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EUROPEAN REAL ESTATE FIRMS IN CRASH SITUATIONS

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ABSTRACT. In this paper, we analyse the crash behaviour of major European real estate firms if compared to blue chips. The single asset risk characteristics in terms of volatility, heavy tailedness and Value-at-Risk is investigated via an extreme value theory approach. First we filter the data with a GARCH model to capture heteroscedasticity effects, then we measure the tail fatness of the residuals by adjusting a generalised Pareto distribution. The diversification effects of the admixture of real estate firms to stock portfolios are observed by correlation, kendalls tau and tail dependence. To obtain an estimate for the tail dependence we fit a transformed Frank copula. We can conclude that real estate firms generally show lighter tails than stocks and that their admixture in portfolios can gain a high diversification for daily returns, that even does not break down in crash situations.

Key words: Real Estate Firms, Equity REITs, Extreme Value Theory, tail behaviour, copula, tail dependence
JEL classification: C13, C22

1. INTRODUCTION

During the last years, incorporated real estate firms (REFs) in Europe have attracted growing attention. One reason is the breakdown of inter-generation contract based retirement pay, demanding state-aided, private retirement insurance, e.g., the Riester Rente in Germany, and giving banks and financial service companies the opportunity to establish large pension funds. Here the requirement of crash stability plays a leading role. Furthermore, insurance companies may have the same interest in order to obtain crash resistant investment strategies for their reserves. Whenever the focus is on portfolio diversification and crash stability, real estate based stocks are of increasing interest, since there is hope of gaining the liquidity and tractability of stocks combined with diversification and stability effects of real estates. In recent time, some efforts have been made to analyse if this aspiration holds.

In Maurer and Sebastian [1998] a portfolio of german REFs is compared to the german stock index DAX, the german bond index REXP and a portfolio of german real estate funds. They observed only a slightly lower volatility of the REFs with respect to the DAX in contrast to a significantly lower volatility of the real estate funds. Furthermore they found a significantly high correlation of the REFs with the DAX whereas there was no correlation with the real estate funds. These findings correspond to empirical studies done for US equity real estate trusts (EREITs), that

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are probably the best analog to the european REF. Giliberto [1990] also observed a high correlation between EREITs and stocks and no correlation of EREITs compared to real estates. By using the residuals of a linear regression he removed the market effects of stock and bond returns on the EREIT returns and showed that there is a significant positive correlation between the regression residuals and real estate returns. This enabled him to follow the existence of a common factor moving EREIT and real estate returns. Myer and Webb [1993] extended this approach by using a vector autoregressive model and running a Granger causality test with the outcome that EREIT returns can Granger cause real estate returns. Furthermore, they analysed the stylized facts of some single EREIT returns and ran different tests of normality. It turned out that the normal hypothesis can not be discarded under most tests and only few data showed significant skewness and kurtosis.

In this paper, we focus on the behaviour of REFs in crash situations and compare them to blue chips. We investigate the single asset attributes as well as the effect of REF admixture to common stock portfolios. It is well known and examined that stock returns have the stylized fact of heavy tails, especially at the loss end. See, e.g., Danielsson and De Vries [1997], Frey and McNeil [2000] and Longin [1999]. The realisations by Myer and Webb [1993] give a first hint that this is not true for EREIT returns. We use Extreme Value Theory (EVT) to proof that intuition. As guidelines to EVT, we refer to Resnick [1987] and Embrechts et al. [1997].

The unexpected high correlation with common stocks and the absence of correlation with real estates stated in the above references are a drawback in the effort of using REFs as a diversification tool in common stock portfolios. However, we will not find such high correlation in our studies and the common factor driving the EREIT and real estate returns mentioned above is an indicator that there should be a diversification effect. Since we are mainly interested in the crash behaviour, we emphasise the dependence of extreme events and measure it using tail dependence. For example Ané and Kharoubi [2001] and Junker and May [2002] have observed that portfolios of common stocks tend to be lower tail dependendent; i.e., a possible existing diversification effect breaks down if extreme losses occurs. For benchmark reasons we also investigate pure blue chip and REF portfolios.

The paper is organized as follows: In Section 2 we present the mathematical concepts needed and summarise facts and definitions about EVT and copulas. Section 3 is devoted to the analysis of financial data and the question of parameter estimation. For single assets, we focus on log-returns of blue chips and European REFs and apply a GARCH-type model to capture conditional heteroskedasticity effects. For each time series, the loss tails of the innovations are fitted by a generalised Pareto distribution (GPD) to obtain a tail index and to get an accurate Value-at-Risk (VaR) and Expected Shortfall estimator as measures of risk. On the aggregated (portfolio) level, the joint distribution function is established along the lines of Junker and May [2002] by a copula function based on a transformed Frank copula. Here we operate on the innovations of the univariate time-series, modeled by their empirical distribution function and estimate the tail dependence. The quality of the estimation is examined by performing a χ^2 goodness-of-fit (gof) test.

2. Mathematical Framework

2.1. **Extreme Value Theory.** First, we recall the definition of the generalised Pareto distribution (GPD). For an overview we refer to Embrechts et al. [1997].

The generalised Pareto distribution with parameters $\xi \in \mathbf{R}$, $\beta > 0$ is defined by

$$G_{\xi,\beta}(x) = \begin{cases} 1 - \left(1 + \frac{\xi x}{\beta}\right)^{-\frac{1}{\xi}}, & \xi \neq 0 \\ 1 - \exp\left(-\frac{x}{\beta}\right), & \xi = 0, \end{cases} \tag{2.1}$$

where $x \geq 0$ for $\xi \geq 0$ and $0 \leq x \leq -\frac{\beta}{\xi}$ for $\xi < 0$.

The shape parameter ξ models the tail behaviour and is therefore called the tail index. If $\xi > 0$ we say the distribution function $G_{\xi,\beta}$ is heavy tailed, for $\xi = 0$ exponential tailed, and $\xi < 0$ light tailed.

The mean excess function is defined by

$$e(u) = E[X - u \mid X > u], \qquad u \in \mathbf{R},$$

where X is a random variable. If the law of X is GPD, the mean excess function is linear.

The GPD is defined on the positive half axis. Often, we need to shift the distribution to some new starting point u that is called threshold. In general, the GPD might only reflect the tail behaviour of a given random variable. In this case we can determine the threshold u by graphical data analysis. We choose u such that the empirical mean excess function

$$\widehat{e}(x) = \frac{1}{N(x)} \sum_{i=1}^{N} x_i 1_{|x_i \geq x}$$

of the observed sample $\{x_1, \ldots, x_N\}$, with $N(x) = |\{x_i \mid x_i \geq x,\ i = 1, \ldots, N\}|$, is approximately linear for $x \geq u$, see Embrechts et al. [1997] pp.352. An estimator for a $p\%$-quantile $\widehat{x}_p > u$ is attained by inverting the GPD

$$\widehat{x}_p = u + \frac{\widehat{\beta}}{\widehat{\xi}} \left(\left(\frac{N}{N(u)}(1-p) \right)^{-\widehat{\xi}} - 1 \right). \tag{2.2}$$

2.2. **Copula concept.** The copula concept is based on a separate statistical treatment of dependence and marginal behaviour. The mathematical idea goes back to Sklar (1955) and Hoeffding (1940). For a detailed discourse the reader is referred to mathematical monographs like Nelsen [1999] or Joe [1997]. We summarise some facts and definitions that turn out to be useful for our approach.

A copula is a multivariate distribution function defined on the unit cube $[0,1]^n$, with uniformly distributed marginals. Let $X_1, \ldots, X_n$ be random variables with continuous distribution functions $F_{X_1}, \ldots, F_{X_n}$. Then the random vector $(X_1, \ldots, X_n)$ has a unique copula C.

Definition 2.1. An n-copula of an n-dimensional random vector $(X_1, ..., X_n)$ is the joint distribution function C of the uniform random vector $(F_{X_1}(X_1), ..., F_{X_n}(X_n))$, where the F_{X_i} are the marginal distribution functions of the X_i.

So the n-dimensional joint distribution function H for $(X_1, \ldots, X_n)$ can be written as follows

$$H(x_1, ..., x_n) = C(F_{X_1}(x_1), ..., F_{X_n}(x_n)), \tag{2.3}$$

and hence the copula C describes the dependence between the univariate random variables $X_1, ..., X_n$. Equation (2.3) is in mathematical literature referred to Sklar's

Theorem and implies, that for continuous multivariate distribution functions the univariate margins and the dependence structure (represented by a copula) can be separated.

In the following, we summarise the dependence concepts used in this article.

Let (x_i, y_i), (x_j, y_j) be realisations of a random vector (X, Y). (x_i, y_i) and (x_j, y_j) are *concordant* if ($x_i < x_j$ and $y_i < y_j$) or ($x_i > x_j$ and $y_i > y_j$) and they are *discordant* if ($x_i < x_j$ and $y_i > y_j$) or ($x_i > x_j$ and $y_i < y_j$).

Definition 2.2. Let (X_1, Y_1) and (X_2, Y_2) be i.i.d. random vectors. Then the *population version of Kendall's* τ for continuous (X, Y) is defined as

$$\tau = \tau_{X,Y} = P[(X_1 - X_2)(Y_1 - Y_2) > 0] - P[(X_1 - X_2)(Y_1 - Y_2) < 0].$$

So Kendall's Tau is the probability for an observation of (X, Y) to be concordant minus the probability to be discordant. For a sample $\{(x_1, y_1), \dots, (x_n, y_n)\}$ of observations from continuous (X, Y), a *sample version of Kendall's* τ can be estimated via

$$t = \frac{c-d}{c+d} = \frac{c-d}{\binom{n}{2}} \tag{2.4}$$

where c is the number of concordant pairs and d the number of discordant pairs. Kendalls Tau avoids some of the pitfalls known for the correlation in a non elliptical framework. Especially we have the relations $\tau_{X,Y} = 1 \Leftrightarrow X, Y$ are comonotone, $\tau_{X,Y} = -1 \Leftrightarrow X, Y$ are countermonotone, what is generally not true for the correlation measure. See, e.g., Embrechts et al. [1999]. Since we are particularly interested in extreme values the following asymptotic measure for tail dependence is a useful tool.

Definition 2.3. A 2-copula C is *lower tail dependent*, if

$$\lim_{u \to 0} \frac{\mathbf{P}[U \leq u, V \leq u]}{u} = \lim_{u \to 0} \frac{C(u,u)}{u} = \lambda_L, \quad \lambda_L \in (0,\, 1],$$

and C is *upper tail dependent* if

$$\lim_{u \to 1} \frac{\mathbf{P}[U > u, V > u]}{1-u} = \lim_{u \to 1} \frac{1 - u - u + C(u,u)}{1-u} = \lambda_U, \quad \lambda_U \in (0,\, 1].$$

For the calculation of the tail dependencies as asymptotic properties of a particular copula, we fit a copula introduced by Junker and May [2002]. They define

(2.5)

$$C_\omega(u,v) := -\tfrac{1}{\theta} \ln \left[1 + \left(e^{-\theta} - 1\right) \exp\left[-\left(\left(-\ln\left[\tfrac{e^{-\theta \cdot u} - 1}{e^{-\theta} - 1}\right]\right)^{\delta} + \left(-\ln\left[\tfrac{e^{-\theta \cdot v} - 1}{e^{-\theta} - 1}\right]\right)^{\delta} \right)^{\frac{1}{\delta}} \right] \right]$$

$$C_\Omega(u,v) := \alpha \cdot (u + v - 1 + C_{\omega_s}(1-u, 1-v)) + (1-\alpha) \cdot C_\omega(u,v),$$

with $\alpha \in [0,\, 1]$ and the parameter vectors $\omega = (\theta, \delta)$ and $\omega_s = (\theta, \delta_s)$, where $\theta \in (-\infty, \infty) \setminus \{0\}$ and $\delta, \delta_s \in [1, \infty)$. The lower (λ_L) and upper (λ_U) tail dependence parameters for C_Ω are given by

$$\begin{aligned} \lambda_L &= \alpha \left(2 - 2^{\frac{1}{\delta_s}}\right) \\ \lambda_U &= (1-\alpha)\left(2 - 2^{\frac{1}{\delta}}\right). \end{aligned} \tag{2.6}$$

For further details we refer to Junker and May [2002].

company	market capitalisation [in Mill. EUR]	number of zero-returns [in % of samplesize]
Land Securities, GB	6.9	2.57
Canary Wharf Finance, GB	4.5	14.73
British Land Company Plc, GB	4.1	2.63
Rodamco CE, NL	3.2	10.48
Unibail, F	2.7	8.26
Hammerson Plc, GB	2.3	11.59
Slough Estates, GB	2.2	11.49
Simco, F	2.1	10.01
Liberty, GB	2.0	23.79
Gecina, F	1.8	15.43
Corio, NL	1.7	17.40
IVG, D	1.4	9.04
Klépierre, F	1.4	12.91
Vallehermoso, E	1.1	4.73
Drott, S	1.0	13.70

TABLE 1. European REFs ranked by their market capitalisation.

3. Empirical studies

We now turn to the question of empirical evidence of a different crash behaviour for REFs compared to common stocks. For this purpose we investigate the 15 biggest european REFs ranked by market capitalisation (see Table 1) and compare them with 15 blue chips (see Table 2), primarily taken from the european market. The data analysed here are daily log-returns in an observed time period ranging from Jan. 1997 to Jan. 2002 for the REFs, and from Oct. 1989 to Oct. 2000 for the blue chips, respectively. As a lower bound measure for liquidity for the REFs, Table 1 shows the number of observed zero log-returns in percentage of the sample size.

All of the observed datasets show heteroskedasticity and some turn out to be autocorrelated. To deal with these effects, we describe the mean by an AR(1) model, and the volatility of the log-returns by a GARCH(1,1) model, i.e. we model the log-returns R_t, say, by

$$\begin{aligned} R_t &= \mu_t + \sigma_t \varepsilon_t \\ \mu_t &= \mu + \alpha R_{t-1} \\ \sigma_t^2 &= \omega + \beta \varepsilon_{t-1}^2 \sigma_{t-1}^2 + \gamma \sigma_{t-1}^2, \end{aligned}$$

where $\alpha = 0$ for the log-returns that do not show autocorrelation. For a related model approach we refer to Frey and McNeil [2000].

3.1. **Single asset studies.**

In the following we want to investigate some attributes, like volatility and heavy taildness, of the REF log-returns. Since we want to compare them with common stocks we here only use data in the overlapping observed time period ranging from Jan. 1997 to Oct. 2000.

We use a Maximum Likelihood estimator to compute the parameters of a GPD describing the loss tail of the innovations. To examine the quality of the fit we

companies	$\widehat{\xi}$	$\widehat{\mu^\diamond}$ [in %]	$\widehat{\sigma^\diamond}$ [in %]	99% VaR [in %]	99% ES [in %]	$\widehat{\frac{\mu^\diamond}{\sigma^\diamond}}$ [in %]	p-value [in %]
BP, GB	0.0667	0.0609	1.9809⋆	4.56	5.40	3.08	1.77
Reuters, GB	0.1784⋆	0.0915	4.3202⋆	10.86	14.61	2.12	49.50
Lloyds, GB	0.0352	0.0841	2.5226°	5.92	7.28	3.33	83.01
Aventis, F	0.4128°	0.1275°	2.6231⋆	6.25	8.62	4.86°	2.21
Totalfina, F	0.2832°	0.0951°	2.4501⋆	5.95	7.54	3.88°	13.55
Allianz, D	0.2894⋆	0.0721	2.4899⋆	6.22	9.04	2.90	89.57
BASF, D	0.3002°	0.0567	2.0187⋆	4.88	6.47	2.81	96.68
Deutsche Telekom, D	0.1965°	0.1178°	3.5110⋆	8.54	11.11	3.35	21.92
Hoechst, D	0.0592	0.0381	5.1417⋆	13.74	17.62	0.74	42.99
VW, D	0.1001°	-0.0134	2.4111⋆	6.43	8.41	-0.56	82.88
Nestlé, CH	-0.0039	0.1027⋆	1.5222⋆	4.13	5.08	6.75°	18.48
Exxon, US	0.2037°	0.0634	1.7731°	4.08	5.13	3.57	95.98
IBM, US	0.2626⋆	0.1333°	2.4300⋆	6.29	8.95	5.49°	61.53
Microsoft, US	0.2019°	0.1097°	2.5458⋆	6.49	8.77	4.31°	91.73
SUN, US	-0.0233	0.4250⋆	3.3762⋆	8.53	9.86	12.59⋆	84.91

TABLE 2. Estimates for the blue chips with the p-values for the fitted GPD model. Values marked with a $\circ$, ($\star$), are significant on a 80%-level (95%-level).

perform a χ^2 goodness-of-fit test based on the data below the chosen thresholds and the GPD parameter estimates. In Table 2, the results for the blue chips are summarised. The tail index ξ measures the innovation risk, the expected volatility $\sigma^\diamond = \frac{\omega}{1-\beta-\gamma}$ of the GARCH(1,1) process gives the volatility risk and the 99% VaR and 99% Expected Shortfall (ES), both calculated with the fitted GPD, quantify the total single asset risk. Here the Expected Shortfall is obtained by a Monte Carlo Simulation with 10 000 runs. The expected mean return $\mu^\diamond = \frac{\mu}{1-\alpha}$ contains the payed risk premium. There are 10 of the 15 blue chips heavy tailed with 80% significance and 3 with 95% significance. There is no significant light tailed blue chip. The p-values[1] of the χ^2 goodness-of-fit tests against the hypothesis of GPD distributed data over the choosen tresholds, indicates satisfying loss tail approximations in addition to BP and Aventis; but even here the hypothesis can not be rejected on a 99% level. Table 3 contains the results for the REFs. Here it seemed to be less usual to observe heavy tailed losses, since only 5 (3) of 15 have an estimated tail index $\xi > 0$ with a significance of 80% (95%) and the real estate firm Drott is the only asset with a light tail in our studies. Also the mean of the estimated tail indices is with 0.0733 for the REFs not as half as big than the 0.1708 mean of the blue chips. Furthermore, the amount of zero-returns in Table 1 indicates a potential illiquidity risk for the REFs. In contrast none of the blue chips has more than 3% zero-returns during the observed time period. Usually such illiquidity of moderate size results in more heavy tailed returns, so the conclusion

[1] The hypothesis of the test can not be rejected for levels higher than $1 - p$.

companies	$\widehat{\xi}$	$\widehat{\mu^\diamond}$ [in %]	$\widehat{\sigma^\diamond}$ [in %]	99% VaR [in %]	99% ES [in %]	$\widehat{\frac{\mu^\diamond}{\sigma^\diamond}}$ [in %]	p-value [in %]
Land Securities, GB	0.2348⋆	-0.0044	1.4920⋆	3.75	5.11	-0.29	22.96
Canary Wharf Finance, GB	0.1982°	0.0526	2.4925⋆	6.85	9.84	2.11	73.14
British Land Company Plc, GB	-0.0745	0.0195	2.0411⋆	5.18	6.18	0.96	19.13
Rodamco CE, NL	0.0145	-0.0480	1.3571⋆	3.66	4.67	-3.53	12.30
Unibail, F	0.0954	0.0652°	1.5000⋆	3.98	5.15	4.35°	63.97
Hammerson Plc, GB	-0.0348	0.0385	1.2709⋆	3.35	4.12	3.03	48.04
Slough Estates, GB	-0.0133	0.0150	1.1701⋆	2.98	3.68	1.28	51.08
Simco, F	-0.0106	0.0038	1.4155⋆	3.65	4.53	0.27	39.40
Liberty, GB	-0.0427	0.0085	1.1271⋆	3.00	3.72	0.76	1.89
Gecina, F	0.0947°	0.0345	1.1625⋆	3.28	4.33	2.97	10.07
Corio, NL	0.3159⋆	0.0009	0.9466⋆	2.82	4.52	0.10	40.68
IVG, D	0.1138	0.0357	1.9163⋆	4.73	6.17	1.86	87.39
Klépierre, F	0.2373⋆	0.0913⋆	1.5196⋆	4.37	6.39	6.01⋆	33.12
Vallehermoso, E	0.1411	0.0566	2.0265⋆	4.56	5.58	2.80	94.25
Drott, S	-0.1702⋆	0.1131°	2.3612⋆	6.23	7.19	4.79°	56.10

Table 3. Estimates for the REFs and the p-values for the fitted GPD model. Values marked with a $\circ$, ($\star$), are significant on a 80%-level (95%-level).

that REFs tend to have less fat tailed innovation distributions than common stocks, is not affected.

The mean expected daily volatility of the REFs (1.59%) is 72% lower as for the blue chips (2.74%), even the estimated volatility of illiqiud assets is usually higher than the true one. Since we do not cover any illiquidity risk in our Value-at-Risk or Expected Shortfall calculation, the lower volatility and less heavy tailed innovations of the REFs results directly to a lower 99%- average VaR (4.16%) and Expected Shortfall (5.41%) with respect to the blue chips (6.86% VaR and 8.93% Expected Shortfall). Comparing the estimated quotients $\frac{\mu^\diamond}{\sigma^\diamond}$ we have a mean value of 1.83% for the REFs and 3.95% for the blue chips and additionally only 3 of the 15 single REFs can beat the equally weighted blue chip portfolio in that sense. This indicates that there is a certain risk premium payed for the common stocks. Hence the market realizes the higher innovation and volatility risk for the blue chips and gives higher price to it than to an eventually illiquidity risk for the REFs. This observation is in line with Glascock and Davidson III [1995], who found for the US market that, on average, real estate firm returns are lower than a benchmark return based on common stocks. They concluded that REFs underperform the market, even on a Sharpe and Treynor risk adjusted basis. However, a Sharpe and Treynor risk adjustment does not cover the observed higher innovation risk for common stocks. So an investment in REFs may still be fair.

portfolio		$\widehat{\lambda}_L$	$\widehat{\rho}$	$\widehat{t}$	p-value [in %]
BP	Lloyds	0.0706**	0.2131	0.1661	73.50
	Reuters	0.1093**	0.2663	0.1808	92.23
Lloyds	Reuters	0.1074**	0.2228	0.1731	59.26
Aventis	Totalfina	0.1522**	0.2978	0.1966	98.58
Allianz	BASF	0.2615**	0.4983	0.3664	41.39
	D. Telek.	0.1972**	0.3659	0.2593	76.01
	Hoechst	0.3071**	0.4686	0.3546	90.40
	VW	0.1766**	0.4688	0.3527	29.85
BASF	D. Telek.	0.1013*	0.2876	0.2001	54.53
	Hoechst	0.3310**	0.6584	0.5241	27.88
	VW	0.2809**	0.5331	0.3980	11.46
D. Telek.	Hoechst	0.2166**	0.2923	0.2058	11.28
	VW	0.2063**	0.2579	0.1772	52.23
Hoechst	VW	0.2417**	0.4752	0.3592	76.25
IBM	Microsoft	0.1733**	0.3691	0.2545	76.85
	Sun	0.0507**	0.3573	0.2451	52.98
Microsoft	Sun	0.1652**	0.4196	0.2914	94.74
Allianz	BP	0.0607**	0.1262	0.0959	73.11
	Nestlé	0.1091**	0.2959	0.2283	28.19
	Microsoft	0.0731**	0.0925	0.0513	84.44

TABLE 4. Estimated lower tail dependency $\widehat{\lambda}_L$, correlation $\widehat{\rho}$ and samples Kendalls Tau $\widehat{t}$ for the blue chip portfolios, and the p-values of the fitted copula model with respect to a χ^2 goodness-of-fit test. All $\widehat{\lambda}_L$ values marked with a ⋆⋆ are significant on a 99% level.

3.2. **Portfolio investigations.** There were no change points in the analysed REFs and blue chips. So the GARCH residuals are iid samples and hence it is no problem to compare the innovation distributions, even if they are generated from different time intervals. This enables us to use the maximal possible time intervall for each investigated portfolio, e.g., Oct. 1989 to Oct. 2000 for the blue chips, Jan. 1997 to Oct. 2000 for the mixed portfolios and Jan. 1997 to Jan. 2002 for the pure REF portfolios.

The lower tail dependencies λ_L - as measures of crash diversification of the investigated portfolios - are obtained by fitting the copula given by equation (2.5) and applying formula (2.6). Furthermore, the estimated correlation ρ and the sample version of Kendalls Tau, t, are stated as general diversification measures, where one should remember the pitfalls of using correlation mentioned above and in, e.g., Embrechts et al. [1999]. Table 4 summarises the results for the blue chip portfolios as benchmark portfolios. We concentrate on country portfolios. All of the 20 observed portfolios, even the few international ones, show lower tail dependency on a 99% significance level in addition to BASF-Deutsche Telekom where it is the 95% level.

portfolio		$\widehat{\lambda}_L$	$\widehat{\rho}$	$\widehat{t}$	p-value [in %]
Land Securities	BP	0.0137**	0.1698	0.1202	97.90
	Lloyds	0.0000	0.1681	0.1092	97.39
	Reuters	0.0244**	0.1727	0.1363	43.46
British Land	BP	0.0537**	0.1821	0.1241	31.81
	Lloyds	0.0137	0.1309	0.0946	96.62
	Reuters	0.1221**	0.1083	0.0942	36.73
Hammerson	BP	0.0306	0.0789	0.0517	27.24
	Lloyds	0.0137	0.0762	0.0468	39.67
	Reuters	0.0710	0.1004	0.0740	92.31
Slough Estates	BP	0.0449	0.0822	0.0411	68.20
	Lloyds	0.0325°	0.0702	0.0319	19.29
	Reuters	0.0229°	0.0398	0.0227	48.11
Liberty	BP	0.0000	0.0923	0.0553	86.91
	Lloyds	0.0241**	-0.0005	-0.0073	82.93
	Reuters	0.0136**	0.0470	0.0483	96.08
Unibail	Aventis	0.0135	0.0304	0.0325	86.24
	Totalfina	0.0531**	0.0640	0.0614	89.90
Simco	Aventis	0.0136	0.0537	0.0584	66.30
	Totalfina	0.0137	0.0102	0.0347	94.84
Klépierre	Aventis	0.0008	0.0379	0.0222	99.82
	Totalfina	0.0515**	0.0181	0.0116	35.10
IVG	Allianz	0.0611*	0.1420	0.0911	91.11
	BASF	0.0000	0.1621	0.1099	45.30
	D. Telek.	0.0332*	0.1498	0.1000	97.32
	Hoechst	0.0000	0.1412	0.0949	79.20
	VW	0.0000	0.1552	0.1041	97.60
IVG	BP	0.0434°	0.1226	0.0819	37.82
	Nestlé	0.0649	0.1417	0.0957	98.94
	Microsoft	0.0240	0.0445	0.0293	95.33

TABLE 5. Estimated lower tail dependency $\widehat{\lambda}_L$, correlation $\widehat{\rho}$ and samples Kendalls Tau $\widehat{t}$ for the mixed portfolios, and the p-values of the fitted copula model with respect to a χ^2 goodness-of-fit test. $\widehat{\lambda}_L$ values marked with a $\circ$, ($\star$), ($\star\star$) are significant on a 80%, (95%), (99%) level.

This indicates the tendency of common stock portfolios to have a minor diversification effect in extreme loss situations, as probably expected from their correlation or Kendalls Tau. The mean size of the lower tail dependency is $\overline{\widehat{\lambda}_L} = 0.17$. These findings are in line with the studies of Ané and Kharoubi [2001] and Junker and May [2002]. The p-values of the fitted copula model with respect to a performed χ^2 goodness-of-fit test indicate that the data are well adapted. Table 5 contains the results for the mixed portfolios, i.e. portfolios containing a common stock and an REF. Here we also concentrate on country portfolios. There is only one port-

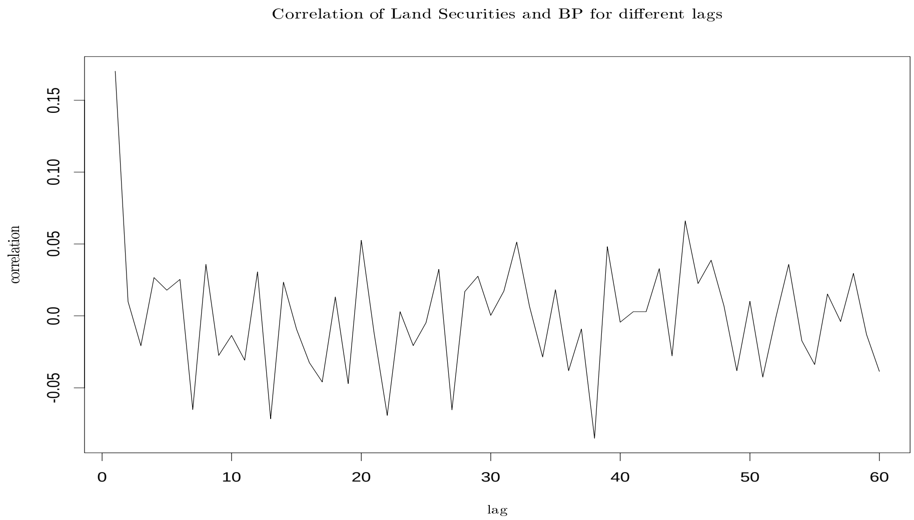

FIGURE 3.1. Correlation of Land Securities with British Petrolium for different lags.

folio (British Land-Reuters) estimated with a moderate high and significant lower tail dependence of $\widehat{\lambda}_L = 0.12$. All other of the 29 investigated mixed portfolios have lower tail dependencies well below 0.1. So the mean size of the lower tail dependency is with $\overline{\widehat{\lambda}_L} = 0.03$ on a 99% level significant lower than for the blue chip portfolios. The computed correlations and Kendalls Tau's are for almost all mixed portfolios lower than for the blue chip portfolios. Hence the mean correlation $\overline{\widehat{\rho}} = 0.10$ and the average Kendalls Tau $\overline{\widehat{t}} = 0.07$, are both approximately 70% lower than the corresponding values $\overline{\widehat{\rho}} = 0.35$ and $\overline{\widehat{t}} = 0.25$ for the common stock portfolios. So there is a high diversification effect of REFs compared to the stocks. This is in contrast to Giliberto [1990] and Maurer and Sebastian [1998] who found high correlation of EREITs and REFs, respectively, with common stocks. Both did not use any heteroscedasticity filter what can cause an overestimated correlation in the absence of homoscedasticity. Furthermore, they studied monthly returns, whereas we investigate daily log-returns. Together with the result of Liu and Mei [1992], who found that EREIT returns show a high predictability compared with stocks and bonds, our contrary findings may indicate a time shifted co-movement of the REFs with the common stocks or the existence of a systematic dependence that is suppressed by a dominating white noise dependence for high frequency data. Hence the observed diversification effects may be of no benefit for a buy and hold strategy. Therefore we compute the correlation and Kendalls Tau for the mixed portfolios with lags up to 60 days (1 quarter), i.e., we calculate $cor(X_{[1,\dots,N-k+1]}, Y_{[k,\dots,N]})$ where X, Y are the innovation time series of the portfolio assets, N the series length and $k = 1, \dots 60$ the lags. We could not find any remarkable and significant laged correlation or Kendalls Tau, see, e.g., the correlation plot of Land Securities versus British Petrolium in Figure 3.1. So we can neglect a time shifted co-movement. To investigate if there is a systematic dependence, we give in Table 6 the correlation and Kendalls Tau for the mixed portfolios with a $1, \dots, 4$ week log-return frequency.

portfolio		$\widehat{\rho_1}$	$\widehat{t_1}$	$\widehat{\rho_2}$	$\widehat{t_2}$	$\widehat{\rho_3}$	$\widehat{t_3}$	$\widehat{\rho_4}$	$\widehat{t_4}$
Land Securities	BP	0.1446	0.1119	0.2080	0.1301	**0.3388**	0.2115	0.3312	**0.2192**
	Lloyds	0.2483	0.1793	0.3115	0.2253	0.3954	**0.2737**	**0.3955**	0.2483
	Reuters	0.1086	0.1112	0.0333	0.0119	0.0682	0.0445	-0.1744	-0.1249
British Land	BP	0.1455	0.1275	0.3090	0.2359	0.4517	0.3159	**0.4800**	**0.3228**
	Lloyds	0.3030	0.2266	0.02511	0.1828	**0.5065**	**0.3744**	0.2771	0.2092
	Reuters	0.1187	0.0811	0.1344	0.0803	**0.1589**	**0.0957**	-0.0236	-0.0305
Hammerson	BP	0.1620	0.0834	0.3977	0.2437	0.4514	0.2965	**0.5725**	**0.3765**
	Lloyds	0.2143	0.1737	0.3125	0.1985	**0.4715**	**0.3072**	0.3318	0.2126
	Reuters	0.1494	**0.1242**	**0.1802**	0.1000	0.1566	0.0558	-0.0254	-0.0583
Slough Estates	BP	0.0483	0.0129	0.3038	0.1869	0.3006	**0.2227**	**0.3181**	0.1693
	Lloyds	0.1809	0.0991	0.1509	0.0864	**0.3304**	**0.2159**	0.2803	0.1497
	Reuters	0.0854	0.0536	0.1163	**0.0798**	**0.1609**	0.0374	-0.0096	0.0638
Liberty	BP	0.2443	0.1576	0.4041	0.2546	**0.4305**	**0.3333**	0.4138	0.2821
	Lloyds	0.1597	0.1017	0.3240	0.2459	0.3235	0.2438	**0.4045**	**0.2993**
	Reuters	-0.0207	0.0221	0.0665	0.0343	**0.1527**	**0.0865**	-0.1372	-0.1397
Unibail	Aventis	0.0829	0.0639	**0.1634**	**0.1149**	0.0690	0.0544	0.0821	0.0846
	Totalfina	0.1440	0.0611	0.1089	0.0831	**0.1990**	**0.1315**	0.0777	0.0021
Simco	Aventis	0.1164	0.0831	0.1508	0.0914	**0.2276**	**0.1584**	0.1726	0.0655
	Totalfina	**0.1956**	0.1062	0.1878	0.1170	0.1919	0.1303	0.1766	**0.1924**
Klépierre	Aventis	0.0564	0.0550	0.0419	0.04911	0.1112	0.0883	**0.1907**	**0.1163**
	Totalfina	-0.0539	-0.0822	-0.0953	-0.1259	**0.0472**	-0.0029	-0.0212	0.0085
IVG	Allianz	0.2943	0.1572	**0.3279**	**0.1791**	0.1488	0.0650	0.1898	0.0731
	BASF	0.2444	0.1548	0.2817	**0.1801**	0.2485	0.1572	**0.3397**	0.1230
	D. Telek.	0.1665	0.0348	**0.1741**	**0.1238**	0.1112	0.0353	0.1292	0.1082
	Hoechst	0.1515	0.1020	0.0978	0.0158	0.2010	0.1459	**0.2782**	**0.1915**
	VW	0.3216	0.1467	0.2968	0.2249	0.1217	0.1183	**0.3399**	**0.2488**
IVG	BP	0.2667	0.2058	0.1984	0.1459	0.2743	0.1867	**0.3800**	**0.2734**
	Nestlé	0.2695	0.1757	0.2377	0.1216	0.2230	0.2110	**0.3714**	**0.2537**
	Microsoft	0.1204	0.0599	0.0618	0.0417	0.1285	0.1164	**0.2686**	**0.1919**

TABLE 6. Correlation and Kendalls Tau for $1, \dots, 4$ week log-return frequencys, where the relativ maximal value is in bold style.

We can not extend this survey to the tail dependence, since the observed time horizon is not long enough to guarantee a sufficient estimator $\widehat{\lambda}_L$. For all portfolios, except for Land Securities-Reuters, the maxima of the log-return correlations and Kendalls Taus occure for middle frequency, mostly for the 3 and 4 week frequency. The scale of the maxima is of the same size as the results of Giliberto [1990] and Maurer and Sebastian [1998]. We can not conclude a long term and systematic dependency, since for half of the investigated portfolios the correlation and Kendalls Tau is already decreasing for the 4 week frequency. A long term study should be subject of further research to gain certainty in this point. However, at this point we can come up with the result of a high diversification effect of REFs for daily

portfolio		$\widehat{\lambda}_L$	$\widehat{\rho}$	$\widehat{t}$	p-value [in %]
Land Securities	British Land	0.1048**	0.4125	0.2785	19.39
	Hammerson	0.0279	0.1686	0.1038	54.77
	Slough Estates	0.0000	0.2029	0.1151	69.37
	Liberty	0.0000	0.0863	0.0651	57.28
British Land	Hammerson	0.0331	0.2224	0.1322	98.02
	Slough Estates	0.0330	0.2196	0.1160	96.85
	Liberty	0.0325	0.1308	0.0827	62.24
Hammerson	Slough Estates	0.0611	0.3573	0.2236	44.74
	Liberty	0.1416**	0.1803	0.0972	85.44
Slough Estates	Liberty	0.1339**	0.1549	0.0774	77.44
Unibail	Simco	0.0611*	0.1386	0.0606	61.85
	Klépierre	0.0669	0.1263	0.0734	84.59
Simco	Klépierre	0.0820	0.1387	0.0608	79.18
IVG	Land Securities	0.0501°	0.0536	0.0355	51.14
	Corio	0.0001	0.0981	0.0455	82.25
	Unibail, F	0.0320	0.0757	0.0383	64.74
	Vallehermoso	0.0887	0.1759	0.0753	87.29

TABLE 7. Estimated lower tail dependency $\widehat{\lambda}_L$, correlation $\widehat{\rho}$ and samples Kendalls Tau $\widehat{t}$ for the REF portfolios, and the p-values of the fitted copula model with respect to a χ^2 goodness-of-fit test. $\widehat{\lambda}_L$ values marked with a $\circ$, ($\star$), ($\star\star$) are significant on a 80%, (95%), (99%) level.

frequency, which, in contrast to common stock portfolios, even in crash situations does not break down.

For completeness we have a look on pure REF portfolios in Table 7. The results are here somehow mixed. For the mostly country portfolios, the mean correlation and Kendalls Tau is with $\overline{\widehat{\rho}} = 0.18$ and $\overline{\widehat{t}} = 0.10$ in-between the range of common stock and mixed portfolios. There are 3 of the 17 portfolios with a significant and moderate size lower tail dependence, whereas the others have an estimated $\widehat{\lambda}_L$ well below 0.1. With $\overline{\widehat{\lambda}_L} = 0.06$ the tail dependence parameters are very low compared to the blue chip portfolios. These findings are remarkable, since at least all REFs are in the same business line of real estates.

4. Conclusion

We use Extreme Value Theorie to examine the crash behaviour in means of heavy tailedness of single asset REFs. In comparison to blue chips they turn out to have less heavy tailed GARCH residuals and hence a lower innovation risk. With an observed lower mean volatility, this results in a lower Value-at-risk and Expected Shortfall.

The concept of lower tail dependence allows us to survey dependence effects in crash situations. We conclude that in the sense of correlation and Kendalls Tau, REFs can gain high diversification effects if admixtured into common stock portfolios. In contrast to pure blue chip portfolios this diversification even does not break down in crash situations, indicated by a very small, in fact not present, lower tail dependence. These findings are for a daily frequency of the observed log-returns, and hence yield a benefit for a buy and sell strategy and a one day risk management improvement. To come up with a statement for a buy and hold framework, further research should be done to examine the long term dependence structure of REFs with common stocks.

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