EXTREME RETURNS AND CONTAGION IN CHINESE AND EUROPEAN EQUITY MARKETS: A COMPARISON OF SSEC AND DAX

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Abstract

Financial "contagion" across equity markets can imply the co-occurrence of periods of high volatility in more than one country, and the existence of contagion can have important financial policy implications. The economy of the People's Republic of China has grown to one of the largest in the world, but retains idiosyncrasies which distinguishes the Chinese equity market from European markets. Our study uses daily returns on the SSEC (Shanghai Securities Exchange Composite) stock index, and daily returns on major European stock indices. The aim of our investigation is to measure the degree of dependency between joint threshold exceedances, in particular: to compare the degree of dependency between joint threshold exceedances of SSEC and some other stock index on the one hand, and a European stock index, the DAX, and some other stock index on the other hand. Our analysis differentiates between bull and bear periods, as well as between positive and negative threshold exceedances. Among our findings is that SSEC shows a lesser degree of dependency than DAX, and that dependency increases during bear periods.

Key words: SSEC; DAX; bivariate threshold exceedances; generalized Pareto distribution; logistic dependence function; daily stock index returns; bull and bear periods; dependence of stock markets

1 Introduction

In the East Asian financial crisis, which started in July 1997 in Thailand, there was one country that appeared to be relatively immune to the regional problems: China. (See Erb, Harvey, et al. [7].) This raises the general question about the international dependence of the Chinese stock market, as compared to other stock markets.

Insight into the degree of dependence may give global investors a clue about the possibility of risk diversification. Since mid-1990s the hedging ability of emerging markets in terms of low or negative correlations with developed market returns has come under scrutiny of investors. However, average performance measures, such as average correlation as one of the basic ingredients of modern portfolio selection (Markowitz [11]) may conceal idiosyncratic behaviour according to the state of the economy and the state of the equity market in a country. Returns in emerging markets appear to be non-normal. Therefore, standard tools of portfolio and risk analysis are likely to fail. This was found by Erb, Harvey, et al. [7] in their analysis of 1990s financial crises in Latin America and East Asia.

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There are several ways to measure the degree of international dependence of stock markets. Evidence of short-run volatility spillovers across markets may be observed utilizing dynamic approaches, for example, modeling a time series on the basis of a multivariate GARCH (MGARCH) process. Examples of research projects in this direction are Xu and Fung [19], who use a bivariate GARCH to investigate the pricing process of Chinese stocks listed at the stock exchanges of Hong Kong and New York; Worthington and Higgs [18] analyse mean and volatility spillovers in Asian equity markets on the basis of nine-dimensional vector autoregressive and GARCH processes.

The dependence of international stock markets manifests itself in particular in times of high volatility, when high gains or high losses are observed. If an assessment of extremal return behaviour is intended, a static approach can be adopted which explicitly takes into account the occurrence and properties of joint extreme returns, or, for the sake of not wasting the information contained in less extreme returns, return exceedances over a given threshold, the 80% (say) quantile of the return distribution.

To model threshold excesses a generalized Pareto distribution (GPD) is appropriate. Once two one-dimensional GPDs have been fitted to individual return series, it is possible to merge them by estimating a dependence function (a copula, see Nelsen [12]) on the basis of joint threshold exceedances. In the context of returns on assets, this approach was used by Longin and Solnik [10] and Schmidbauer and Rösch [14]. The copula provides a parameter which is capable to quantify the degree of dependence between the return exceedances.

In the present study, we use the SSEC (Shanghai Securities Exchange Composite) stock index to represent the performance of the Chinese stock market. It is therefore necessary to look at the idiosyncrasies of the Chinese stock market[1].

The stocks listed on the Shanghai Securities Exchange (SSE) are divided into A shares and B shares, where A shares are designated for domestic investors and B shares are designated for all (in particular, foreign) investors. By the end of December 2004, the number of stocks listed on SSE was 881, of which 827 were A share companies and 54 were B share companies. A shares are denominated in RMB, while B shares are denominated in US dollars, which in converted into RMB for stock index calculation. In the year 2004, A shares accounted for slightly more than 99% of total trading turnover at SSE, while B shares accounted for less than 1%. Calculated on tradable market share capitalization, the turnover ratio of A shares and B shares were 308% and 58%, respectively, which puts the relatively low foreign trading activity into perspective again. — Constituent stocks of the SSEC stock index are all A share and B share companies listed on the SSE.

The German stock index DAX is a performance index comprising the 30 largest German companies in terms of order book volume and market capitalization trading at Frankfurt Stock Exchange[2]. It represents about 75% of capital turnover of stock trade in Frankfurt Stock Exchange. There is no German analogue to the division into A shares and B shares found at Shanghai Stock Exchange, which makes traded shares freely accessible to investors.

In our analysis, we treat positive and negative threshold exceedances separately. It is well-known from many studies that positive and negative shocks do not have the same effect of the subsequent behaviour of a time series of returns. In particular, it has been found that the volatility of returns on an asset after negative shocks tends to be higher than after positive shocks. There are two competing explanations for this phenomenon: The *leverage hypothesis* (Black [1]) states that when the price of a company falls (that is, there is a negative shock to the price), the value of its equity also falls, thus increasing the company's leverage (debt-

[1] The following facts were taken from [15]

[2] See www.deutsche-boerse.de.

to-equity ratio). Higher risk, indicating higher business riskiness, will induce more volatility. The *volatility-feedback hypothesis* (Campbell and Hentschel [3]), on the other hand, holds that a positive shock to volatility will drive down returns, if expected dividends are unchanged.

We are thus led to the following hypotheses:

- The degree of dependence is higher for negative returns than for positive returns.
- The degree of dependence is higher in bull periods than in bear periods.
- The degree of dependence is generally higher in the case of Germany than in the case of China.

In the following, we will investigate if these hypotheses can be supported by evidence. The methods used in the present paper are based on Schmidbauer and Rösch [14]; all computations were carried out in R [13]. — This paper is organized as follows. Section 2 provides an overview of the data on which our investigations are based. Section 3 explains elementary statistical properties of the return data we used and looks into the correlation of returns on DAX and SSEC with other international stock indices. Section 4 and 5 explain which univariate and bivariate stochastic models we use and how we proceed to fit data. In Section 6, we define what is meant by bull and bear periods and how we determine if a given day belongs to either of them. Results are reported and commented in Section 7. Finally, Section 8 gives a summary and discusses some conclusions.

2 Data

Our goal in the present article is to investigate the degree of international dependence between large gains (losses) of SSEC and other international stock indices on the one hand and between large gains (losses) of DAX and other international stock indices on the other hand. The empirical basis of our study consists of 37 time series of daily closing quotes, beginning between January and July 1997, with the only exception of SMSI, which starts in July 1998. See Table 2 for a list of all stock indices used.

Simple daily returns were computed from these series. The object of interest is then the bivariate distribution of return excesses of a certain threshold, or more precisely: the bivariate distribution of joint return excesses (of two stock index returns on the same day or within a short period, see below) of SSEC (or DAX) as first component, and return excesses of one of the other stock indices as second component.

3 Basic Properties of the Stock Indices SSEC and DAX

Figures 1 through 3 give an impression of the daily performances of the two stock indices under focus. To the naked eye, daily returns on DAX appear to be more volatile than on SSEC, whereas extreme returns tend to be more extreme, as compared to the medium 50%, in the case of SSEC. The basic statistical figures in Table 1 confirm this impression. For both indices, the kurtosis of the return distribution is found significantly different from 0, but only in the case of SSEC the symmetry hypothesis can be rejected.

The correlation of weekly returns is one indicator of the co-movement of international stock indices. Table 2 shows weekly return correlations of the 37 international stock indices we considered with SSEC and DAX (gdaxi). Weekly returns were defined as the percent change from Tuesday to the subsequent Tuesday; if a Tuesday closing value was not available, the Wednesday closing value was substituted, and the Monday closing value was substituted if the Wednesday

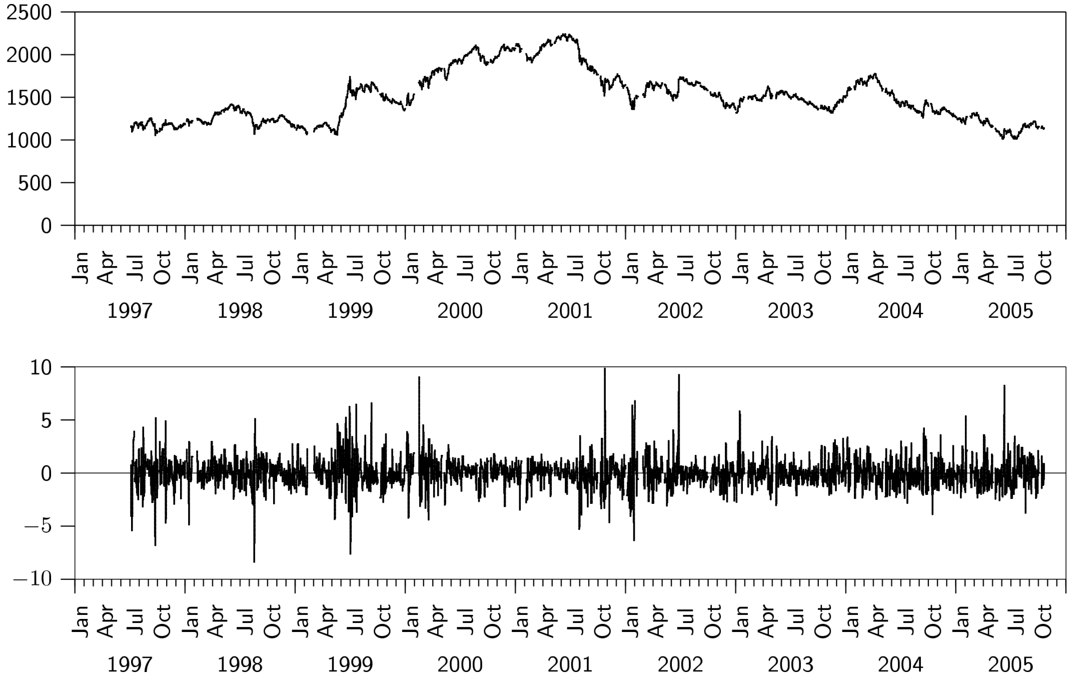

Figure 1: ssec: level series and daily returns

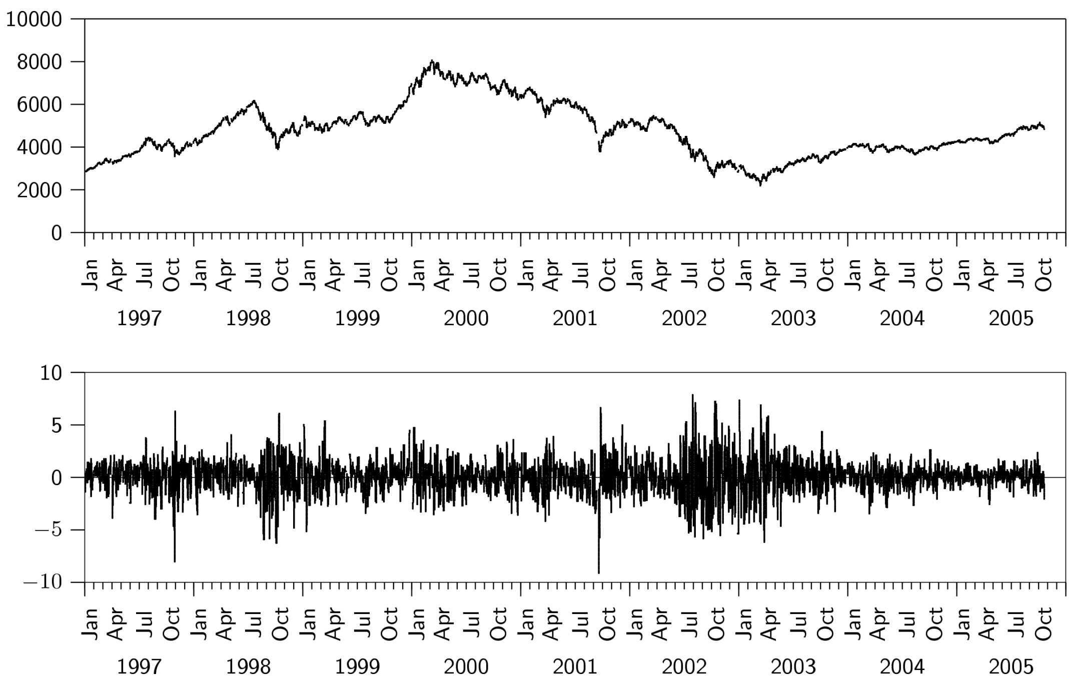

Figure 2: gdaxi: level series and daily returns

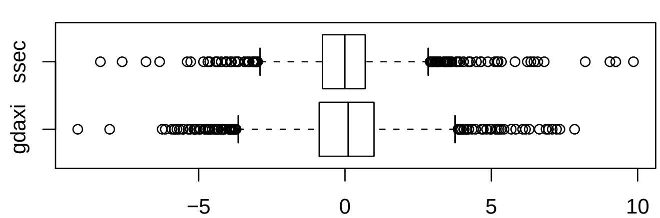

Figure 3: Boxplot of daily returns on SSEC and DAX

	SSEC	DAX
first day	1997-07-03	1997-01-02
last day	2005-10-20	2005-10-20
observations	1992	2223
NAs	174	73
mean	0.00780	0.03760
std error	0.03149	0.03767
var	2.11308	2.82890
std deviation	1.45364	1.68193
skewness	0.53547	−0.09199
std error	0.28821	0.12636
kurtosis	5.59796	2.35068
std error	1.04032	0.41488
min	−8.35766	−9.13144
lower quartile	−0.77105	−0.88192
median	−0.00264	0.10619
upper quartile	0.69008	0.99245
max	9.85684	7.84521
day of min	1998-08-17	2001-09-17
day of max	2001-10-23	2002-07-29

Table 1: Basic statistical properties of SSEC and DAX

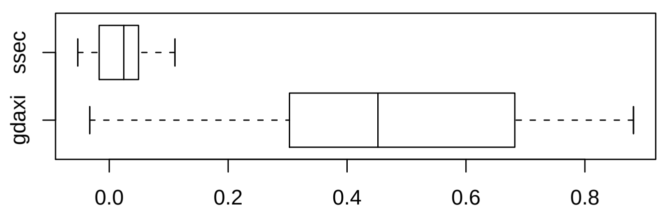

Figure 4: Boxplot of correlation of weekly returns (SSEC/DAX with international stock indices)

value was not available either. A week with Monday, Tuesday and Wednesday values missing was reported as not available.

Weekly return correlation for DAX is highest with stock indices from Germany's European neighbours: France, 0.882; Netherlands, 0.875; Sweden, 0.826; Switzerland, 0.816; UK: 0.784; while Dow-Jones is ranking eighth. For the Chinese SSEC, correlations are generally much lower, but ranking them by magnitude also reflects geographical vicinity: Hong Kong, 0.111; Singapore, 0.106; Malaysia, 0.088; Indonesia; 0.087; India, 0.085. From rank five onward, however, there is no more correspondence between geography and correlation: px50 from the Czech Republic has the same correlation with SSEC as India's bsesn.

Figure 4 gives a graphical summary display of the weekly return correlations of Table 2 in the form of boxplots. Although the comparison of weekly return correlations reveals differences between SSEC and DAX, it has several shortcomings:

- It does not distinguish between positive and negative returns.
- It does not look at extreme returns (high gains or losses).
- It does not distinguish between bull and bear periods.

name	place	SSEC	DAX	name	place	SSEC	DAX
aex	Netherlands	−0.017	0.875	kse	Pakistan	0.063	0.071
aord	Australia	0.030	0.585	merv	Argentina	0.033	0.277
atx	Austria	0.038	0.494	mibtel	Italy	−0.009	0.778
bfx	Belgium	0.005	0.755	mtms	Russia	0.026	0.305
bsesn	India	0.085	0.247	mxx	Mexico	−0.020	0.516
bvsp	Brazil	0.012	0.417	n225	Japan	0.049	0.473
ccsi	Egypt	0.024	0.070	nz	New Zealand	0.035	0.402
cse	Sri Lanka	−0.038	0.058	psi	Philippines	0.049	0.303
dji	USA	−0.018	0.728	px50	Czech Republic	0.085	0.411
fchi	France	−0.049	0.882	seti	Thailand	0.049	0.322
ftse	UK	−0.024	0.784	smsi	Spain	−0.038	0.682
gdaxi	Germany	−0.033	1.000	ssec	China	1.000	−0.033
gspc	USA	0.009	0.681	ssmi	Switzerland	−0.051	0.816
gsptse	Canada	0.020	0.691	sti	Singapore	0.106	0.426
hsi	Hong Kong	0.111	0.522	sxaxpi	Sweden	−0.053	0.826
jkse	Indonesia	0.087	0.243	ta100	Israel	−0.002	0.452
kfx	Denmark	−0.001	0.631	twii	Taiwan	0.055	0.448
klse	Malaysia	0.088	0.254	xu100	Turkey	0.019	0.254
ks11	South Korea	0.032	0.341				

Table 2: Correlation of weekly returns (SSEC/DAX with international stock indices)

- It yields only an average measure, not a conditional one.
- Correlation may be spurious.

In the following, we focus on the first three items — and offer an alternative approach.

4 Univariate Threshold Exceedances

Let $R_1, \ldots, R_n$ denote the returns from n days. If these are iid random variables, then, for sufficiently large n and u, the conditional distribution function of the excess

$$R - u, \quad \text{conditional on} \quad R > u,$$

is approximately given by (see Coles [6]):

$$F(x; k, \sigma) = \begin{cases} 1 - \left(1 - k\dfrac{x}{\sigma}\right)^{1/k}, & k \neq 0 \\ 1 - \exp\left(-\dfrac{x}{\sigma}\right), & k = 0 \end{cases}$$

This is the distribution function of the generalized Pareto distribution (GPD). Here, $\sigma > 0$ is a scale parameter; it depends on the threshold and on the underlying probability density function. The shape parameter k is called the tail index, since it characterizes the tail of the density function:

- The case $k < 0$ corresponds to fat-tailed distributions; in this case, the GPD reduces to the Pareto distribution. In fact, when $k \leq -\frac{1}{2}$, the second and higher moments of the original distribution do not exist.

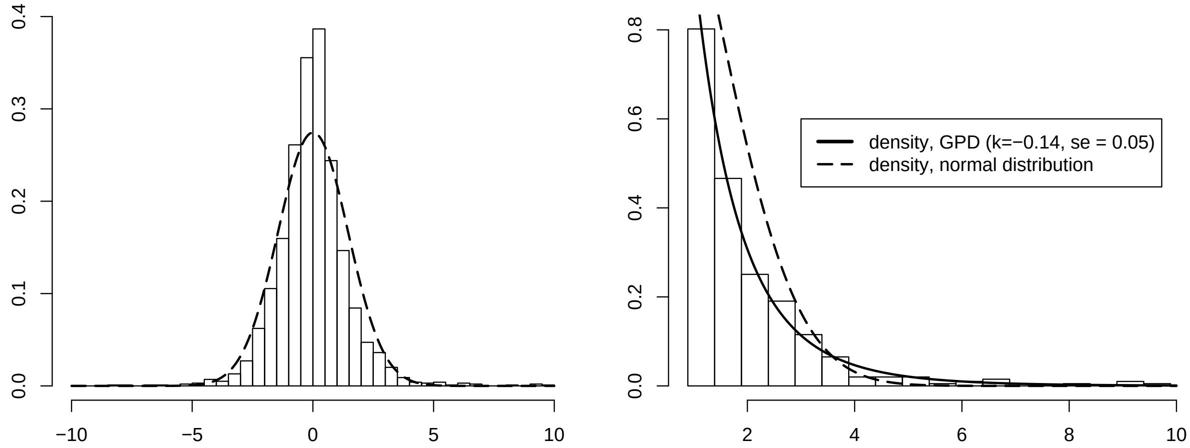

Figure 5: Histogram of returns on SSEC, normal distribution and GPD; upper tail

- The case $k = 0$ corresponds to thin-tailed distributions; the GPD then reduces to the exponential distribution with mean σ.
- The case $k > 0$ corresponds to distributions with no tail (i.e. finite distributions). When $k = 1$, the GPD becomes a uniform distribution on the interval $[0, \sigma]$.

In the present study, we use the method of maximum likelihood (ML) to estimate the parameters k and s whenever possible. In cases where ML did not lead to reasonable results, we use the elemental percentile method (EPM) by Castillo and Hadi [5].

Figure 5 shows a histogram of the empirical distribution of daily returns on SSEC from 1997 through 2005, together with the normal density (the dashed line) with mean and density estimated from the data. It is clear from the left-hand chart that the normal distribution does not adequately describe observed returns, the main reason being that the normal distribution does not have heavy tails. The right-hand picture in Figure 5 shows a histogram of the upper tail of the distribution in finer resolution, from the 80% quantile ($q_{0.8} = 0.894$) onwards. The shortcomings of the normal distribution are now more obvious: It overestimates the probability of moderate excesses of $q_{0.8}$, while it underestimates the probability of huge excesses. This renders it inadequate for risk analysis, which focuses on the tails of a distribution. The solid line shows the estimated density of the GPD; the (ML-) estimated tail index $k = -0.14$ and its asymptotic-theory standard error of 0.05 indicate a heavy upper tail. Simple visual inspection reveals the much better fit to data of the GPD, and indeed the Kolmogorov-Smirnov test does not reject the null hypothesis that the stochastic model behind the observed tail is a GPD.

This good fit is in spite of the fact that the conditions implying approximately GPD-distributed threshold excesses are not fulfilled in the present case: An iid return sequence amounts to a very special form of the random walk hypothesis (see Campbell et al. [4]), which is rejected in the case of SSEC.

5 Bivariate Threshold Exceedances

We study the distribution of joint return excesses of the two stock indices in question in order to investigate the degree of extreme dependence. A joint exceedance in said to occur whenever the returns of both stock indices are smaller than their respective 20% quantiles (in the case of negative returns) or larger than their respective 80% quantiles (in the case of positive returns) on the same day (or a neighbouring day, see below). As before, we consider only the latter case in the subsequent explanation of the model.

The joint distribution (more precisely, the conditional joint distribution given both indices exceed their respective 80% quantile q_i) is modeled on the basis of a dependence function

$$D(y_1, y_2) = \left(y_1^{1/\alpha} + y_2^{1/\alpha}\right)^{\alpha}, \tag{1}$$

where $y_i = -\ln F(x_i; k_i, \sigma_i)$, and $x_i = r_i - q_i$ is the return excess, that is, a realization of the random variable $R_i - q_i$ $(i = 1, 2)$, and F is again the cdf of the GPD. The joint distribution function of return excesses is

$$\begin{aligned} G(x_1, x_2) &= P(R_1 \leq x_1 + q_1, R_2 \leq x_2 + q_2 | R_1 > q_1, R_2 > q_2) \\ &= \exp[-D(y_1, y_2)] \;=\; \exp\left[-\left(y_1^{1/\alpha} + y_2^{1/\alpha}\right)^{\alpha}\right]. \end{aligned} \tag{2}$$

The parameter $0 < \alpha \leq 1$ quantifies the degree of (positive) dependence between the return exceedances. Independence (i.e., $G(x_1, x_2) = \exp[-(y_1 + y_2)]$) corresponds to $\alpha = 1$, while complete dependence (i.e., $G(x_1, x_2) = \exp[-\max(y_1, y_2)]$) is obtained as $\alpha \to 0$. The model (1) is known as the symmetric logistic (Gumbel [8]) model. It is a special case of a so-called Archimedean copula (a copula is a multivariate cdf with uniform marginals), see Nelsen [12]. In using the model in equation (2), we assume that conditioning on the joint event "$R_1 > q_1, R_2 > q_2$" preserves the validity of the GPD class for describing univariate exceedances. An Archimedean copula, according to Juri and Wüthrich [9], "describes naturally the dependence structure for bivariate samples in the upper tails of two random variables."

Although the magnitude of the parameter α is capable of measuring the degree of dependence in the bivariate distribution (2), the parameter $\tau = 2 - 2^{\alpha}$ is preferred in the present study, because it has a direct interpretation in terms of probabilities: It can be shown that [3]

$$\tau = \lim_{x \to \infty} P(X_2 > x | X_1 > x), \tag{3}$$

where the X_i denote the return excesses. Since the relation between *alpha* and τ is strictly monotonically decreasing, a high (low) value of τ indicates a high (low, respectively) degree of dependence. The limiting cases $\tau = 0$ and $\tau = 1$ correspond to complete independence and perfect dependence respectively.

A typical example of two fitted models is shown in Figure 6. Displayed are the contour lines of the bivariate densities of distributions given in (2), fitted to joint threshold excesses of FTSE and DAX (the left graph in Figure 6) and to joint threshold excesses of FTSE and SSEC (the right graph). Each graph shows the contour lines for two models: the symmetric copula, i.e. model (2) (the fat lines), as well as a fitted density where independence was imposed (the thin lines), that is, with $\alpha = 1$ substituted in (2). Data from bull and bear periods were used to estimate the parameters. Comparing the graphs reveals that the difference between the model which allows for dependence and the model with imposed independence is much wider for the pair FTSE/DAX than for the pair FTSE/SSEC: The degree of dependence in threshold exceedances is much less for the latter pair. This observation is in line with our findings in Section 3 as well as with our hypothesis concerning the respective degrees of international dependence of DAX and SSEC. The case of FTSE was chosen for this example because FTSE is one of the few stock indices which display a relatively interdependence with both DAX and SSEC (see Table 2 and the results below).

6 Bull and Bear Periods

Our analysis of threshold exceedances distinguishes between bear and bull periods. Each day for which a stock return is available belongs to either a bear or a bull period. We determine the

[3] See Tawn [16], Coles [6].

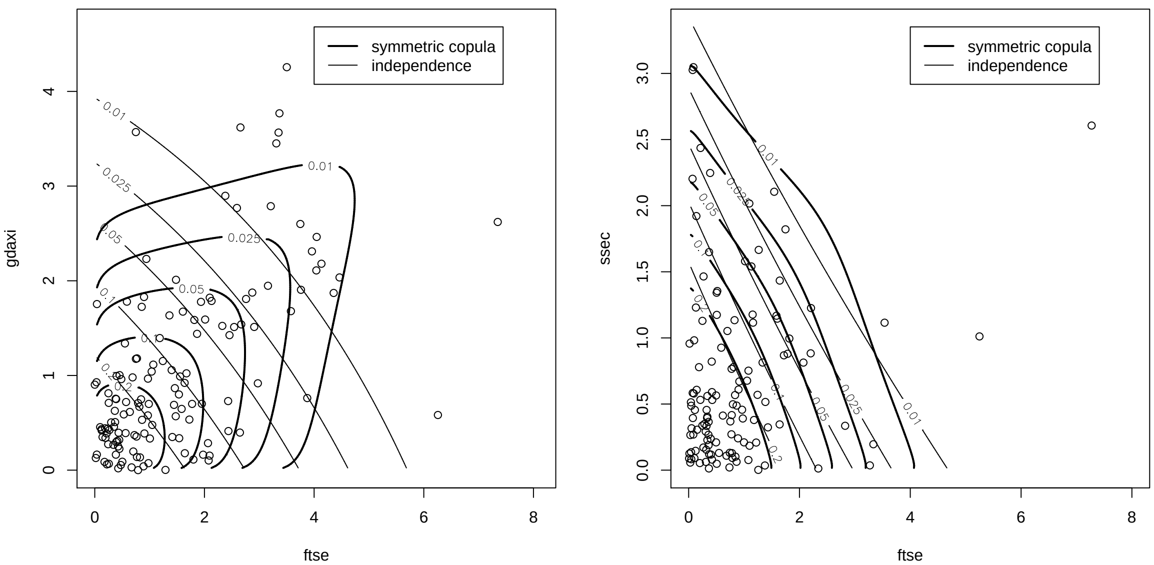

Figure 6: Contour plots of the joint densities

SSEC:		DAX:	
first day	beginning of	first day	beginning of
2003-11-24	bull	2004-03-03	bear
2004-04-15	bear	2004-04-09	bull
2004-09-17	bull	2004-05-04	bear
2004-10-13	bear	2004-06-04	bull
2005-02-11	bull	2004-07-09	bear
2005-03-15	bear	2004-09-02	bull
2005-07-27	bull	2005-04-11	bear
2005-09-30	bear	2005-05-16	bull

Table 3: Recent changes in period

kind of period for each day by smoothing the series of returns: Essentially, a linear one-sided filter with decreasing weights, extending over the last 50 days, is applied to the series of returns. Then a day is defined to belong to a bear (bull) period if the smoothed series is decreasing (increasing) for that day. Table 3 shows recent changes from one period to the other for SSEC and DAX prior to mid-October 2005. — When we speak of the behaviour of a *pair* of stock indices during a bear (bull) period, we mean: a bear (bull, resp.) period with respect to the *first* index in the pair.

7 International Dependence of Threshold Exceedances: Results

Since we focus on the dependence of threshold exceedances, our results will be given in terms of the parameter τ. Table 4 lists, for each combination of bear / bull and negative / positive, the five stock indices that were found to possess the highest value of τ with respect to SSEC and DAX, respectively, indicating a high degree of dependence in joint threshold exceedances. The stock indices printed in **bold** font are those which also appear among the eight highest weekly correlations (see Table 2).

The results in Table 4 reveal that weekly correlation and the association of threshold ex-

Highest τ w.r.t. SSEC:							
bear neg		bear pos		bull neg		bull pos	
klse	0.125	**kse**	0.177	nz50	0.161	**hsi**	0.124
ftse	0.124	mxx	0.065	sxaxpi	0.152	mxx	0.093
smsi	0.112	aord	0.052	ta100	0.118	**jkse**	0.071
seti	0.098	**hsi**	0.041	seti	0.095	gspc	0.061
jkse	0.084	psi	0.024	**sti**	0.090	**kse**	0.038
Highest τ w.r.t. DAX:							
bear neg		bear pos		bull neg		bull pos	
mibtel	0.521	**fchi**	0.466	**fchi**	0.441	**aex**	0.414
aex	0.485	**ssmi**	0.451	**aex**	0.413	**fchi**	0.396
fchi	0.474	**aex**	0.437	**sxaxpi**	0.362	**ssmi**	0.311
bfx	0.465	**dji**	0.402	**ssmi**	0.360	smsi	0.307
ftse	0.433	smsi	0.393	**bfx**	0.292	**sxaxpi**	0.286

Table 4: The stock indices with the highest value of τ w.r.t. SSEC and DAX

ceedances is much more consistent in the case of DAX than in the case of SSEC: For example, those stock indices with which DAX is most closely associated in bear periods in the case of high losses all have high weekly return correlations with DAX.

The behaviour of SSEC is much more elusive: Stock indices with whose returns SSEC has a relatively high correlation are not necessarily those with which there is the highest association in threshold exceedances. It can also be said that in the case of SSEC, it is not possible to draw conclusions from the weekly return correlation to the dependence in the tails of the joint return distribution.

Table 7 finally shows boxplots of the distributions of the estimated parameter τ among all country combinations we considered by period and direction of return (negative / positive). It becomes obvious that the degree of international dependence in times of high volatility is generally much higher for DAX than for SSEC. However, SSEC displays a clear difference between negative and positive threshold exceedances: The degree of dependence is much less in the case of positive exceedances. Furthermore, the degree of dependence is slightly higher during bear periods than during bull periods in the case of DAX.

8 Summary and Conclusions

The economy of the People's Republic of China has grown to one of the largest in the world, but retains idiosyncrasies which distinguishes the Chinese equity market from European markets. Our goal was to compare the degree of dependency, during bull and bear periods, between joint threshold exceedances of SSEC and some other stock index on the one hand, and a European stock index, the DAX, and some other stock index on the other hand. The empirical basis of the study consisted of 37 time series of daily closing quotes, starting in mid-1997. We distinguished between positive and negative exceedances and considered excesses beyond the 20%, respectively 80% quantile of the return distribution. The pairs of generalized Pareto distributions of excesses were merged by a copula providing a means to measure the degree of dependency in times of threshold exceedance.

It was found that the degree of international dependence is much higher for the German stock index DAX than for the Chinese SSEC. This is obvious from the weekly correlations as

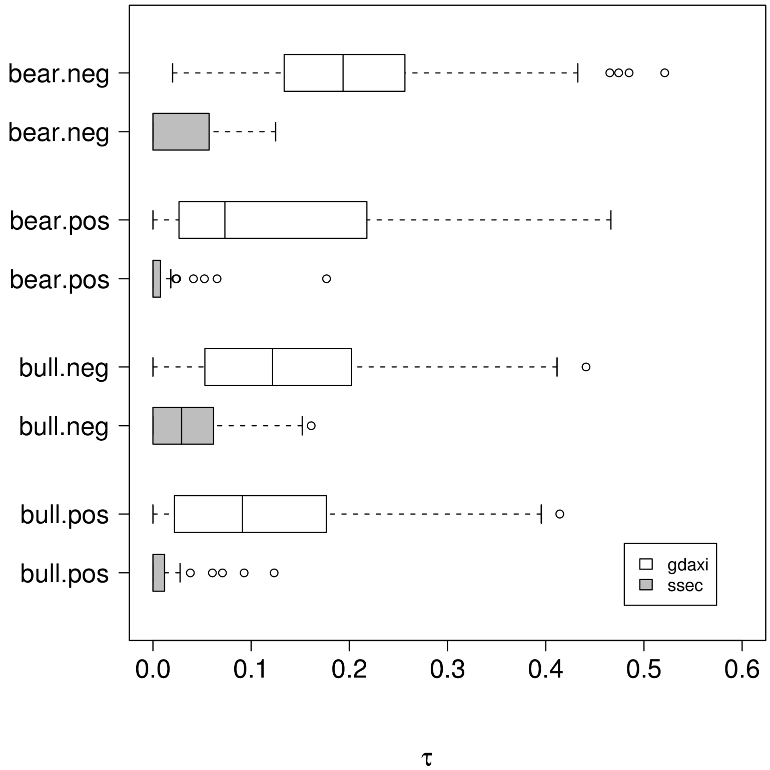

Figure 7: Boxplots of τ by period

well as from an analysis of bivariate threshold exceedances. Dependence is higher in the case of negative shocks — for both indices. Dependence during bear periods tends to be higher than in bull periods for DAX only.

Despite the high rate of growth in the Chinese economy since market oriented reforms in 1978, the Chinese stock market appears to be relatively immune against foreign shocks. Policies aimed at slowing down capital flows may be held responsible. Our results are in line with some GARCH-approach based findings by Brooks and Ragunathan [2]. In their study of information transfer between the two Chinese stock markets in Shanghai and Shenzen, each with two main classes of shares, A and B, restricted to domestic and foreign investors respectively, they found spillovers in the mean, but not in volatility from A to B shares and vice versa.

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