surface of the densities for Gaussian and Student's T Copulas with various parameter values. The formulas of two Copula densities can be referred to Cherubini et al. [17]. Gaussian Copula only has one parameter, the correlation coefficient ρ. While Student's T Copula has two parameters, the correlation coefficient ρ and the degree of freedom ν, the latter controls the level dependence in tails. And when ν approaches infinity, the Student's T Copula would degenerate to Gaussian Copula.

of beta, size, and book-to-market value in affecting stock returns. Second, we also consider the other two financial factors, leverage and the earning-price ratios. In addition, we want to test for the relation of liquidity with stock returns. Finally, inspired by Easley et al. [15] and Lu and Wong [22], we introduce the effect of momentum and volatility too. The calculations of these asset pricing factors are given in the following paragraphs.

3.1. Size. Due to the unique structure of corporate governance, many shares of the listed Chinese firms are prohibited from trading. These shares include the state-owned shares and the legal person shares [23]. We therefore employ the market capitalization of tradable shares to represent the firm size. In Tables 3 and 4, the numbers of firm sizes are all given as the market capitalization divided by 1 million (it is because the values of market capitalization are usually very large numbers). And further, in the cross-sectional regression, the logarithm of firm sizes is taken as explanatory variable.

3.2. Book-to-Market, Leverage, and Earnings-Price Ratio. Book-to-market is the book value divided by the market value of tradable shares, while leverage is the ratio of debt to asset. The earnings-price ratio is zero if the earnings are negative, and the earnings are divided by prices when the earnings are positive. To ensure that the accounting data are available prior to observing the returns, we extract the values of these factors from the latest financial report at least three months before and analyze the effect of these extracted values on stock returns (This is because, in the CSMAR database, we have only semiannual financial reports before 2002, but since 2002 we can obtain quarterly financial reports. So, e.g., the financial factors affecting stock returns in August are from reports in June of the same year or December of the preceding year).

3.3. Liquidity. Abundant literature including Brennan et al. [24] and Amihud [25] found that liquidity is an important factor determining the expected returns. One of the most famous liquidity measures is Amihud's measure, which is calculated by

$$\mathrm{AMIHUD}_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{\left|R_{i,t,d}\right|}{\mathrm{DOLVOL}_{i,t,d}} \times 10^6, \tag{8}$$

where $R_{i,t,d}$ and $\mathrm{DOLVOL}_{i,t,d}$ represent the daily returns and volume at day d in month t of stock i, and $D_{i,t}$ is the trading days of stock i in month t. This measure always results in extreme values, so we also calculate its square root as Hasbrouk's [26] suggestion:

$$\mathrm{AMIHUD}_{i,t}^{1/2} = \frac{1}{D_{i,t}} \sqrt{\sum_{d=1}^{D_{i,t}} \frac{\left|R_{i,t,d}\right|}{\mathrm{DOLVOL}_{i,t,d}} \times 10^6}. \tag{9}$$

These two measures are negatively related to liquidity, with higher values implying illiquid stocks. We also introduce another liquidity measure, Turnover, which is calculated as

$$\mathrm{Turn}_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{\mathrm{DOLVOL}_{i,t,d}}{\mathrm{DTMV}_{i,t,d}}, \tag{10}$$

where $\mathrm{DTMV}_{i,t,d}$ represents market value of tradable shares on day d in month t of stock i. Turnover is positively related to liquidity, with higher values implying more liquid stocks.

3.4. Momentum and Volatility. It is well-known that the historical stock prices contain information about the future stock returns, so we also involve two additional factors, momentum and volatility, which have been widely used in the previous asset pricing literature including Easley et al. [15] and Lu and Wong [22]. In our paper, momentum is calculated as the average percentage of weekly returns over the preceding two years, and volatility is the standard deviation of the weekly returns over the preceding two years.

3.5. Beta, Downside Beta, and Tail Dependence. Each month, we employ the monthly returns of the preceding two years to calculate market betas, and the weekly returns[6] of the preceding two years to calculate the tail dependence coefficients (TDCs) of individual stocks with the market. The beta and TDC calculated using such methods are usually called "preranking beta and TDC," and we use them to sort the stocks and construct the portfolios. However, if we employ these preranking betas and TDCs of individual stocks in the regression, the estimators are likely to subject to an errors-in-variables (EIV) problem (see [27]). Hence, in a similar way to the approach of Fama and French [14] and Easley et al. [15], we also calculate the "postranking portfolio betas and TDCs" as follows. We first classify the stocks into three portfolios based on size and further classify each of the three obtained portfolios into three subportfolios based on preranking betas or TDCs, and we could obtain nine subportfolios in total. We calculate the betas or TDCs of the nine subportfolios based on the full-period observations, and the "postranking beta or TDC" of each stock is defined as the betas or TDCs of the corresponding subportfolios it belongs to. It should be noted that assigning full-period portfolio betas or TDCs to individual stocks does not mean that a stock's beta or TDC is constant, since a stock could move across portfolios due to the month-to-month changes in the size and in the estimates of its preranking betas or TDCs. Besides, we also involve the downside beta defined by Ang et al. [11] into our analysis:

$$\beta_i^- = \frac{\operatorname{cov}\left(r_i, r_m \mid r_m < \mu_m\right)}{\operatorname{var}\left(r_m \mid r_m < \mu_m\right)}, \tag{11}$$

where r_i and r_m denote the excess returns of individual stock and the market excess returns, respectively, while μ_m is the average of market returns. The downside beta is also calculated using the similar procedure given above, and we compare its effect on stock returns with that of tail dependence[7].

Summary statistics of the factors mentioned above are provided in Table 2. Our main concern is the relations of TDC with other variables. Firstly, we find that the correlation between size and TDC is the largest in absolute value, implying that small firms tend to have strong tail dependence with the market. Another appealing finding is that the square root of Amihud's measure shows a positive relation with TDC, which means illiquid stocks' tail dependence with the whole market is stronger. However, if Turnover is used as another liquidity measure, the result is just opposite but insignificant (the prices of liquid stocks are more likely to crash down together with the whole market). Among the three financial factors, TDC has significant correlations with leverage and earnings-price ratio, but the correlation between TDC and book-to-market value is insignificant. In addition, momentum is negatively correlated with TDC while volatility is positively correlated with TDC, but both correlations are insignificant again. Finally, tail dependence has a positive relation with betas but its relation with downside beta is insignificant[8].

4. Empirical Evidence

Before analyzing the effect of tail dependence on the stock returns, we need to verify that such tail dependence does exist. Firstly, we calculate the full-sample estimation of tail dependence using all the observations during our sample period and present its distribution in Figure 2(a). The histogram indicates that only few stocks have tail dependence coefficients close to zero, while most tail dependence coefficients lies in the range of 0.25–0.45. Next, the rolling estimation of tail dependence (we use previous two years' observations to estimate a tail dependence coefficient each month and then roll the window one-step forward to get the estimate of the next month) is given in Figure 2(b) to show its time variation. We find that during most of the sample period, nearly 75% of stocks have a tail dependence coefficient larger than zero. Besides, the lines of mean and the other

Table 2: Asset pricing factors. Panel (a) in this table contains the means, standard deviations, minimums, medians, and maximums of the variables we study in our paper. All statistics are calculated from the full sample, that is, pooling all months. TDC and BETA are the postranking portfolio TDCs and betas, while DBETA is downside beta. SIZE is the market capitalization of tradable shares in RMB million. BTM, LEV, and E/P represent the book-to-market, leverage, and earnings-price ratio, respectively. The following are the square root of Amihud's liquidity measure denoted by ASQT and the Turnover denoted by TURN. MTM is the momentum calculated as the average percentage returns over the preceding two years, while VOL is the standard deviation of the weekly returns over the preceding two years. Panel (b) provides the time-series means of monthly correlations of the variables. The values in the upper lower triangular part are Pearson's correlations, while the Spearman's rank correlations in italic type are given in the lower triangular part. The correlations with superscript "$*$" are significantly different from zero at 5%.

	TDC	BETA	DBETA	SIZE	BTM	LEV	E/P	ASQT	TURN	MTM	VOL
(a) Descriptive statistics											
Mean	0.705	0.975	1.020	1.442	0.525	0.567	0.019	0.349	19.982	0.203	5.301
St. dev.	0.150	0.053	0.783	1.573	0.207	0.640	0.024	0.256	14.281	0.702	1.310
Min	0.341	0.897	−1.513	0.094	0.050	0.038	0.000	0.071	1.371	−1.933	2.456
Median	0.783	0.986	1.030	0.950	0.512	0.516	0.015	0.314	16.566	0.166	5.124
Max	0.803	1.062	4.066	12.298	1.180	8.272	0.202	2.768	107.673	2.670	12.295
(b) Pearson/Spearman correlations											
TDC		0.583*	0.035	−0.646*	−0.085	0.107*	−0.326*	0.358*	0.169	−0.218	0.155
BETA	*0.660**		0.025	−0.561*	−0.147	0.093*	−0.302*	0.421*	0.171	−0.217	0.121
DBETA	*0.031*	*0.037*		−0.027	0.014	−0.017	−0.037	0.012	0.027	−0.099	0.212
SIZE	*−0.801**	*−0.735**	*−0.018*		0.119	−0.117*	0.286*	−0.446*	−0.161	0.241	−0.126
BTM	*−0.125*	*−0.123*	0.022	*0.226*		−0.107	0.213	−0.177	−0.098	−0.229	−0.270*
LEV	*0.191**	*0.173**	0.012	*−0.260**	*0.089*		−0.122	0.207	0.083	−0.103	0.115
E/P	*−0.411**	*−0.357**	−0.012	*0.455**	*0.239*	*−0.200**		−0.220	−0.095	0.173	−0.200
ASQT	*0.603**	*0.553**	0.015	*−0.778**	*−0.156*	*0.190*	*−0.347**		−0.184*	−0.216	0.103
TURN	*0.252*	*0.225**	0.040	*−0.269**	*−0.105*	*0.114*	*−0.183*	*−0.219*		0.038	0.229
MTM	*−0.225*	*−0.209*	−0.076	*0.252*	*−0.237*	*−0.069*	*0.230*	*−0.277*	*0.065*		0.033
VOL	*0.183*	*0.167*	0.203	*−0.228*	*−0.260**	*0.190**	*−0.312**	*0.120*	*0.259*	*0.038*	

Table 3: Summary statistics for portfolios sorted by preranking TDCs. This table presents the full-period tail dependence coefficients, and the time-series averages of other characteristics for portfolios sorted by preranking tail dependence coefficients (TDCs) monthly. RETURN here is the average of postranking monthly returns. All other variables are defined as in Table 2. The portfolios with subscripts from 1 to 5 contain the stocks ranked by the preranking TDCs from the lowest to the highest.

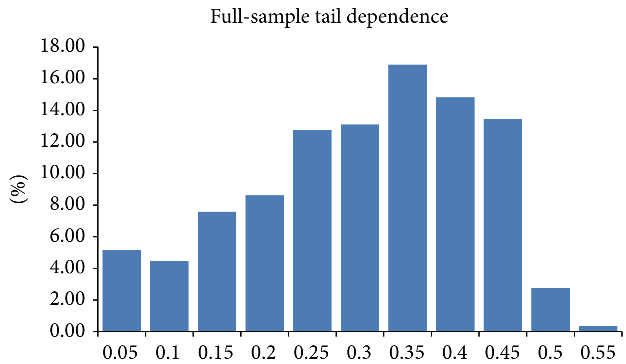
Portfolios	RETURN	TDC	BETA	DBETA	SIZE	BTM	LEV	E/P	ASQT	TURN	MTM	VOL
TDC_1	−0.287	0.600	0.841	0.918	2.743	0.517	0.489	0.032	0.273	15.989	0.491	5.008
TDC_2	−0.317	0.791	0.950	1.022	1.522	0.523	0.542	0.022	0.315	18.700	0.273	5.274
TDC_3	−0.193	0.827	1.001	1.020	1.188	0.540	0.550	0.019	0.344	20.548	0.153	5.353
TDC_4	−0.148	0.846	1.025	1.057	0.969	0.531	0.581	0.014	0.384	21.108	0.092	5.425
TDC_5	−0.090	0.823	1.056	1.085	0.738	0.512	0.675	0.010	0.431	23.636	0.020	5.447

quartile indicate that the tail dependence becomes stronger and stronger from 1999 to 2008. Therefore, we could conclude from Figure 2 that most stocks of Shanghai Exchange have nonignorable tail dependence with the whole market.

After verifying the existence of tail dependence, now we turn to our main concern; that is, is this tail dependence a determinant of the stocks returns in Shanghai's market? Our hypothesis is that the stronger tail dependence implies higher risks that individual stocks' prices fall down heavily as the market declines and thus requires a higher risk premium. Therefore, we expect a positive relation between tail dependence and stock returns. Now, we begin to examine the role of tail dependence in asset pricing by the approaches of portfolio analysis and regression analysis.

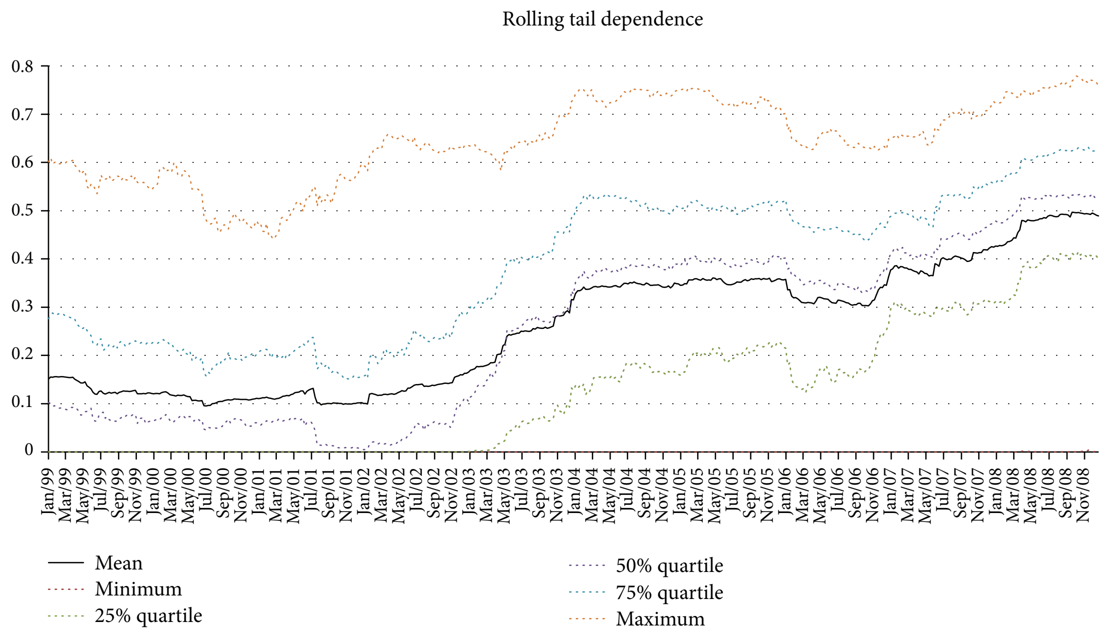
4.1. Portfolio Analysis. In portfolio analysis, each month we classify the stocks based on the factors of preceding month, and average (equal-weighted) the stock returns as portfolio returns. First, we sort all the Shanghai A stocks into five portfolios based on the preranking tail dependence and present the average returns and other characteristics of the constructed portfolios in Table 3.

It is clear that the portfolios with higher preranking tail dependence coefficients tend to yield higher average returns. Average returns especially rise from −0.287% for the lowest TDC portfolio to −0.090% for the highest (although this rise is not monotonic as the postranking return of TDC1 is a bit higher than TDC2). The simple TDC sort seems to support our prediction of a positive relation between tail



Descriptive statistics:
Mean: 0.275460
Minimum: 0.000042
25% quartile: 0.198083
50% quartile: 0.295112
75% quartile: 0.375431
Maximum: 0.524258

(a)



(b)

Figure 2: The existence of tail dependence. To verify the existence of tail dependence, we show the distribution of full-sample (1997–2008) tail dependence by the histogram and the related statistics in (a). At each time t, we employ previous two years' observations to estimate the tail dependences for all stocks and provide the dynamics of their mean, minimum, three quartiles, and maximum from 1999 to 2008 in (b).

dependence and average stock returns. Nevertheless, this evidence may be muddied by the tight relations between TDC and other variables, since we could observe that betas and leverage monotonically increase with preranking TDCs, while size and earnings-price ratios decrease monotonically with preranking TDCs. The directions of all these relations are consistent with the sample correlations reported in Table 2.

In order to control the effect of other risk factors correlated with tail dependence and examine whether the relationship of tail dependence with stock returns occurs because of the covariance of tail dependence and other factors, we sort the portfolios twice, first on the basis of a risk factor and then on the basis of the preranking TDCs. Then the characteristics of these constructed portfolios are presented in Table 4. The two-pass sort on size and TDC says that variation in tail dependence that is tied to size is positively related to average return, but variation in tail dependence unrelated to size is not compensated in the average stock returns in Shanghai's market. Besides, when we sort the portfolio first by the square root of Amihud's measure, in the subquintiles we can find that the relations of stock returns with preranking TDCs almost disappear. If sorting the portfolios first by Turnover, the relations between tail dependence and stock returns are positive in each subquintile. Momentum also tends to contaminate the positive relation between TDCs and the stock

Table 4: Returns, tail dependence, and other factors. Portfolios are formed monthly. In each month, the stocks are classified into three quintiles based on the preceding month's value of a risk factor, and then each quintile is subdivided into three portfolios according to preranking TDCs. The full-period portfolio tail dependence coefficients and the time-series averages of other characteristics are presented in this table. RETURN here is the average of postranking monthly portfolios returns, and all other variables are defined as in Table 2. From 1 to 3, the corresponding variables are increasing.

Ranking by:													
X	TDC	RETURN	TDC	BETA	DBETA	SIZE	BTM	LEV	E/P	ASQT	TURN	MTM	VOL
					Panel A: X = BETA								
1	1	−0.464	0.556	0.304	0.864	2.749	0.461	0.506	0.031	0.272	17.127	0.716	5.631
1	2	−0.372	0.772	0.325	1.022	1.245	0.439	0.626	0.018	0.358	22.604	0.369	6.286
1	3	−0.177	0.780	0.339	1.018	0.719	0.434	0.741	0.009	0.445	26.037	0.149	6.675
2	1	−0.271	0.695	0.485	1.042	2.108	0.542	0.524	0.028	0.287	16.731	0.289	5.007
2	2	−0.284	0.787	0.494	1.089	1.210	0.542	0.520	0.018	0.338	20.431	0.112	5.351
2	3	−0.230	0.812	0.494	1.143	0.746	0.505	0.678	0.008	0.423	23.093	0.011	5.625
3	1	−0.052	0.670	0.712	0.940	2.108	0.616	0.463	0.028	0.283	15.255	0.135	4.073
3	2	−0.022	0.791	0.664	1.018	1.224	0.613	0.510	0.021	0.339	18.134	0.032	4.426
3	3	0.019	0.793	0.656	1.047	0.855	0.574	0.532	0.014	0.397	20.461	0.010	4.623
					Panel B: X = DBETA								
1	1	−0.361	0.550	0.474	0.251	2.260	0.488	0.533	0.029	0.295	16.643	0.480	4.946
1	2	−0.233	0.758	0.475	0.254	1.202	0.525	0.564	0.018	0.343	20.568	0.213	5.204
1	3	−0.158	0.786	0.504	0.351	0.828	0.516	0.596	0.011	0.395	23.270	0.090	5.319
2	1	−0.252	0.573	0.492	1.020	2.275	0.541	0.483	0.028	0.289	16.847	0.377	4.980
2	2	−0.263	0.763	0.544	1.026	1.267	0.561	0.521	0.018	0.350	19.224	0.104	5.116
2	3	−0.138	0.787	0.561	1.035	0.819	0.530	0.694	0.011	0.423	21.233	0.000	5.240
3	1	−0.275	0.589	0.429	1.793	2.224	0.528	0.499	0.027	0.284	18.263	0.332	5.611
3	2	−0.107	0.763	0.480	1.742	1.245	0.522	0.593	0.019	0.346	20.806	0.177	5.632
3	3	−0.068	0.785	0.509	1.717	0.817	0.512	0.624	0.012	0.420	23.103	0.060	5.678
					Panel C: X = SIZE								
1	1	−0.106	0.783	0.418	0.950	0.436	0.436	0.710	0.020	0.510	23.441	0.106	5.799
1	2	−0.080	0.803	0.484	1.019	0.411	0.467	0.638	0.010	0.491	23.211	−0.007	5.599
1	3	−0.022	0.794	0.504	1.073	0.408	0.482	0.769	0.007	0.489	25.544	−0.070	5.591
2	1	−0.310	0.741	0.508	0.973	1.019	0.499	0.506	0.024	0.330	18.328	0.315	5.100
2	2	−0.168	0.798	0.520	1.063	0.985	0.548	0.528	0.018	0.321	20.432	0.150	5.270
2	3	−0.209	0.783	0.561	1.085	0.914	0.577	0.543	0.013	0.337	20.233	0.090	5.198
3	1	−0.420	0.341	0.438	0.933	3.690	0.543	0.458	0.034	0.202	14.447	0.561	4.868
3	2	−0.254	0.654	0.491	1.016	2.805	0.568	0.460	0.026	0.215	16.493	0.422	5.084
3	3	−0.279	0.727	0.542	1.105	2.242	0.606	0.506	0.022	0.241	18.339	0.306	5.240
					Panel D: X = BTM								
1	1	−0.478	0.593	0.426	0.832	2.220	0.310	0.498	0.023	0.318	16.670	0.697	5.423
1	2	−0.384	0.788	0.426	1.044	1.033	0.311	0.637	0.013	0.380	21.230	0.351	5.859
1	3	−0.356	0.791	0.469	1.085	0.751	0.311	0.802	0.008	0.461	23.689	0.182	5.852
2	1	−0.325	0.698	0.451	1.027	2.360	0.514	0.500	0.030	0.282	17.711	0.331	5.078
2	2	−0.195	0.801	0.502	1.061	1.143	0.520	0.522	0.019	0.348	21.009	0.149	5.292
2	3	−0.117	0.804	0.534	1.092	0.857	0.513	0.556	0.012	0.415	22.214	0.030	5.374
3	1	−0.070	0.639	0.530	1.017	2.351	0.759	0.511	0.033	0.258	16.876	0.173	4.827
3	2	0.014	0.769	0.557	0.995	1.358	0.751	0.530	0.023	0.311	19.149	−0.009	4.969
3	3	0.051	0.785	0.576	1.029	0.856	0.740	0.552	0.013	0.371	21.449	−0.068	5.044
					Panel E: X = LEV								
1	1	−0.258	0.598	0.459	0.978	2.841	0.486	0.298	0.030	0.258	16.370	0.385	5.052
1	2	−0.181	0.781	0.523	0.992	1.344	0.507	0.301	0.021	0.308	19.275	0.191	5.129
1	3	−0.092	0.820	0.558	1.038	0.929	0.495	0.308	0.013	0.367	20.951	0.119	5.195
2	1	−0.270	0.659	0.509	0.953	2.386	0.535	0.515	0.027	0.275	15.575	0.437	4.962
2	2	−0.183	0.777	0.509	1.011	1.308	0.558	0.515	0.019	0.326	20.216	0.187	5.276
2	3	−0.117	0.791	0.537	1.122	0.859	0.528	0.517	0.012	0.390	22.971	0.108	5.419

Table 4: Continued.

Ranking by: X	TDC	RETURN	TDC	BETA	DBETA	SIZE	BTM	LEV	E/P	ASQT	TURN	MTM	VOL
3	1	−0.394	0.689	0.424	0.967	1.654	0.543	0.786	0.028	0.344	19.394	0.381	5.390
3	2	−0.219	0.797	0.462	1.066	0.947	0.544	0.855	0.016	0.404	21.695	0.093	5.690
3	3	−0.152	0.793	0.492	1.061	0.667	0.528	0.998	0.008	0.471	23.534	−0.067	5.603
Panel F: X = E/P													
1	1	−0.755	0.767	0.402	0.979	1.105	0.456	0.673	0.004	0.387	21.240	0.080	5.827
1	2	−0.537	0.805	0.474	1.054	0.773	0.486	0.680	0.003	0.426	22.219	−0.060	5.745
1	3	−0.346	0.782	0.494	1.092	0.623	0.492	0.785	0.002	0.456	24.707	−0.098	5.696
2	1	−0.515	0.690	0.461	1.000	2.234	0.487	0.475	0.016	0.281	16.677	0.376	5.159
2	2	−0.244	0.791	0.503	1.045	1.185	0.532	0.498	0.015	0.338	20.602	0.240	5.341
2	3	0.070	0.807	0.546	1.053	0.949	0.533	0.513	0.014	0.381	21.587	0.200	5.252
3	1	0.040	0.383	0.491	0.912	2.974	0.555	0.479	0.046	0.251	15.906	0.544	4.873
3	2	0.094	0.659	0.526	0.997	1.826	0.586	0.493	0.039	0.289	17.427	0.347	4.873
3	3	0.362	0.722	0.575	1.062	1.208	0.595	0.511	0.036	0.337	19.842	0.214	4.949
Panel G: X = ASQT													
1	1	−0.456	0.399	0.470	0.937	3.844	0.540	0.462	0.034	0.182	16.908	0.592	4.962
1	2	−0.380	0.689	0.475	1.007	2.398	0.548	0.485	0.024	0.204	21.216	0.449	5.219
1	3	−0.538	0.755	0.499	1.102	1.742	0.551	0.541	0.018	0.234	24.719	0.303	5.435
2	1	−0.251	0.738	0.483	1.002	1.363	0.532	0.485	0.026	0.313	16.565	0.240	5.091
2	2	−0.258	0.792	0.523	1.064	1.006	0.568	0.512	0.018	0.320	19.841	0.096	5.271
2	3	−0.189	0.795	0.545	1.075	0.819	0.556	0.544	0.012	0.341	22.238	0.077	5.312
3	1	0.020	0.762	0.451	0.936	0.726	0.455	0.659	0.021	0.527	16.471	0.138	5.440
3	2	0.018	0.817	0.505	0.989	0.550	0.486	0.637	0.012	0.498	19.647	0.014	5.479
3	3	0.153	0.786	0.512	1.090	0.441	0.486	0.786	0.008	0.522	22.715	−0.073	5.534
Panel H: X = TURN													
1	1	−0.164	0.539	0.478	0.880	2.828	0.531	0.497	0.029	0.334	10.220	0.370	4.748
1	2	0.079	0.755	0.543	1.001	1.617	0.560	0.546	0.022	0.382	12.110	0.167	4.976
1	3	0.343	0.777	0.569	1.021	1.111	0.563	0.564	0.014	0.445	13.950	0.043	5.113
2	1	−0.052	0.682	0.455	0.973	2.128	0.533	0.494	0.028	0.262	17.482	0.417	5.189
2	2	−0.073	0.806	0.505	1.026	1.128	0.544	0.547	0.019	0.347	18.883	0.136	5.325
2	3	0.034	0.812	0.536	1.089	0.816	0.523	0.643	0.011	0.426	20.068	0.001	5.355
3	1	−0.776	0.689	0.455	1.032	1.617	0.492	0.524	0.027	0.245	28.108	0.429	5.563
3	2	−0.703	0.782	0.449	1.058	0.966	0.495	0.589	0.015	0.319	28.936	0.202	5.725
3	3	−0.533	0.776	0.481	1.102	0.685	0.481	0.704	0.009	0.391	30.206	0.066	5.718
Panel I: X = MTM													
1	1	−0.133	0.740	0.470	1.093	1.643	0.567	0.599	0.023	0.353	18.367	−0.497	5.226
1	2	0.098	0.789	0.477	1.089	0.981	0.575	0.621	0.014	0.389	19.835	−0.467	5.245
1	3	0.095	0.796	0.499	1.134	0.696	0.555	0.766	0.008	0.466	22.233	−0.453	5.416
2	1	−0.222	0.721	0.484	0.961	2.049	0.564	0.507	0.027	0.317	17.089	0.170	5.023
2	2	−0.156	0.803	0.526	0.988	1.115	0.551	0.506	0.018	0.347	20.155	0.176	5.144
2	3	−0.116	0.790	0.545	1.052	0.796	0.524	0.575	0.012	0.400	22.315	0.169	5.235
3	1	−0.352	0.388	0.448	0.837	2.801	0.462	0.490	0.032	0.240	16.197	1.062	5.227
3	2	−0.534	0.684	0.502	0.981	1.695	0.461	0.504	0.023	0.285	20.143	0.911	5.519
3	3	−0.555	0.742	0.512	1.042	1.171	0.465	0.537	0.018	0.347	23.587	0.761	5.684
Panel J: X = VOL													
1	1	−0.187	0.493	0.473	0.780	2.684	0.536	0.476	0.032	0.271	14.607	0.346	3.977
1	2	0.004	0.757	0.519	0.862	1.403	0.593	0.481	0.025	0.322	17.705	0.159	4.093
1	3	0.085	0.787	0.521	0.912	0.952	0.592	0.512	0.018	0.377	19.646	0.043	4.239
2	1	−0.211	0.703	0.485	1.042	2.216	0.540	0.511	0.029	0.290	16.998	0.359	5.116
2	2	−0.243	0.798	0.517	1.032	1.223	0.565	0.527	0.017	0.337	20.160	0.120	5.129
2	3	−0.145	0.792	0.538	1.059	0.834	0.533	0.613	0.011	0.401	22.383	0.059	5.149

Table 4: Continued.

Ranking by:														
X	TDC	RETURN	TDC	BETA	DBETA	SIZE	BTM	LEV	E/P	ASQT	TURN	MTM	VOL
3	1	−0.632	0.723	0.468	1.196	1.892	0.463	0.559	0.021	0.309	20.695	0.431	6.701
3	2	−0.288	0.793	0.464	1.128	0.948	0.446	0.676	0.014	0.379	23.106	0.227	6.691
3	3	−0.249	0.799	0.483	1.176	0.788	0.456	0.746	0.008	0.457	24.647	0.083	6.597

returns, as shown by Panel H of Table 4. However, the remaining factors including beta, downside beta, book-to-market, leverage, earnings-price ratios, and volatility cannot disturb the positive relation of tail dependence with stock returns. In summary, our portfolio analysis shows that the returns of stocks whose tail dependence with the whole market is stronger will be higher; only few factors might contaminate this positive relation of tail dependence with stock returns.

When looking at the stability issue of tail dependence, we can find that the ranking of TDCs is highly preserved. For the portfolios sorted only by preranking TDCs, the postranking portfolio TDCs show an increasing pattern, albeit the exception of the highest TDC portfolio. It is probably because the stocks in this portfolio are relatively small and illiquid, thus resulting in a bit lower tail dependence than the fourth portfolio. The results of twice-sorted portfolios also indicate that tail dependence is highly stable.

Whatever the first risk factor is, from the characteristics of subportfolios sorted on the basis of preranking tail dependence, we can examine the relations between the postranking factors and the preranking TDCs. Among all the postranking factors, the decreasing size and momentum as well as the increasing earnings-price ratios are the most appealing. Except for several cases of no remarkable relations, linear beta, downside beta, leverage, Turnover, and volatility display positive relations with preranking TDCs too. The relation of postranking book-to-market values with preranking TDCs is not compelling again. All these relations share the similar directions to those contemporaneous correlations in Table 2.

Besides, putting the characteristics in each subquintile aside, we can also extract the relations of average returns with each risk factor other than tail dependence. It can be clearly seen that small stocks and the stocks of high-leverage firms tend to earn higher returns, whereas beta, downside beta, boot-to-market value, and earnings-price ratios have positive relations with the stock returns. Moreover the relation of liquidity with stock returns is consistently negative, no matter based on the square root of Amihud's measure or Turnover. Momentum and volatility also present a negative relation with stock returns.

4.2. Cross-Sectional Regression. The month-by-month cross-sectional regression of the stock returns on various risk factors is also widely used in existing as a formal asset-pricing test, so we employ the standard methodology of Fama and MacBeth [19] to further test the relationships found in portfolio analysis. The cross section of stock returns is monthly regressed on the tail dependence and other factors, and then the time-series averages and standard deviations of monthly coefficients are used to analyze whether these asset pricing factors are explanatory for stock returns. First, we turn to the primary interest in our paper, examining whether tail dependence is a determinant of the returns of Shanghai stocks and provides additional information beyond other risk factors (especially beta) for asset valuation by observing the coefficients of TDCs in various regressions. In order to avoid the error-in-variables (EIV) problem, we use the postranking TDCs in the regression analysis.

The results presented in Table 5 verify our hypotheses in the Introduction that those stocks with stronger tail dependence with the whole market will have higher returns. Even after controlling the effect of other factors, the coefficients of tail dependence are consistently significant and positive in all the regressions. Moreover, involving tail dependence in the various regressions can achieve the improvements in R^2 from 0.23% to 0.42%, as shown by the last column of Table 5. In contrast, we cannot find any significant relationship with the stock returns for betas, which is inconsistent with classical CAPM theory but in line with the results for mature markets in Fama and French [14], Chalmers and Kadlec [28], Datar et al. [29], and Easley et al. [15]. This is probably because beta only measures the overall market risk, but actually the existence of short-sale constraints would generate a much stronger downside than upside risk. Such extreme downside market risk cannot be captured by the downside beta defined by Ang et al. [11], as we can find that all their coefficients are insignificant either.

Therefore, our measure of tail dependence, which can describe this risk of individual stocks crashing down together with the entire market, presents a more significant ability of explaining the cross-sectional stock returns than linear beta and even downside beta, and this ability still exists after controlling the effect of other factors. Our results might imply that tail dependence tends to contain some additional information beyond the widely cited factors (especially the linear beta) in previous literature and thus call for future studies to consider it a new possible asset pricing factor.

From the results in Table 5, we could also examine whether those factors proved to affect the stock returns in mature markets will help to explain the returns of Shanghai stocks. First, the size effect, implying that average returns on small stocks are relatively high, has been well-documented in the literature as early as by Banz [30], but in our paper most of the coefficients for size in various regressions are insignificant albeit with negative signs. The only three positive slopes appear in the regressions involving the square root of Amihud's measure, but they are still insignificant. Easley et al. [15] also give a positive relation of size with stock

Table 5: Cross-sectional regression. This table contains the time-series averages of the coefficients from the month-by-month regression using the standard Fama and MacBeth [19] methodology. The dependence variable is the monthly excess returns of individual stocks. The explanatory variables include postranking tail dependence coefficients and other variables are defined as in Table 2 (except that the variable "SIZE" is further taken as the logarithm). The time-series averages of adjusted R^2 are reported in the last column. T-values are given in parentheses, while the values given in square brackets of last column are the improvements in R^2 by including TDC. "$*$" denotes the fact that the corresponding coefficients are significantly different from zero at the confidence level of 5%.

Panel A: analysis based on market factors												
C	TDC	DBETA	BETA									R^2
−0.614	0.902*											2.76%
(−1.380)	(2.148)											
−0.252		0.038										0.89%
(−0.674)		(0.588)										
−1.190			1.026									2.90%
(−0.936)			(0.750)									
−0.676	0.998*	0.052	−0.002									4.17%
(−0.636)	(2.480)	(0.934)	(−0.112)									
Panel B: analysis based on Fama-French factors												
C	TDC	DBETA	BETA	SIZE	BTM							R^2
−1.133			0.582	−0.049	0.891*							4.57%
(−1.223)			(0.589)	(−1.061)	(4.089)							
−1.186		0.041	0.509	−0.049	0.873*							5.02%
(−1.268)		(0.763)	(0.523)	(−1.086)	(4.078)							
−1.014	0.963*		0.194	−0.033	0.851*							4.99%
(−1.074)	(2.970)		(0.217)	(−0.774)	(3.973)							[+0.42%]
−1.051	0.956*	0.051	0.131	−0.033	0.840*							5.40%
(−1.114)	(2.938)	(0.945)	(0.147)	(−0.784)	(3.979)							[+0.38%]
Panel C: analysis based on Fama-French factors and other factors												
C	TDC	DBETA	BETA	SIZE	BTM	LEV	E/P	ASQT	TURN	MTM	VOL	R^2
−2.101	0.927*		0.788	−0.045	0.583*	−0.085	16.543*					8.14%
(−2.468)	(2.603)		(0.976)	(−1.110)	(2.814)	(−0.863)	(4.343)					[+0.31%]
−1.527	0.824*		−0.238	0.017	0.637*	−1.140	16.782*	1.246*				10.16%
(−1.845)	(2.321)		(−0.293)	(0.423)	(3.185)	(−1.472)	(4.465)	(3.353)				[+0.30%]
−2.251	1.179*		1.476	−0.062	0.527*	−0.099	16.038*		−0.024*			9.82%
(−2.729)	(3.632)		(1.888)	(−1.502)	(2.595)	(−1.001)	(4.258)		(−6.616)			[+0.31%]
−1.143	0.845*		0.092	−0.014	0.210	−0.124	18.657*			−0.333*		9.82%
(−1.399)	(2.366)		(0.118)	(−0.369)	(1.093)	(−1.182)	(5.162)			(−3.849)		[+0.26%]
−1.851	0.946*		0.761	−0.034	0.504*	−0.071	16.164*				−0.035	8.89%
(−2.109)	(2.682)		(0.946)	(−0.858)	(2.417)	(−0.710)	(4.436)				(−1.022)	[+0.29%]
−1.147	0.929*		0.311	0.000	0.293	−0.170	17.090*	0.484	−0.021*	−0.229*	0.017	13.52%
(−1.425)	(2.928)		(0.403)	(0.010)	(1.547)	(−1.676)	(5.073)	(1.274)	(−5.200)	(−2.672)	(0.562)	[+0.23%]
−1.323		0.031	1.054	−0.035	0.326	−0.152	17.048*	0.514	−0.021*	−0.223*	0.023	13.65%
(−1.651)		(0.584)	(1.340)	(−0.932)	(1.726)	(−1.506)	(5.064)	(1.346)	(−5.082)	(−2.592)	(0.665)	
−1.158	0.919*	0.043	0.295	0.002	0.282	−0.168	17.208*	0.475	−0.022*	−0.219*	0.020	13.88%
(−1.434)	(2.875)	(0.801)	(0.380)	(0.045)	(1.502)	(−1.664)	(5.133)	(1.255)	(−5.233)	(−2.548)	(0.572)	[+0.23%]

returns, while our insignificant negative coefficients are in line with Copeland et al. [31], whose focus is information-based trading but with a similar sample to ours (also based on the data of Shanghai A shares).

Among the three factors related to financial information, book-to-market and earnings-price ratio both display positive relations with stock returns. This goes against the extentive doubts on the quality of financial statements in China and is inconsistent with the well-known fact that the speculative individual investors who dominate the Chinese stock markets cannot understand the book values accurately. Fama and French [14] found that adding both size and book-to-market to the regression kills the explanatory power of earnings-price ratios, but our analysis shows that all the coefficients of earnings-price ratios are consistently positive and significant. Differently, although the portfolio analysis indicates that the stock returns decrease slightly with leverage, we find that such negative relations are insignificant, which is in line with Fama and French [14].

Inspired by the findings of Brennan et al. [24], Datar et al. [29], and Amihud [25], we also analyze the relation of stock returns with liquidity. We find that the coefficients of both the square root of Amihud's measure and Turnover consistently show that the returns of illiquid stocks tend to be higher. However, it should be noted that when these two variables are both included in one regression, the coefficients of the square root of Amihud's measure become will become insignificant (but still positive).

For the two variables calculated using historical prices, the coefficients of momentum are all significantly negative. This finding is consistent with Copeland et al. [31] and reflects that there is a high degree of mean reversion in China's stock markets, implying that news generates excessive price movement in one period and consequent overreaction tends to be followed by reversal in the next. In contrast, we cannot get a consistent conclusion from the coefficients of volatility.

4.3. Time-Series Regression. The cross-sectional evidence above has verified that the tail dependence risk significantly affects the stock returns of Shanghai A shares, and this effect will not disappear even after adding other factors in the regressions. If this tail dependence of individual stocks with the market truly reflects a pricing factor, one can also construct a return proxy from the portfolios sorted according to tail dependences as in Fama and French [32], and the stock returns should vary with this proxy over time according to the APT model. Therefore, in this section, we will further investigate the time-series behavior of such a constructed proxy for Shanghai A share stocks.

We construct the proxy for tail dependence following a procedure similar to that in Fama and French [32]: each month, we divide all the stocks in our sample into five groups based on the tail dependences, with the same number of stock in each group. Then, the mimicking portfolio "MP_TDC" is constructed to proxy for the risk factor related to tail dependence. It is calculated, especially, as the (monthly) difference between the average returns of the portfolio with the highest tail dependences and the average returns of the portfolio with the lowest tail dependences. Since we want to control the effect of other pricing factors in the time-series regression, the mimicking portfolios to proxy for other factors (including size, book-to-market value, leverage, earning-price ratio, square root of Amihud's measure, Turnover, momentum, and volatility) are also constructed in a similar way. For each factor, all the stocks are first divided into five groups, and the proxy for size, "SML," is calculated as the difference between the average returns of the portfolio with the smallest firm sizes and the average returns of the portfolio with the largest firm sizes. The proxy for book-to-market value, "HML," is calculated as the difference between the average returns of the portfolio with the largest book-to-market values and the average returns of the portfolio with the smallest book-to-market values. The proxy for leverage, "MP_LEV," is the difference between the average returns of the portfolio with the largest leverage values and the average returns of the portfolio with the smallest leverage values, and so on.

Similar to Fama and French [32], we use the excess returns on nine portfolios, formed on size and book-to-market value, as the dependence variables in our time-series regression. The nine portfolios are constructed as follows. Firstly, at each month, we divide all the stocks into three portfolios based on firm sizes. Next, the stocks in each of the three portfolios are further divided into 3 subportfolios based on book-to-market values. Finally, we obtain nine portfolios in total. Together with the market returns, the proxies for tail dependence and other pricing factors are tested on the obtained nine size and book-to-market value sorted portfolios.

We first turn to our main concern in this paper, the performance of the tail dependence proxy in the time-series regression. The evidence in Table 6(a) shows that, if the proxy for tail dependence is added into the Fama-French's three-factor model, the adjusted R^2 will achieve an improvement from 1.8% to 4.7%. More importantly, all the 9 portfolios are loaded positively and significantly on the proxy for tail dependence at the confidence level of 5%. The results in Table 6(b) further indicate that, even after the proxies for other pricing factors are also included in the time-series regression, the slopes of the proxy for tail dependence remain significantly positive except for one portfolio (positive but insignificant). In the full model of Table 6(b), we also observe an increase of the adjusted R^2 by adding the proxy for tail dependence into the regressions. We thus advocate that, for Shanghai A stocks, the portfolio constructed to mimic the risk factor related to tail dependence could help to capture common variation in returns, no matter what else is in the time-series regressions. This represents evidence that the tail dependence of individual stocks with the whole market is indeed a proxy for the sensitivity to common risk factors in stock returns.

Among other pricing factors, the performance of market returns is the most remarkable. All the slopes of market returns are highly significant and close to one. In other words, the market factor explains a large portion of the variations in stock portfolio returns. The slopes of the "SML" proxy are positive for the portfolios of small stocks and the slopes of the "HML" proxy are significantly positive for the portfolios with the largest book-to-market values. Besides, all the portfolios are positively loaded on the proxy for leverage but this variable is insignificant. The slopes of the proxy for volatility

TABLE 6: (a) Regression of portfolio returns on the proxy for tail dependence and Fama-French factors. This table shows results from regressing each of the nine size and book-to-market value sorted portfolios' excess returns on three factors in Fama-French model and the proxy for tail dependence; that is, $R_t - \mathrm{RF}_t = a + b(\mathrm{RM}_t - \mathrm{RF}_t) + s\mathrm{SML}_t + h\mathrm{HML}_t + k_{\mathrm{TDC}}\mathrm{MP\_TDC} + e_t$, where R_t represent each portfolio's returns, RM_t represent market returns, and RF_t are risk-free rates. SML, HML, and MP_TDC are the proxies for size, book-to-market value, and tail dependence, respectively. "∗" denotes the fact that the corresponding coefficients are significantly different from zero at the confidence level of 5%. (b) Regression of portfolio returns on the proxies for tail dependence and all the other factors. This table shows results from regressing each of the nine size and book-to-market value sorted portfolios' excess returns on three factors in Fama-French model, the proxy for tail dependence, and the proxies for other factors; that is, $R_t - \mathrm{RF}_t = a + b(\mathrm{RM}_t - \mathrm{RF}_t) + s\mathrm{SML}_t + h\mathrm{HML}_t + k_{\mathrm{LEV}}\mathrm{MP\_LEV} + k_{\mathrm{E/P}}\mathrm{MP\_E/P} + k_{\mathrm{ASQT}}\mathrm{MP\_ASQT} + k_{\mathrm{TURN}}\mathrm{MP\_TURN} + k_{\mathrm{MTM}}\mathrm{MP\_MTM} + k_{\mathrm{VOL}}\mathrm{MP\_VOL} + k_{\mathrm{TDC}}\mathrm{MP\_TDC} + e_t$, where R_t represent each portfolio's returns, RM_t represent market returns, and RF_t are risk-free rates. SML, HML, MP_LEV, MP_E/P, MP_ASQT, MP_TURN, MP_MTM, MP_VOL, and MP_TDC are, respectively, the proxies for size, book-to-market value, leverage, earning-price ratio, square root of Amihud's measure, Turnover, momentum, volatility, and tail dependence. "∗" denotes the fact that the corresponding coefficients are significantly different from zero at the confidence level of 5%.

(a)

	Low	Median	High	Low	Median	High
		a			$t(a)$	
Small	−0.428	−0.221	−0.254	−1.688	−0.866	−1.069
Median	−0.381	−0.509	−0.315	−1.484	−1.960	−1.310
Large	−0.327	−0.450	−0.457	−1.341	−1.804	−1.962
		b			$t(b)$	
Small	0.998*	0.962*	1.010*	20.105	18.978	21.544
Median	0.963*	1.018*	0.966*	19.332	19.998	20.470
Large	0.946*	1.027*	0.994*	19.822	20.674	21.389
		s			$t(s)$	
Small	0.544*	0.435*	0.439*	4.539	3.553	3.881
Median	0.040	0.079	0.074	0.334	0.645	0.648
Large	−0.386*	−0.072	−0.106	−3.352	−0.604	−0.946
		h			$t(h)$	
Small	−0.212	0.214	0.418*	−1.723	1.710	3.608
Median	−0.115	0.132	0.461*	−0.937	1.048	3.947
Large	−0.307*	0.253*	0.473*	−2.604	2.061	4.116
		k_{TDC}			$t(k_{\mathrm{TDC}})$	
Small	0.548*	0.677*	0.715*	4.546	5.501	6.288
Median	0.570*	0.616*	0.678*	4.713	4.985	5.917
Large	0.556*	0.418*	0.509*	5.797	3.468	4.508
		R^2			Increase of R^2 by adding proxy for TDC	
Small	84.3%	82.8%	86.1%	2.6%	4.3%	4.7%
Median	80.0%	81.1%	82.7%	3.7%	3.9%	5.1%
Large	80.7%	80.6%	82.4%	3.7%	1.8%	2.9%

(b)

	Low	Median	High	Low	Median	High
		a			$t(a)$	
Small	−0.075	−0.084	−0.051	−0.189	−0.216	−0.129
Median	−0.140	−0.124	−0.049	−0.360	−0.304	−0.128
Large	−0.065	−0.118	−0.062	−0.170	−0.290	−0.157
		b			$t(b)$	
Small	0.965*	0.922*	0.978*	18.906	17.960	20.470
Median	0.931*	0.988*	0.933*	18.016	18.893	19.273
Large	0.912*	0.991*	0.957*	18.579	19.756	20.408
		s			$t(s)$	
Small	0.464*	0.303	0.304	2.056	1.335	1.439
Median	0.091	0.024	−0.009	0.398	0.102	−0.040
Large	−0.246	−0.117	−0.018	−1.135	−0.527	−0.089

(b) Continued.

		h			$t(h)$	
Small	−0.199	0.253	0.537*	−1.356	1.707	3.896
Median	−0.056	0.076	0.421*	−0.375	0.504	3.022
Large	−0.212	0.223	0.478*	−1.500	1.546	3.537
		k_{LEV}			$t(k_{\mathrm{LEV}})$	
Small	0.152	0.156	0.029	0.753	0.736	0.148
Median	0.215	0.144	0.265	1.010	0.669	1.331
Large	0.219	0.077	0.102	1.081	0.372	0.529
		$k_{\mathrm{E/P}}$			$t(k_{\mathrm{E/P}})$	
Small	−0.012	−0.214	−0.113	−0.088	−1.528	−0.869
Median	−0.234	0.061	−0.077	−1.664	0.429	−0.582
Large	−0.048	0.057	−0.015	−0.360	0.418	−0.116
		k_{ASQT}			$t(k_{\mathrm{ASQT}})$	
Small	0.015	−0.009	0.107	0.058	−0.036	0.454
Median	−0.154	−0.008	0.019	−0.607	−0.031	0.080
Large	−0.110	−0.057	−0.239	−0.456	−0.231	−1.037
		k_{TURN}			$t(k_{\mathrm{TURN}})$	
Small	−0.087	−0.057	−0.132	−0.535	−0.345	−0.864
Median	0.122	−0.173	−0.143	0.737	−1.032	−0.928
Large	−0.022	−0.166	0.094	−0.142	−1.036	0.625
		k_{MTM}			$t(k_{\mathrm{MTM}})$	
Small	0.187	0.168	−0.004	1.545	1.376	−0.031
Median	0.040	0.244*	0.212	0.323	1.967	1.849
Large	−0.065	0.247*	0.205	−0.560	2.078	1.845
		k_{VOL}			$t(k_{\mathrm{VOL}})$	
Small	0.341*	0.304	0.303	2.033	1.803	1.927
Median	0.232	0.259	0.223	1.365	1.508	1.401
Large	0.298	0.342*	0.397*	1.846	2.076	2.575
		k_{TDC}			$t(k_{\mathrm{TDC}})$	
Small	0.343*	0.383*	0.490*	2.241	2.485	3.418
Median	0.403*	0.424*	0.448*	2.603	2.701	3.089
Large	0.438*	0.190	0.345*	2.977	1.260	2.456
		R^2			Increase of R^2 by adding proxy for TDC	
Small	84.7%	83.7%	86.6%	0.6%	0.7%	1.3%
Median	80.1%	81.5%	83.2%	1.1%	1.0%	1.3%
Large	81.1%	81.7%	83.4%	1.3%	0.1%	0.7%

are also consistently positive. No consensus could be found for the results of other pricing factors. It is also important to examine the pattern in the intercepts. All the intercepts are insignificantly negative, but we can find that T values of intercepts in the full model are lower than those in the model only including the Fama-French factors and the proxy for tail dependence. This means that adding other pricing factors into the time-series regression can help to bring the intercepts to zero.

5. Conclusion

The existence of short-sale constraints in many stock markets always makes a large amount of the adverse information pent-up. When the market is shocked by an event and declines, this originally sidelined information would be flushing out to the market and generate the extreme downside risk, which is rather stronger than upside risk. However, as a linear measure of overall market risk, the beta in classical CAPM cannot distinguish the difference between them.

Therefore, this paper introduces a nonlinear measure, tail dependence, to capture this extreme downside market risk that individual stocks crash down together with the market. It can be viewed as a different perspective on "market risk" beyond linear beta and thus requires compensation. By employing the sound Copula theory to model the dependence structure between individual stocks and the market, their tail dependence can be easily estimated. We attempt to give the answers to the following two questions. First, does this tail dependence with the market indeed exist? And if it exists, is this tail dependence a determinant of stock returns?

We build elaborate empirical analysis based on the data of Shanghai A shares, and our results verify that most Shanghai A-share stocks do crash down together with the market, evident by their nonzero tail dependence coefficients. Furthermore, the tail dependence of individual stocks with the market is proved to have additional explanatory power beyond linear beta and other factors for the cross-sectional stock returns of Shanghai's market. The stocks with stronger tail dependence will always have higher returns, and, even after controlling the effect of other asset pricing factors, this positive relation is still significant. The evidence of the time-series regression further suggests that, if a portfolio is constructed to mimic the risk factors related to tail dependence, the returns of this mimicking portfolio can also help capture reasonable common variations in returns of Shanghai A shares. Both these findings inspire us that the tail dependence may contain certain information that beta and other pricing factors well-cited by previous studies cannot provide, and thus we advocate that this tail dependence should be also taken into account in future studies.

During our sample period, short selling is strictly prohibited in Shanghai stock market. In other markets, even if short selling is not strictly prohibited, the short-sale constraints still exist due to the cost, risk, and institutional restrictions associated with short-selling. For example, Hong and Stein [6] suggest that "mutual fund managers, by virtue of their charters or regulations, are often deterred from taking short position." Therefore, we could further use the data of such markets to widely examine the robustness of the relation between tail dependence and stock returns found in our paper. Moreover, our work can also be extended in another direction: it would be interesting to analyze the upper tail dependence. Since the patterns of the tail dependence with the whole market are likely to be different across stocks, we could use the mixture of Copulas introduced by Hu [7] to explore both the upper and lower tail dependence between individual stocks and the market and compare their roles in determining stock returns. If the lower tail dependence coefficients can explain stock returns but upper tail dependence coefficients cannot, it might provide further supporting evidence for the conjecture put forward in this paper.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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Endnotes

1. Shanghai and Shenzhen Exchange markets began to accept the declaration of Margin Trading and Short Selling from March 31, 2010, and the first financial future, CSI 300 Stock Index Future, was listed on April 16, 2010.

2. Copula is defined by Nelsen [16] as "functions that join or couple multivariate distribution functions to their one-dimensional marginal distribution functions." Copulas can measure the nonlinear dependence structure, and, with the parameters of many stylized Copulas, the tail dependence, which refers to the relationship between random variables resulting from extreme observations in the upper and lower quadrants of the joint distribution function, can be calculated by certain formulas. We will provide more explanations in Section 2.

3. The authors appreciate an anonymous referee reminding them of this literature.

4. For the simple bivariate case in this paper, denote the individual stocks' returns and the market returns by X and Y. Then, formula (2) can be simplified as $F(x, y) = C(F(x), G(y))$, where $F(x, y)$ is the joint distribution of X and Y, and $F(x)$ and $G(y)$ are their marginal distributions, respectively.

5. In order to assure we have sufficient data for the following asset pricing analysis, each month, we use only the recent two years' observations to estimate the Copula parameters and calculate the lower tail dependence coefficients. Therefore, we employ the empirical marginal distributions for individual stocks and the market to avoid the estimation of marginal distributions' parameters. And also, due to the scarcity of data, we choose the Clayton Copula instead of Student's T Copula, since the Student's T Copula has one more parameter. The Clayton Copula has lower tail dependence and thus already allows us to capture the extreme downside market risk that the individual stocks crash together with the whole market. Although the Student's T Copula has both upper and lower tail dependences, the dependence degrees in two tails are symmetric. However, it is well-known that the dependence structure of financial returns is asymmetric. So, we cannot say which one is better than the other for the two Copulas. The Clayton Copula is chosen only from the operational perspective.

6. Using weekly returns instead of monthly returns to calculate the tail dependence is because the Clayton Copula is a complex nonlinear model which requires more observations to estimate. In order to retain sufficient data for the following regression analysis on asset pricing, we employ the minimum sample size of two years to estimate the tail dependence coefficients. However, we have implemented robust test, that is, changing the sample size from two years to five years, and the results show that the rank of stocks' tail dependence coefficients would almost not change, which is also indicated in the subsequent portfolio analysis (the postranking TDC is indeed increasing as with the increase in the preranking TDC).

7. From formula (11), we can exactly see that, in the definition of downside beta, the distribution is divided into two parts, and the downside beta is calculated based on the left part. Differently, the tail dependence coefficient is not calculated based on the entire left part, but only based on the extreme left tail. So, it is quite possible that the tail dependence coefficient and downside beta of

one stock are of different rank, as they contain different information.

8. The positive relation between beta and TDC here is probably because the extreme comovements in tails can be viewed as a part of the overall relations, so two variables with strong tail dependence may also present a strong overall linear relation, provided that their relations in other parts of the distributions are not too weak. Nevertheless, we will show in the following that, despite their positive relations, the role of tail dependence in affecting the stock returns is rather more significant than linear beta.

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