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Are there comovements in the default risk of reinsurance companies?

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Very preliminary –do not quote or distribute without permission of the author

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ABSTRACT

This study analyses the dependence between the default risk of six of the world's largest reinsurance companies. Default risk is modelled on the basis of the structural Merton approach. A correlation analysis reveals that the dependence between the default risk of these companies covers a broad range of values from negative to positive correlation. The default risk of some of the larger reinsurers seem to be dependent. A bivariate extreme value approach shows that this seems also to hold for rare unfavourable values of default risk. Parametric and nonparametric approaches are used to estimate the dependence function which capture dependence of rare events. Test show that it seems reasonable to assume asymptotic dependence among block maxima of default risk for those cases where the correlation analysis hinted towards stronger dependence. In most cases however, there is no asymptotic dependence. These results are preliminary and must be interpreted with caution. They also need to be put into perspective as the default risk of reinsurance companies, and particularly the one of large reinsurance companies, is very low.

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Key words: Reinsurance, bivariate extreme value analysis, copula, dependence function, asymptotic dependence, parametric estimation, nonparametric estimation

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1. Introduction

In the four years from 1988 to 1991, Lloyd's of London incurred total losses before tax which exceeded £6.9bn. Underwriters had reinsured one another's excess of loss policies giving rise to what became known as the "LMX (London Excess of Loss Market) spiral". More recently, the global reinsurance industry faced several dramatic events. The Australian reinsurance industry was shaken by the sudden market exit of GIO Re and NewCap Re in 1999 and the downgrading of Reinsurance Australia Corp. in 2000. In 2002, the Swedish reinsurance company Aterförsäkringsktiebolaget LUAP, with net premiums written of about $245m pa, failed. In 2003, Gerling-Konzern Globale Rückversicherungs-AG's collapsed and "defaulted" on its coupon payment. One of the sector's largest entities, it owed considerable sums in the form of reinsurance receivables to other players. During that same year, the rating agency Moody's announced "the death of the AAA reinsurer"[2], after first Employers Re and then the two only triple A-rated issuers in the European reinsurance sector, Munich Re and Swiss Re, were all downgraded. Still in that year, several companies were placed into run-off (e.g. Trenwick America Reinsurance Corp., Sirius International Insurance Corp.'s Bermudian operation, Scandinavian Reinsurance Co. Ltd, or AXA' two U.S. subsidiaries) and the closure of SCOR's CRP subgroup compromised Commercial Risk Reinsurance Co. Ltd. and Commercial Risk Re-insurance Co. Ltd.[3]. The year after, Converium, once a hailed newcomer, faced serious unexpected financial trouble.

These events indicate that the financial health of reinsurers can fluctuate considerably and the breaking down of major players in the reinsurance sector - although not a frequent event - is not a remote possibility[4]. They also indicate that financial problems in one reinsurance company may have their origin in a shock which affects large parts of the whole sector, opening the potential for several simultaneous failures. This possibility is also underlined by a comparison of the cumulative total of insured losses since 1988 with the resources of the reinsurance industry, which questions the ability of the reinsurance market to deal with large, catastrophic events (Cummins and Weiss, 2000).

There is a discussion about whether the failure of a reinsurance company can have wider consequences. Regulators, chiefly among them the Financial Stability Forum, have expressed concern over the potential for systemic risk in the reinsurance sector[5]. Although others consider the systemic risk to be relatively small (Swiss Re, 2003), there was a consensus large enough at the IAIS to elaborate principles and standards[6]. The European Commission fast-tracked a Directive on reinsurance supervision which basically transposes the solvency regime of primary insurers to reinsurance companies[7].

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[2] Moody's (2003): "European Reinsurance – The Markets Take their Bite", Moody's Investors Service, Special Comment, September.

[3] Standard&Poor's (2003): "Global Insurance Highlights".

[4] A list of reinsurer bankruptcies from 1980 to 2002 can be found in Sigma (2003): "Reinsurance – a systemic risk?".

[5] See for example the statement by the chairman on 22 April 2004 or the press release published after the Toronto meeting in September 2002. This concern is reinforced by a recent study which suggests that insurance companies in difficulties have an exposure towards reinsurance companies which is twice the value of the exposure of their more healthy competitors (Moody's Investor Service, *Special Comment,* 2003).

[6] The International Association of Insurance Supervisors (IAIS) published "Principles on minimum requirements for supervision of reinsurers" in 2002, "Standards on supervision of reinsurers" in 2003 and "Standards on disclosure concerning technical performance and risks for non-life insurers and reinsurers" in 2004.

[7] The Directive has been adopted by the European Parliament in June 2005 and its adoption by the European Council is expected before the end of 2005.

The present work intends to contribute to the discussion about risk in the reinsurance sector by analysing the extent to which default risk of reinsurance companies is interlinked. Six of the world's very largest reinsurance companies (Munich Re, MR; Swiss Re, SR; Hannover Re, HR; SCOR, SC; Partner Re, PR; and Everest Re, ER) are analysed over periods spanning between 6 and 17 years[8] until the end of 2004. These companies, which are those among the large players who fulfil the data requirements of the statistical methods used here, represented in 2003 about 50 % of net premiums written by the global reinsurance industry.

The link between the default risk of reinsurance companies is investigated by two means: a correlation analysis of default risk and an investigation of the extreme dependence of default risk. Default risk is captured by the means of a structural approach. This approach has been previously used in the context of insurance companies by Santomero and Chung (1992) who calculated implied volatilities of asset returns. To investigate dependence a variety of bivariate extreme value distributions will be used – insofar as this is justified by tests of asymptotic dependence. Several estimation methods are applied to ensure robustness of the results. Bivariate extreme value analysis has been previously applied to financial data to examine dependence between risk measures, but never to the risk profile of insurance companies. Hartmann, Straetmans and de Vries (2004) and Poon, Rockinger and Tawn (2004) analysed the returns of major stock indices, and Hartmann, Straetmans and de Vries (2005) investigated equity returns of banks.

Section 2 presents the methods used: firstly, details of the structural Merton approach are given which is used here to capture default risk, secondly, different approaches to correlation are explained, finally, different concepts of extreme value theory are presented which are used to investigate dependence of rare unfavourable events. Section 3 gives details about the data used and discusses several issues linked to the empirical implementation of the structural Merton approach. Section 4 presents the results and section 5 concludes.

2. Methodology

2.1. Default risk

Default risk is captured on the basis of the model proposed by Black and Scholes (1973) and Merton (1974), which has been used for empirical implementations, among others, by Jones, Mason and Rosenfeld (1984) and Crosbie and Bohn (2003)[9]. This model only relies on stock market information to establish a link between the default risk of a firm and its capital structure. It views the value of a firm's equity, V_E, and debt as contingent claims issued against the firm's underlying asset value, V_A. Equities are assumed to receive no dividend and debt is a pure discount bond with payment D at maturity T. The value of the assets is assumed to follow a lognormal diffusion process,

$$dV_A = \mu \; V_A \; dt + \sigma_A \; dW, \tag{1}$$

where μ is the expected return on assets, σ_A the constant volatility of the assets and dW a Wiener process. At maturity, the value of the assets is given by:

$$\ln V_A(T) = \ln V_A + \left(\mu - \frac{\sigma_A^2}{2} \right) T + \sigma_A \sqrt{T} \; \varepsilon, \tag{2}$$

[8] For two companies the period spans 17 years, for one company it covers 15 years, for another one 10 years and for the two remaining companies 7 and 6 years.

[9] See Grouhy, Galai and Mark (2001) for a presentation of this literature.

with ε being the random component of the firm's return on assets which is normally distributed with zero mean and unit variance. Substituting (2) in the definition of the distance from the default point, ddp := lnV_A - lnD, and rearranging gives the distance-to-default, DtD:

$$DtD := \frac{dp}{\sigma_A \sqrt{T}} - \varepsilon = \frac{\ln\left(\frac{V_A}{D}\right) + \left(\mu - \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}}. \quad (3)$$

The market value of the equity, V_E, at maturity is related to the value of the assets through

$$V_E := e^{-rT} E\left[\max\left(V_A - D, 0\right)\right], \quad (4)$$

i.e. the value of equity is a call option on the value of the assets of the firm with as striking price the promised debt payment (r is the constant risk free interest rate.). Therefore

$$V_E = V_A \; N(d1) - e^{-r\,T} \; D \; N(d2), \quad (5)$$

where $N(x)$ is the cumulative probability distribution function for a variable, x, that is normally distributed with zero mean and unit variance, and

$$d1 = \frac{\ln\left(\frac{V_A}{D}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}}, \quad (6)$$

$$d2 = d1 - \sigma_A \sqrt{T} \; . \quad (7)$$

By applying Ito's lemma to (5) and comparing the diffusion coefficient of the equation obtained to that of the equity value dynamics, the instantaneous volatility of equity at time zero, σ_E, is:

$$\sigma_E = \sigma_A \frac{V_A}{V_E} N\,(d1)\,, \quad (8)$$

with the hedge ratio of the option being equal to $N(d1)$[10].

The system of equations (5) and (8) can be solved to obtain the values of V_A and σ_A which are then used to calculate the distance-to-default. To go further and estimate relative probabilities of default on this basis, one would need default frequencies which are not available for reinsurance companies. The distance-to-default is therefore taken here as an indicator of default risk.

2.2. Correlation analysis of default risk[11]

The correlation analysis will be performed by the means of several indicators. The traditional measure of linear correlation, the Pearson correlation, is only suitable for variables with a multivariate normal distribution, and not invariant under non-linear, strictly increasing transformations. The linear correlation coefficient is therefore estimated through Kendall's tau transform proposed by Lindskog,

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[10] The fact that the instantaneous equity volatility is stochastic will be discussed later.

[11] For more details see Embrechts, McNeil and Straumann (1999).

McNeil and Schmock (2001)[12]. In contrast to standard linear correlation, this estimator is efficient and robust for elliptical distributions (which include distributions with heavy tails).

An alternative to linear correlation analysis are measures of rank correlation. These are more robust when data do not come from a bivariate normal distribution. Their main advantages are invariance under monotonic transformations and a satisfactory handling of perfect dependence. Here, Kendall's tau and Spearman's rho are used to estimate a rank-based measure of association.

However, correlation analysis is only one measure of stochastic dependence among others and dependence may not be adequately captured by a correlation coefficient. This is particularly true for variables with heavy-tailed distributions and when the focus is on events triggered by joint negative extreme values as is the case here.

2.3. Dependence of block maxima of default risk[13]

2.3.1. Bivariate extreme value distributions

Let *(X,Y)* be a pair of *n* random variables with joint Fréchet distribution *F*, which is divided into *m* blocks (here months) with approximately *n* units (here days) each, and the block maxima are denoted by

$$M_{x,n} := Max\,(X_1, X_2, ..., X_n)\ ,\ M_{y,n} := Max\,(Y_1, Y_2, ..., Y_n) \\ \text{and}\ M_n^* := (M_{x,n}/n, M_{y,n}/n). \tag{9}$$

The vectors are rescaled. For a random pair *(X,Y)* with generalized marginal distributions, if

$$P\{M_{x,n}^* \le x, M_{y,n}^* \le y\} \xrightarrow{d} G(x,y),\ \ x>0,\quad y>0, \tag{10}$$

G is the class of bivariate extreme value distributions

$$G(x,y) = \exp\{-V(\tilde{x},\tilde{y})\}, \tag{11}$$

with

$$V(x,y) = 2\int_0^1 \max\left(\frac{w}{x}, \frac{1-w}{y}\right) dH(w)\,, \tag{12}$$

where *V* is homogeneous of order –1, *H* is a distribution function in [0,1] satisfying the mean constraint, and x and y are transformed as follows

$$\tilde{z} = \left[1+\xi_z\left(\frac{z-\mu_z}{\sigma_z}\right)\right]^{1/\xi_z} \quad \text{with}\quad 1+\xi_z\left(\frac{z-\mu_z}{\sigma_z}\right) > 0\,, \tag{13}$$

where μ_z, σ_z and ξ_z are respectively the location, shape and scale parameters to be estimated by maximum likelihood.

Here, a parametric subfamily of H is used, the logistic family (Gumbel, 1960), because of its ability to model all the way from independence to complete dependence (Klüppelberg and May, 1998). *G* thus becomes

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[12] The relation between the linear correlation coefficient ρ and Kendall's tau, τ, is $\rho = \sin\,(\frac{\pi}{2}\tau)$.

[13] For an introduction into extreme value theory with an emphasis on multivariate extremes see Falk, Hüsler and Reiss (2004).

$$G(x,y) = \exp\left\{-(x^{-1/\alpha} + y^{-1/\alpha})^{\alpha}\right\}, \quad x>0,\ y>0,\ \alpha \in (0,1). \tag{14}$$

As α -> 1 resp. α -> 0,

$$G(x,y) \to \exp\left\{-(x^{-1} + y^{-1)}\right\} \text{ and } G(x,y) \to \exp\left\{\max(x^{-1}, y^{-1)}\right\} \tag{15}$$

correspond to independent and completely dependent variables respectively.

2.3.2. Dependence functions

Any bivariate extreme value distribution function can be represented in the form

$$G(x,y) = \exp\left\{ -(\tilde{x} + \tilde{y})\, A\left(\frac{\tilde{x}}{\tilde{x}+\tilde{y}}\right)\right\}, \tag{16}$$

such that

$$A(w) = -\log\left\{G\,(x^{-1}(w), y^{-1}(1-w))\right\} \text{ with } w \in [0,1]. \tag{17}$$

A, which does not depend on the marginal parameters, is called the dependence function (Pickands, 1981). It follows that *A(0) = A(1) = 1*, and that *A(.)* is a convex function with

$$\max(w, 1-w) \le A(w) \le 1 \qquad \text{for all } 0 \le w \le 1. \tag{18}$$

In the case of independence, *A(1/2) = 1* and at complete independence *A(1/2) = 0.5*. The dependence functions can be represented in a plot with as triangular borders the constraint on the convex function.

Nonparametric (Capéraà, Fougères and Genest, 1997) and parametric estimation methods (Tawn, 1988) will be used to estimate the dependence function. Parametric methods will allow to take into account time trends where appropriate.

The dependence structure is summarised by two distribution-free measures (Coles, Heffernan and Tawn, 1999).

$$\chi(u) = 2 - \frac{\log P\left\{F_X(X) < u,\ F_Y(Y) < u\right\}}{\log u} \tag{19}$$

only informs about dependence and fails to provide information for asymptotically independent distributions. This measure takes values in the interval [0,1] with (0,1] corresponding to asymptotic dependence. To capture asymptotic independence another measure is needed:

$$\bar{\chi}(u) = \frac{2\log(1-u)}{\log P\left\{F_X(X) > u,\ F_Y(Y) > u\right\}} - 1. \tag{20}$$

This measure lies within the range [-1,1] with [-1,1) corresponding to asymptotic independence. Thus, $(\chi > 0, \bar{\chi} = 1)$ indicates asymptotic dependence whereby χ measures the strength of dependence, and ($(\chi = 0, \bar{\chi} < 1)$ indicates asymptotic independence with $\bar{\chi}$ measuring the strength of dependence. Both measures will be plotted with a 95% confidence interval. They allow to test for asymptotic behaviour before using the logistic family which has the property to be asymptotically dependent. The interest here mainly lies in cases where the logistic model is appropriate and thus in the value of χ.

3. Data

The equity prices required for the calculation of the distance-to-default have been taken from Datastream. This was also the source for some government bond yields. Most data on government bond yields come however from central banks (this is the case for Germany, Switzerland and the

U.S.). Data on debt is from Bloomberg. The availability of bond yields restricts the maximum period which can be analysed (instead of January 1981 – December 2004 for equity prices, yields are only available from December 1987 on or later).

The expected asset return is taken to be equal to the empirical average asset growth rate. Equity volatility, σ_E, in equation (5) is stochastic and in all rigour the conventional option pricing model can therefore not be applied. However, Bensoussan, Crouhy and Galai (1994) argue that using equation (5) gives a good approximation. Equity volatility was estimated by a 6-months moving average of the standard deviation of the daily absolute returns. Imposing volatility to be constant over a certain time interval seems acceptable as long as leverage does not change in a substantial way. The complexity of the liability structure - in reality there are different maturities and types of debt - is simplified. The maturity of debt is assumed to be one year, i.e. the annual report is perceived by equity holders as the maturity date of their option. The sum of short-term debt (at a 1-year horizon) and half of total debt was used to construct an indicator of debt. Although long-term debt matures after the time horizon taken as reference here, its partial inclusion is sensible as the interest payments on long-term debt is part of the short-term debt. In addition, the larger long-term debt, the more difficult it becomes to roll over short-term debt, which should decrease the distance-to-default. In general, the default point lies somewhere between total liabilities and short-term liabilities. Infra-annual data on debt were obtained by fitting a cubic spline to the year-end balance sheet values. Government bond yields were used as a proxy for the risk free rate. In the case of Swiss Re, stock market data cover a much longer time period than available Swiss government bond yields. Two sets of data have therefore been considered: firstly, Swiss Re stock data in conjunction with Swiss government bonds data for the period from 1994 on, and secondly, the same stock data together with German government bond yield data for a period covering approximately 25 years until the end of the year 2004.

4. Results

Both the correlation between log returns and between the default risk indicators will be analysed. Log returns are taken by some financial regulators as supplementary indicators of financial difficulties. Here they will mainly be used at the end of the analysis to help with the interpretation of the results.

The summary statistics and normality tests reveal that neither the log returns of equity prices nor the distance-to-default values are normally distributed. Standard errors obtained by the GMM procedure proposed by Richardson and Smith (1993) show that excess kurtosis uniformly does not correspond to a normal distribution at the 5% level (except for the log returns of Partner Re). Log returns are, in contrast to the default risk indicator, not skewed. Non-normality is confirmed by the Jarque-Bera test. The Wald statistic, which tests the null hypothesis that skewness and excess kurtosis are jointly equal to zero, also uniformly rejects the distributions as being normal. Standard tests (Box-Pierce-Lijung test at order 5 and 10) reveal that there is significant autocorrelation. Ordinary correlation measures are inappropriate to analyse dependence between log returns or default risk. Moreover, the results suggest that the use of the bivariate extreme value approach to examine rare default risk values is justified.

4.1. Correlation analysis

The correlation coefficients calculated for the log returns show that there is some dependence between firms in the same country or region. The highest coefficients are found for the pair of American companies PRER and German companies HRMR, as well as for the German-Swiss companies pairs MRSR and HRSR.

Concerning the default risk indicator, the different correlation coefficients convey a consistent picture. The French company Scor has a default risk which is often barely associated with the default risk of the other companies. In the case of Partner Re there is even a negative correlation (and similar for the period before 1994 for the link to Swiss Re). Perhaps surprisingly, there is some positive correlation between the U.S. company Everest Re and respectively Hannover Re and Swiss Re (whereas the default risk indicators of these later companies are not correlated to the same extent). The outstanding result is the high correlation between the default risk of Munich Re and Swiss Re.

For these two companies the coefficients show already a high value for the whole period of 17 years. The coefficient is even higher when the periods from 1994 on is considered. The correlation coefficient is somewhat higher when the default risk indicator is calculated with German government bond yields rather than Swiss government bond yields.

In what follows, dependence is examined further with a focus on rare values of high default risk.

4.2. Checking for asymptotic (in)dependence

To apply the extreme value approach, the series of default risk indicators have been transformed into monthly block maxima. This transformation helps to alleviate the autocorrelation in the daily series. As the logistic model will be used, it is necessary to check for asymptotic dependence, which is implied by this model.

The graphs of the two dependence measures χ and $\bar{\chi}$ suggests the possibility of asymptotic dependence mainly for the companies pair MRSR. For HRER and SRER asymptotic dependence still seem to be possible, whereas for the other companies pairs it is difficult to conclude in favour of asymptotic dependence or independence (see figure 1). One reason is that the variations in the dependence measures increase as u tends towards 0. In the three cases identified, the estimation of the bivariate extreme value distribution by the logistic model does not seem to be inappropriate. This will also be confirmed by the estimations presented hereafter.

4.3. Bivariate extreme value estimations

After transformation to unit Fréchet margins, the influence of the marginal distributions on the joint tail probabilities is eliminated, in contrast to correlation analysis (Ledford and Tawn, 1996; Draisma, Drees, Ferreira and Genest, 2001).

For some of the estimations, the usual asymptotic properties do not hold (as the values of both shape parameters are not greater than -0.5). However, including time trends for the location parameter, leads in general to restore these properties. As already mentioned, the logistic model is not appropriate for all cases. Nevertheless, results are given for all companies pairs. Interestingly, the estimations of the logistic model indicate dependence (relatively low values of the dependence parameter) in those cases where the correlation coefficients was found to be comparatively high, and independence (value for the dependence parameter close to one) for the pairs for which the correlation coefficients were low and the graphical tests showed the absence of asymptotic dependence.

4.4. Dependence measure

In general, extreme values of default risk of reinsurance companies are not particularly dependent or independent. However, for the two largest companies Munich Re and Swiss Re, there is strong dependence since the beginning of 1994. In 2003, Munich Re and Swiss Re represented in terms of net premiums written about 33 % of the global reinsurance industry.

The default risk of Munich Re, Hannover Re and Swiss Re on the one hand and the default risk of Everest Re on the other hand are also dependent and particularly so in the case of Swiss Re. A comparatively strong dependence also exists between the default risk of Hannover Re and Partner Re.

There is strong independence between the default risk of Hannover Re on the one hand and Munich Re and Swiss Re on the other. The default risk of SCOR and Swiss Re are also strongly independent.

For reasons of space, only the graphs for the companies pairs MRSR (case of dependence) and MRPR (example of independence) are shown here (see figure 2).

Two not necessarily exclusive interpretations seem possible for the result of the strong correlation of default risk and the dependence between the default risk of Munich Re and Swiss Re. The dependence could correspond to a common risk profile. Indeed, the increasing trend in natural catastrophes and the exposure to a number of other catastrophes could have generated such a common risk exposure. Alternatively, the results obtained could also be a sign of a common perception of market participants, which may not be grounded in a common risk profile. Investors could react to bad news in a similar way with respect to all those companies where they, rightly or wrongly, expect broadly similar exposures. Finally, with respect to the first interpretation, it is noteworthy that the correlation and dependence between the default risk of some larger reinsurance companies seem to be in line with Borch's theorem (Borch, 1962). Not only rare unfavourable values of default indicators point in this direction, but also the link between positive and negative log returns. In the Pareto optimal insurance arrangement each insurer will hold a share of the market portfolio of risk. This result can also be read across to the reinsurance market (see Cummins and Weiss, 2000). As a result, at least in theory, the portfolios of reinsurance companies are perfectly correlated. However, this theoretical result holds only when transactions costs are zero, and there is no asymmetric information or barrier to trade. Obviously, these remarks are only tentative in nature and the issue would need to be investigated more thoroughly.

5. Conclusions

This study analyses the dependence between the default risk of six of the world's largest reinsurance companies. Default risk is modelled on the basis of the structural Merton approach. A correlation analysis reveals that the dependence between the default risk of these companies covers a broad range of values from negative to positive correlation. The default risk of some of the larger reinsurers seem to be dependent. A bivariate extreme value approach shows that this seems also to hold for rare unfavourable values of default risk. Parametric and nonparametric approaches are used to estimate the dependence function which capture dependence of rare events. Test show that it seems reasonable to assume asymptotic dependence among block maxima of default risk for those cases where the correlation analysis hinted towards stronger dependence. In most cases however, there is no asymptotic dependence. These results are preliminary and must be interpreted with caution. They also need to be put into perspective as the default risk of reinsurance companies, and particularly the one of large reinsurance companies, is very low.

Future work could check these results with respect to asymmetries in the bivariate extreme value distribution. Also, the sample of companies considered should be enlarged. Finally, it is necessary to investigate the different interpretations of the result.

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TABLES

Table 1

Summary statistics for log-returns

Company	Nbr obs	Skewness stand err p-value	Excess kurtosis stand err p-value	Jarque-Bera statistics p-value	Wald statistics p-value	Ljung-Box Q(5) Q(10)
Everest Re	2387	0.335 0.219 0.126	4.096 1.008 0.000	1710.973 0.000	16.674 0.000	11.960 19.024
Partner Re	2889	-0.697 1.031 0.499	19.778 12.967 0.127	47284.525 0.000	29.410 0.000	29.527 47.293
Score	4067	1.267 2.227 0.569	65.869 33.266 0.048	735946.431 0.000	12.164 0.002	8.039 19.602
Swiss Re	6205	-0.289 0.449 0.519	16.226 3.293 0.000	68132.845 0.000	30.334 0.000	50.878 61.618
Hannover Re	2606	-0.542 0.425 0.202	10.279 2.411 0.000	11589.470 0.000	26.482 0.000	22.825 32.742
Munich Re	6205	-0.304 0.205 0.138	7.529 0.967 0.000	14746.458 0.000	62.873 0.000	50.249 54.887

Maximal length: 1981/1/5 – 2004/11/26

Table 2

Summary statistics for distance-to-default values

Company	Nbr obs	Skewness stand err p-value	Excess kurtosis stand err p-value	Jarque-Bera statistics p-value	Wald statistics p-value	Ljung-Box Q(5) Q(10)
Everest Re	1530	1.664 0.133 0.000	82.152 16.661 0.000	429780.758 0.000	24.506 0.000	190.94 252.355
Partner Re	1795	1.046 0.266 0.000	40.856 5.300 0.000	125020.122 0.000	61.870 0.000	258.553 311.861
Score	3515	0.694 0.085 0.000	40.345 5.331 0.000	238631.628 0.000	63.365 0.000	517.833 549.742
Swiss Re (GER bonds)	4271	1.341 0.318 0.000	816.842 145.970 0.000	118687343.63 0.000	32.412 0.000	641.906 953.264
Swiss Re (SW bonds	2251	1.679 0.450 0.000	11.816 2.057 0.000	13167.016 0.000	34.279 0.000	2372.000 3281.633
Hannover Re	2448	0.121 0.075 0.000	69.569 14.986 0.000	493248.584 0.000	22.388 0.000	333.984 360.914
Munich Re	4502	1.625 0.319 0.000	407.175 109.049 0.000	3110145779 0.000	39.705 0.000	21.203 25.155

Maximal length: 1987/12/1 – 2004/11/26

Table 3

Acronyms of reinsurance companies analysed

Reinsurance company	Acronym	Reinsurance company	Acronym
Munich Re	MR	SCOR	SC
Swiss Re	SR	Partner Re	PR
Hannover Re	HR	Everest Re	ER

Table 4

Correlation coefficients of daily (positive and negative) log-returns

Companies pair	Kendall's tau	Spearman's rho	Pearson linear correlation coefficient	Lin. correlation coeff. by Kendall's tau transform
MRSR	0.217	0.308	0.396	0.583
HRER	0.092	0.134	0.122	0.191
SRER	0.109	0.161	0.177	0.275
HRPR	0.144	0.097	0.144	0.225
MRER	0.120	0.174	0.176	0.272
HRMR	0.200	0.289	0.373	0.553
PRER	0.267	0.374	0.428	0.623
HRSR	0.198	0.286	0.340	0.587
SCER	0.082	0.121	0.093	0.146
SRPR	0.104	0.154	0.183	0.283
MRPR	0.122	0.180	0.184	0.286
MRSC	0.146	0.210	0.240	0.369
HRSC	0.149	0.215	0.264	0.402
SRSC	0.151	0.217	0.237	0.364
SCPR	0.069	0.102	0.007	0.115

Table 5

Correlation coefficients of monthly distance-to-default block minima

Companies pair	Kendall's tau	Spearman's rho	Pearson linear correlation coefficient	Lin. correlation coeff. by Kendall's tau transform
MRSR (S bds; 1995->)	0.404	0.578	0.717	0.903
MRSR (GER bonds)	0.370	0.541	0.697	0.889
MRSR (G bds; 1994->)	0.664	0.853	0.826	0.963
HRER	0.344	0.499	0.494	0.700
SRER	0.342	0.492	0.426	0.621
HRPR	0.306	0.446	0.466	0.668
MRER	0.300	0.443	0.383	0.566
HRMR	0.217	0.352	0.259	0.396
PRER	0.212	0.306	0.234	0.359
HRSR	0.139	0.220	0.258	0.395
SCER	0.137	0.198	0.229	0.352
SRPR	0.062	0.090	0.083	0.129
MRPR	0.065	0.089	0.044	0.070
HRSC	-0.071	-0.111	-0.120	-0.187
SRSC	-0.167	-0.217	-0.127	-0.197
SCPR	-0.358	-0.508	-0.570	-0.780

Table 6

Estimates of location, location trend, scale, shape, and dependence parameters

standards errors

	Deviance	Loc 1	L-trend 1	Scale 1	Shape 1	Loc 2	L-trend 2	Scale 2	Shape 2	Depend.
MRSR	605	9.853	0.176	0.776	-0.441	7.896	-2.040	1.566	-0.247	0.734
(S bds; 1995->)		0.081	0.197	0.058	0.049	0.163	0.53	0.109	0.053	0.066
MRSR	1432	3.457	-5.336	2.114	-0.268	8.569	-0.878	1.144	-0.441	0.583
(GER bonds)		0.154	0.236	0.105	0.029	0.086	0.130	0.059	0.047	0.038
MRSR	931	1.566	-6.103	2.259	-0.229	8.284	-1.329	1.294	-0.438	0.664
(G bds; 1994->)		0.581	0.582	0.142	0.050	0.120	0.308	0.084	0.064	0.038
HRER	605	9.853	0.176	0.777	-0.441	7.896	-2.043	1.155	-0.247	0.734
		0. 80	0.197	0.057	0.049	0.164	0.534	0.127	0.053	0.067
SRER	434	7.654	-	1.271	-0.495	9.055	-	1.132	0.992	0.672
		0.163	-	0.116	0.059	0.164	-	0.122	0.142	0.077
HRPR	366	9.806	0.285	0.836	-0.423	10.303	1.376	0.731	-0.134	0.728
		0.101	0.299	0.071	0.075	0.091	0.407	0.061	0.088	0.077
MRER	481	-0.509	0.650	2.058	-0.760	8.149	-0.749	1.157	-0.100	0.730
		0.265	0.247	0.232	0.093	0.179	0.857	0.137	0.159	0.075
HRMR	838	9.901	-	0.805	-0.422	4.211	-	2.757	-0.083	0.999
		0.076	-	0.065	0.092	0.290	-	0.181	0.063	0.000
PRER	410	10.213	-	0.754	-0.043	9.085	-	1.112	-0.004	0.847
		0.112	-	0.084	0.146	0.163	-	0.122	0.134	0.080
SRHR	627	7.880	-	1.655	-0.284	9.869	-	0.776	-0.451	0.853
		0.173	-	0.117	0.052	0.081	-	0.058	0.057	0.072
SCER	468	9.301	-	1.568	-0.460	9.199	-	1.200	-0.232	0.807
		0.212	-	0.185	0.102	0.167	-	0.136	0.097	0.062
SRPR	462	7.533	-	1.345	-0.512	10.259	-	0.774	-0.124	0.971
		0.158	-	0.117	0.053	0.106	-	0.082	0.142	0.089
MRPR	514	6.615	-	1.940	-0.628	10.261	-	0.809	-0.186	0.999
		0.211	-	0.189	0.147	0.106	-	0.094	0.134	0.000
HRSC	632	9.883	-	0.701	-0.419	9.492	-	1.552	-0.477	0.966
		0.071	-	0.051	0.048	0.195	-	0.189	0.160	0.035
SRSC	1140	8.601	-	1.262	-0.589	9.536	-	1.224	-0.345	0.999
		0.101	-	0.067	0.038	0.1.6	-	0.070	0.055	0.000
SCPR	502	9.741	-	1.815	-0.526	10.340	-	0.862	-0.171	0.999
		0.212	-	0.417	0.750	0.110	-	0.100	0.187	0.000

Table 7

Dependence structure

	Dependence-Chi
MRSR (SW bonds)	0.3590
MRSR (GER bonds)	0.4634
MRSR (GER bonds, 1994 ->)	0.6642
HRER	0.3370
SRER	0.4066
HRPR	0.3441
MRER	0.3410
HRMR	0.0005
PRER	0.2010
SRHR	0.1940
SCER	0.2508
SRPR	0.0396
MRPR	0.0014
HRSC	0.0460
SRSC	0.0011
SCPR	0.0010

FIGURES

Figure 1

χ and $\overline{\chi}$ plots

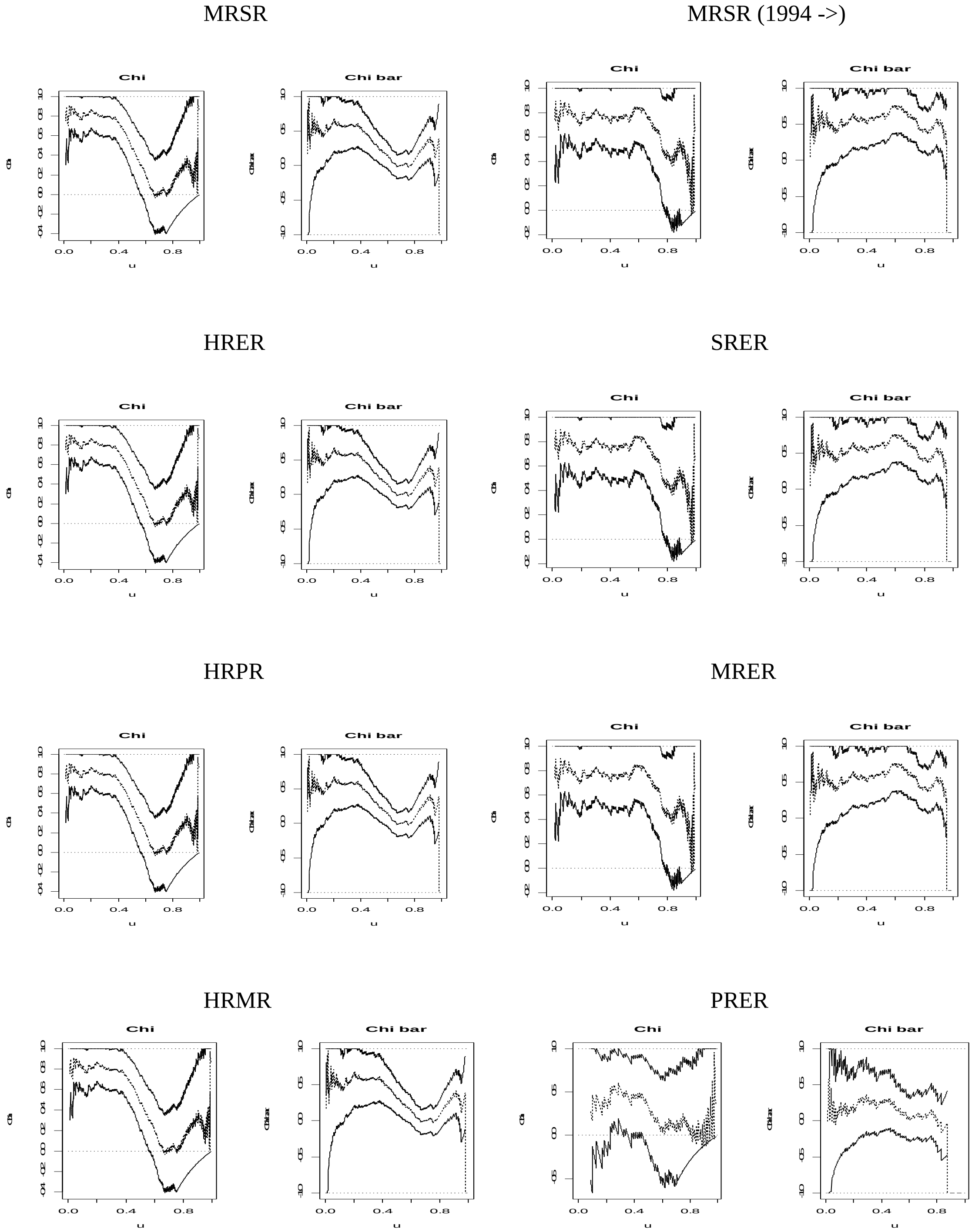


Figure 1 (continued)
χ and $\overline{\chi}$ plots

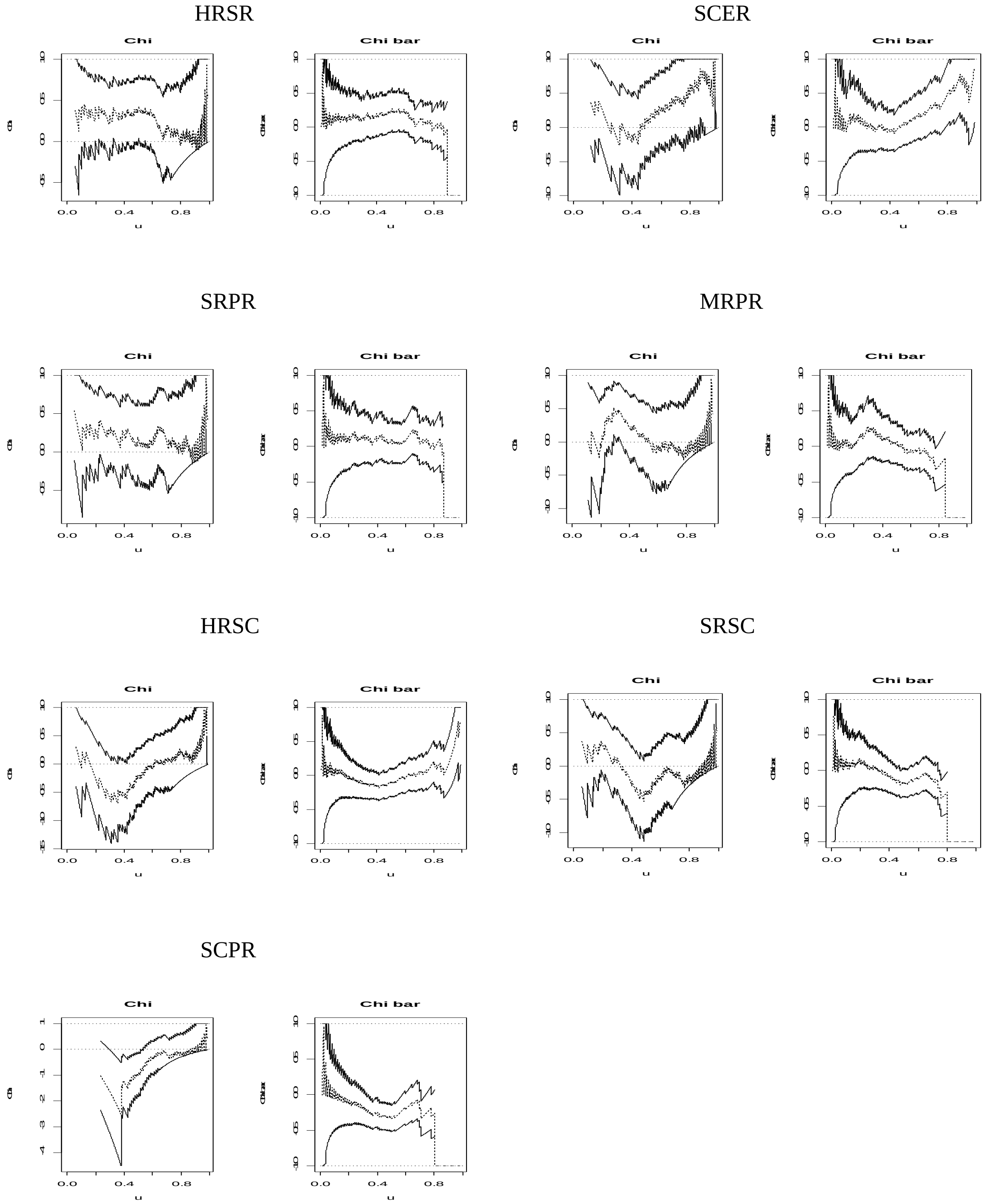
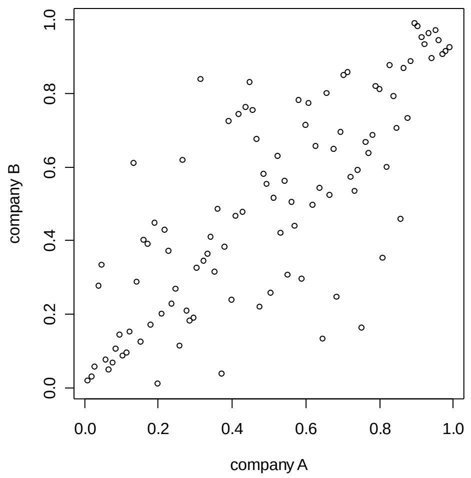


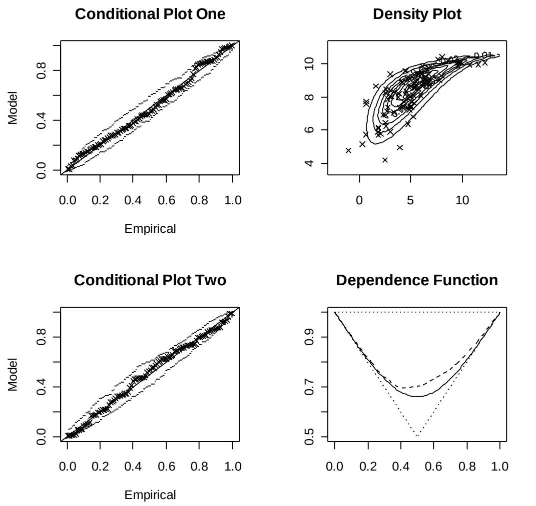
Figure 2
Dependence structure
Two examples (dependence: MRSR, independence: MRPR)

Bi-plots after transformation to uniform margins

Dependence function

MRSR (German bonds, 1994 ->)





MRPR