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Working Paper

2009-34

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ARE BANKING SYSTEMS INCREASINGLY FRAGILE? INVESTIGATING FINANCIAL INSTITUTIONS' CDS RETURNS EXTREME CO-MOVEMENTS

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This version: September 2009

Abstract: This paper investigates potential contagion among the major financial institutions in developed economies. Using Credit Default Swaps (CDS) premia as a measure of credit or counterparty risk, our analysis focuses on the extreme co-movements of Financial Institutions' default contracts during the high level of stress undergone by the CDS markets in the aftermath of the 2007 sub-prime crisis. Our approach is twofold: first, under different tail dependence scenarios, we calibrate several multivariate linear propagation models of constant correlation. Our Monte Carlo simulation study finds evidence of contagion for Financial Institutions- notably in the US-and captures a non-normal dependence structure in the tails for the traded contracts. Second, we estimate a multivariate Dynamic Conditional Correlation-GARCH (DCC-GARCH) model, and demonstrate significant ARCH and GARCH effects, as well as time-varying correlations in CDS spreads variations. Our overall analysis rejects the assumption of constant correlation. More importantly, it advocates changing structures in tail dependence for CDS series during times of financial turmoil as an important feature of banks' increased fragility.

Keywords: Bank fragility, Counterparty risk, Financial crises, Extreme co-movements, Conditional Correlation, Multivariate GARCH, Monte Carlo simulation.

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1 Introduction

The study of markets linkages in periods of market turbulences has come central stage in empirical financial research since the 1990's major financial crises. Common to all these episodes was the attribution of the shock propagation mechanism across asset classes and/or regions, to changes in linkages pertaining to transmission channels other then those of economic fundamentals. The concept of financial contagion thus emerged to describe significant increases or structural shifts in cross market co-movements, while any continued market correlation at high levels is considered to be interdependence (Forbes and Rigobon, 2002). With the event of the 2007 sub-prime crisis and the world's most systemically important banking systems failing to pass the stress test, the study of contagion within the framework of financial and banking systems' stability became of paramount importance.

During the 1990s decade, contagion crucially revolved around the notion of correlation breakdown: in periods of market stress, the propagation of shocks and hence their systematic nature would only be empirically accounted for through a statistically significant increase of correlation. This 'breakdown' would specifically distinguish periods of normal market conditions from those of market crash. Yet several limitations in using structural shifts in correlation as a conclusive measure of contagion were soon evidenced by Boyer et al (1999) who showed that tests for changes in correlation that do not take into account conditional heteroskedasticity may be strongly biased. They showed that due to volatility increases during times of market stress, the correlation between two asset or market returns conditioning on the extreme realizations of one of them is likely to yield a correlation breakdown, even if the true data generation process's unconditional correlation is constant. Moreover they evidenced the selection bias induced by an arbitrary sub-sampling procedure conditioning on high and low volatility.
A further drawback in using correlation is that it is intrinsically biased towards the normal distribution. As Bae et al. (2003) have noted, the main assumption about the effects of financial contagion lies in the fact that changes in the dependence structure seem to occur in a different way for large negative returns than in the case of small negative returns. Being a global measure of association, correlation doesn't accommodate such non-linearity in changes in the dependence structure.

Recognising the need to go beyond the linear approach, studies based on extreme value theory (EVT) were able to address the correlation breakdown caveats. More importantly, the shift was made from a dependence structure located around the centre of a given distribution to an assessment of dependence in the tails. As de Vries (2005) pointed out, "what happens in the limit is a strong interpretation of what constitutes a crash. It is also informative about what happens at extreme but finite sample points"[2]. The advantage of semi–parametric EVT models becomes even more obvious in the case of heavy tailed marginal distributions, as they are able to capture relevant information in terms of extremes and extremes' dependencies. Another advantage of EVT is the flexibility it provides researchers in modelling and exploring the features of contagion as dependence can either asymptotically increase or vanish, regardless of correlation or correlation dynamics.

[2] De Vries (2005), page 2.

The empirical analysis presented in this paper draws on EVT's implicit assumptions in the study of bank fragility. It is careful in distinguishing correlation dynamics from tail dependence breaks. The proposed methodological approach accommodates two of the most important dimensions of markets' behaviour around crises: non-linearity in dependence and heavy tailed distributions of asset returns. The first contribution of this study is to broaden our understanding of banks fragility at a time where the assessment of potential systemic breakdown of financial institutions is crucial for policymakers. The ongoing elaboration of nationalisation schemes, bail-out plans, liquidity facilities, stress-test initiatives and the revisiting of banks' business models along with Basel II's credit risk approach, demonstrate the path taken towards the stabilisation and reform of the global financial system. Second, it makes use of a dataset consisting of daily prices of Credit Default Swap (CDS) contracts. To our best knowledge, no empirical analysis of contagion was previously done using financial institutions' CDS premia[3]. Third, the research presented here encompasses the shortcomings of correlation-based analyses in two ways: following Bae et al. (2003), it focuses on CDS markets' synchronized tail events by using a non-parametric measure of joint downside and upside extreme outcomes. Second, it sheds light on both the dependence structure and dependence dynamics of CDS markets by estimating a multivariate Dynamic Conditional Correlation-GARCH model (Engle, 2002). The model's estimates are then used in a Monte Carlo simulation to study the joint occurrences of extreme movements. Contrary to Bae et al. (2003) and Minderhoud (2003), we need not assume a high volatility regime[4] or a constant correlation structure underlying the sample period true dynamic process: the methodology used enables us to address the heteroskedasticity issue raised by Boyer et al. (1999) and Forbes and Rigobon (2002) as well as avoiding the selection bias induced by arbitrary conditioning sets. At the very same time, our approach encompasses the incremental nature of correlation dynamics, and evidences contagion as per the estimated DCC-GARCH time-varying conditional correlations. Finally, it presents an advantage over EVT methods in that it distinguishes asymptotic dependence from asymptotic independence without solely relying on parametric modelling of the tail parts of the marginal distributions.

The major findings of this paper are summarized as follows. First, this study finds evidence of a time-varying correlation structure for financial institutions' credit default swaps contracts trading in Euro and US Dollar (USD). Significant estimates of dynamic conditional correlations parameters show that the assumption of constant conditional correlation is not supported empirically within both American and European local banking and insurance sectors. Second, three different types of tail dependence are identified for our measure of extreme co-movements

[3] The contagion literature has primarily made use of stock and bonds markets indices. See Baig and Goldfajn (1998), Ramchand and Susmel (1998), Chesney and Jondeau (2000), Longin and Solnik (2001), Ang and Bekaert (2002), Bae, Karolyi and Stulz (2003), Hartman, Straetmans and de Vries (2004) and Rodriguez (2007) among others. On the other hand, empirical research using firm specific CDS premia has focused on the study of lead-lag relationships between several asset classes and credit derivatives markets (Norden and Weber (2004)), on the investigation of the default and non default components of bond spreads (Longstaff, Mithal, and Neis (2004)) or the market reaction of industry competitors surrounding credit events (Jorion and Zhang (2007)). Contagion analysis, as captured by significant correlation breakdowns in the auto industry was carried out by Coudert and Gex (2008).

[4] Bae et al (2003) explore whether contagion based on observed excess co-movements can stem from a relative increase in the volatility of stock market indices' returns. They compute a time-varying variance-covariance matrix, identify two sub-periods of low and high volatility and study the returns' multivariate distribution parameters conditioning on those two –sub periods. They simulate returns for the entire sample period returns based on the high volatility sample's parameters and find evidence of contagion. Our approach is different in that it simulates CDS price variations while accounting for continuously dynamic conditional volatilities and correlations, i.e., without resorting to sub-period samples.

regardless of the CDS returns' correlation dynamics. CDS co-movements can either be asymptotically dependent with tails exhibiting a high degree of co-dependence. Alternatively they can be asymptotically independent as evidenced by a multivariate normal distribution reflecting weak probabilities of extreme co-movements. Or an increasing and hence changing tail dependence structure would characterise Banks and Insurance CDS returns. We dub the latter feature as increased fragility underlying Banking and/ or Insurance sectors. Increased tail dependence in highly volatile CDS markets was found for the banking sectors in the US, France and Germany as well as the UK insurance sector. Along with tail dependence breaks, asymmetry was also evidenced, except for US Banks. A non-normal dependence structure was found to characterise insurance companies' extreme co-movements in the US, Germany and France. Their CDS returns seem to be asymptotically dependent- as evidenced by a multivariate t distribution- but this dependence in the tails is rather stable. Finally, co-movements of Spanish banks are independent in the tails as we found that a multivariate normal distribution better describes their CDS downside and upside extreme co-movements.

The remainder of the paper in structured in the following way. Section 2 describes the data and statistics of CDS returns. Section 3 describes the non-parametric measure of extreme co-movements or CDS co-exceedances, presents a multivariate DCC-GARCH model and the procedure of testing for constant correlation. We also discuss our Monte Carlo simulation approach. Section 4 reports the estimation and numerical simulations results. Section 5 concludes.

2 Data

2.1 Credit Default Swaps

We are particularly interested in CDS market prices for the assessment of an existing dependence structure between financial institutions in developed economies. A CDS is a bilateral over-the-counter (OTC) transaction under which the buyer of protection is insured against a reference entity's credit risk and pays the seller of protection periodic payments of a fixed coupon or premium expressed as a function of the CDS contract notional value. The stream of payments is continuous over the maturity of the contract unless a specified credit event occurs and triggers a default contingent payment to the buyer of protection. Credit events include bankruptcy, failure to pay outstanding debt obligations and restructuring of a bond or loan. Default settlement is carried out in two ways: either the protection buyer delivers, in exchange of par to the protection seller, any bond issued by the defaulted entity that meets the referenced bond criteria in the contract (physical settlement), or the protection seller pays the buyer the cash amount of par less recovery (cash settlement).
The CDS premium reflects the risk-neutral weighted cost of providing insurance against default. A CDS fair premium equates the present value of payments to the present value of expected default loss[5]. CDS premia are thus very often regarded as a direct measure of credit worthiness of a borrower and unlike corporate bond spreads, they

[5] A CDS premium thus incorporates both the issuer's probability of default and the recovery rate in the event of default. The probability weighted expected loss on a given obligation is equal to Protection Notional*(1-Recovery rate)*Probability of Default of the issuer.

are not affected by tax and liquidity effects[6]. Moreover, CDS prices provide information in regards to both the cumulative probability of default and the conditional probability of default (the latter also called hazard rate) of an issuer, and shed light on the market's perception on both credit risk and its term structure.

2.2 Data collection and treatment

We conducted our analysis using data from Credit Market Analysis (CMA) which spans from December 31st, 2004 to November 13th, 2008 (1009 observations). CMA receives CDS prices quotes from a consortium of fixed income sell –side and buy-side contributors such as asset managers, banks and hedge funds. Prices are either executed trades, or indicative bids on specific entities for different tenors and debt seniorities, or fair value model derived. Senior CDS mid spreads for the most actively traded and liquid maturity, i.e., 5 years, were collected on Banks and Insurance companies in Europe and the United States. The selection procedure excluded single name CDSs for which prices weren't available at the starting date of our sample. To ensure data quality and completeness, CMA quotes were first compiled from Thomson Financial Datastream, and then compared to the same set as well as a different set of contributors' prices sourced from Bloomberg. Flat curves, i.e., a price last value repeatedly reported, mainly when there is not enough contributors to the pricing of the CDS contract, were avoided either by relying on Bloomberg generic pricing (the aggregation of contributors' intraday prices) or they were simply removed. The data collection process led us to the selection of 34 names sampled in the following way[7]:

US Banks: Wells Fargo &Co., Citigroup Inc., Bank of America Corp., Wachovia Corp., JPMorgan Chase & Co.
UK Banks: Barclays Bank PLC, HSBC Bank PLC, Lloyds TSB Bank PLC, Royal Bank of Scotland Group PLC.
France Banks: Crédit Agricole S.A, Natixis S.A., Société Générale, BNP Paribas.
Germany Banks: Bayerische Hypo- und Vereinsbank AG (HVB), Deutsche Bank AG, Commerzbank AG, Dresdner Bank AG, WestLB AG.
Spain Banks: Banco Bilbao Vizcaya Argentaria S.A.(BBVA), Banco Santander Central Hispano S.A., Caja de Ahorros de Valencia, Castellon y Alicante (Bancaja).

US Insurance: Genworth Financial Inc., Lincoln National Corp., Ace Ltd., MetLife Inc.
UK Insurance: Old Mutual PLC, Aviva PLC, Legal & General Group PLC, Royal & Sun, Royal & Sun Alliance Insurance PLC
France Insurance: AXA, SCOR SE
Germany Insurance: Allianz SE, Hannover Rueckversicherung AG, Munich Reinsurance Co.

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[6] Despite their contractual nature, CDS contracts' premia could include a non-default component, as recent investigations of a possible liquidity effect in the CDS market pointed out to positively priced liquidity risk. Liquidity risk for less actively traded CDS could be particularly large for short term (less then 5 years) CDS contracts. See Tang and Yan (2007).

[7] Single name- CDSs are all denominated in local currency, respectively US Dollar and Euro for American and European Entities, except for Spanish Bancaja, for which we chose USD CDS on a USD-denominated free float bond for quotes accuracy purposes.

2.3 *Descriptive statistics of CDS data*

We carry out our Monte Carlo simulation experiments as well as the DCC-GARCH model estimation on each of the samples listed in the previous sub-section. The variable of interest is daily CDS premia changes which were obtained by calculating the first differences of the natural log of CDS prices. Summary statistics for all Banks and Insurers' transformed series are presented in Appendix 1.a. The augmented Dickey-Fuller test[8] statistics reveal that all series are mean stationary. The Ljung-Box test statistics denote serial correlation for all countries' series, with the notable exception of US and UK Banks, and two out of three Spanish banks. The daily average CDS return is practically zero for all financial institutions. Both standard excess kurtosis and skewness suggest that extreme premia variations may be present in the series. The Jarque-Bera test statistic strongly rejects normality for all financial institutions' CDS returns[9]. Another noteworthy statistic is Moors' robust excess kurtosis[10] statistic, which for all series, shows a large difference with the conventional one thus indicating the presence of a small number of outliers, a typical feature of both CDS price and returns series (see Appendix 1.c).

All CDS returns series exhibit a similar pattern in terms of heavy-tailed return distributions and stationarity. More importantly, all country samples seem to experience synchronised movements of widening and tightening CDS spreads over time. This concomitant behaviour is obvious as depicted by the series' spread levels in Appendix 1.b, and provides a good ground for investigating for a potentially dynamic correlation structure as market conditions change from normal to turbulent during crises times.

CDS return series exhibit large return and volatility clustering since the start of the sub-prime crisis in July 2007, as seen in Appendix.1.c. We therefore are particularly aware that conditional heteroskedasticity needs to be accounted for when analysing CDS returns co-movements, as any pair-wise correlation between CDS returns across countries is likely to increase during a highly volatile period, implying a contagion phenomenon that may not be present in the series. Finally, because the DCC-GARCH model is robust to heteroskedasticity-induced bias in correlation and because we are keen on exploring the conditional correlation structure throughout the entire period, we did not subsequently resort to *normal* versus *stress* sub-sampling of our data.

[8] Augmented Dickey-Fuller tests also rejected both trend and intercept in CDS returns series, except for Old Mutual PLC, for which we included a significant deterministic time trend. Even though CDS price series present structural breaks, we did not test the null of unit root against the break-stationarity alternative to the extent the variable of interest is CDS returns (premia changes).

[9] Under the null hypothesis, the Jarque-Bera test statistic follows a Chi-Square distribution with two degrees of freedom.

[10] Moors (1988) robust kurtosis coefficient is computed as $(E_7 - E_5) + (E_3 - E_1) / E_6 - E_2$ where $E_i = F^{-1}(i/8)$ is the *i*th octile for each of the CDS returns' series. Because it's an octile-based measure, the coefficient is robust to outliers, specially in the case of a large number of observations. For a normallydistributed variable with zero mean and unit variance, Moors' robust kurtosis is equal to 1.23. Ou rexcess robust kurtosis is thus centered around that value. For a survey of robust third and fourth moments and their applications, see Kim and White (2004).

3 Methodology

3.1 Investigating extreme returns dependence: a Monte Carlo simulation approach

The analysis of increased banks fragility is based on the assumption of an increasing dependence structure of CDS extreme returns. Joint credit events and/or credit quality deteriorations occur when entities either are exposed to a cyclical shock, or market-wide adverse factor, or are subject to close linkages. The latter, consensually defined as contagion in the existing literature, is favourable to an increased dependence structure in times of market stress and constitutes a channel for the transmission of idiosyncratic or entity-specific shocks. It is important to note that CDS premia reflect the market perception of counterparty and/or credit risk. That is, in the case of financial institutions, credit dependence can either be real (e.g. loan syndication activities or interbank market ties) or virtually perceived by the market (e.g. the fear of insurance companies' over-exposure to illiquid risky assets).

We are interested in investigating whether or not the 2007 financial crisis was capable of revealing an increased fragility, regardless of the causes of credit or counterparty risk deterioration, in the banking and insurance sectors in the US, the UK, Germany, France and Spain. In other words, in times of high volatility either induced by market downturns, or contagion driven, financial institutions can grow more and more dependent in the tails. In order to gauge this increased fragility, we follow Bae et al. (2003) in defining an extreme return, or 'exceedance', as one that is located in the 5 percent tails of the overall CDS return distribution. We then identify the number of joint occurrences of returns exceeding their respective thresholds, and define the count of those joint occurrences as our non-parametric measure of extreme dependence. Tables 3 and 4 present the results for the US Banks and Insurance samples. For those two samples, the distribution of extreme co-movements is asymmetric as the days during which credit risk deteriorations of three or more banks or insurance companies were simultaneously observed outnumbered the days of bottom tails co-exceedances.

We then turn to the investigation of the dependence structure of those extreme co-movements by simulating a pseudo-random distribution of co-exceedances that would result if correlation were constant during the sample period. To this end, we resort to a multivariate CDS return generating model that we calibrate using the CDS returns true dependence assumptions obtained with the Cholesky decomposition of the returns' variance-covariance matrix which we assume at this stage constant. We then consecutively simulate two regimes of tail dependence: a weak tail dependence (low co-kurtosis implying asymptotic independence) regime generated by a multivariate distribution with Gaussian marginals, and a strong tail dependence (high co-kurtosis implying asymptotic dependence) regime based on t-distributed marginals of the joint distribution of CDS returns[11]. Degrees of freedom underlying the strong tail dependence regime are equal to n+k-1, where n is the number of issuer in each sample and k takes values ranging from 1 to 25. We deliberately set k equal to 1 in order to ensure the strongest asymptotic dependence in our data generating process, so that each Student-t marginal distribution has k degrees of freedom. 1009 daily

[11] We chose the multivariate normal and Student-t distributions for their elliptical properties. Elliptically contoured distributions are characterized by their marginals and their correlation matrix. The multivariate Student-t is introduced to capture a non normal dependence in the tails of the series. Each marginal distribution is symmetric with zero mean, unit variance, zero skewness and a kurtosis equal to $3(v-2)/(v-4)$. For a detailed presentation of elliptical distributions, see Jondeau et al. (2007)

observations for each issuer are then generated with 5000 replications. The numerical simulation provides us with a distribution of co-exceedances against which we benchmark the data true joint occurrences of bottom and top tails returns.

In a second simulation experiment, we assume a time-varying dependence structure between financial institutions CDS returns. Dynamic correlations are parametrically modelled by fitting a multivariate DCC-GARCH model (Engle, 2002) to each sample of our study. Since it is already well know that the joint tails of multivariate GARCH type models, and especially ones with conditionally fat-tailed errors, can produce many more joint exceedances than the corresponding unconditional distributions, the assumption we are seeking to test is the following: if any contagion was evidenced based on our benchmark model of constant correlation, can the true data extreme co-movements be accounted for once we assume a dynamic dependence structure? In other words, could the observed contagion be due to an increase in linkages between financial institutions in periods of market turmoil, and once dynamic correlations are accounted for, neither contagion nor asymptotic dependence would any longer characterize our samples? We proceed the following way: the DCC-GARCH model estimates are used as inputs to our Monte Carlo simulation. Using the assumptions of conditional volatilities and conditional correlations, we run 5000 simulations of financial institutions CDS returns from a DCC-GARCH (1,1). In the simulation set-up, innovations are consecutively assumed to follow a multivariate normal distribution and a multivariate Student t-distribution. For each sample, the degrees of freedom are taken from our first simulation experiment and kept unchanged. The simulated DCC-GARCH model provides us with a distribution of co-exceedances. We then match-up the obtained results to those of our linear model of constant correlation. The following sub-section briefly presents the DCC-GARCH methodology.

3.2 Econometric methodology

In order to examine the time-varying interactions within each country-based CDS sample, we resort to the estimation of a multivariate DCC-GARCH model. Along with presenting a univariate-like framework of GARCH interpretation, multivariate DCC-GARCH models allow for GARCH dynamics in the estimation of the conditional variances and conditional correlations: by calculating the DCC parameters, the method estimates time-varying conditional correlations as a function of previous realizations of both volatilities and correlations.

Consider the following vector specifications:

$$y_t = \mu + \varepsilon_t$$
$$y_t \,|\, \mathrm{I}_{t-1} \sim N(0, H_t)$$
$$\varepsilon_t = z_t D_t$$

$H_t = D_t R_t D_t$ and $D_t = diag(h_{1,t}^{1/2}, \ldots, h_{N,t}^{1/2})$ are $N \times N$ matrices, where D_t is a diagonal matrix of time-varying standard deviations obtained from univariate GARCH equations, and H_t and R_t are the conditional covariance matrix and the dynamic conditional correlation matrix respectively of the vector stochastic process ε_t.

The matrix H_t has its i^{th}, j^{th}element given by $h_{ijt} = \rho_{ijt}\sqrt{h_{iit}h_{ijt}}, \forall i \neq j$. The time-varying correlation structure is defined as :

$$R_t = (diagQ_t)^{-1/2} Q_t (diagQ_t)^{-1/2}$$
$$Q_t = (1-\theta_1-\theta_2)Q + \theta_1 z_{t-1} z'_{t-1} + \theta_2 Q_{t-1}$$

where θ_1 and θ_2 are the DCC positive scalar parameters driving the current conditional correlations through past standardized shocks and past conditional correlations respectively, such as $\theta_1 + \theta_2 < 1$ to ensure positive definiteness of Q_t. Q_t and Q are the $N \times N$ conditional covariance matrix and unconditional variance matrix of z_t. Finally Q_t is re-scaled to ensure ones on the diagonal are obtained in the final correlation matrix R_t.

The first stage of the DCC-GARCH estimation involves fitting univariate GARCH equations to the series, and yields estimates of D_t. Residuals are standardized using estimated standard deviations $h_{i,t}^{1/2}$ that is $z_{i,t} = \varepsilon_{i,t} / \sqrt{h_{i,t}}$ where $z_{i,t}$ are then used to estimate the DCC parameters.

As proposed by Engle (2002), the log likelihood function can thus be written in two components, allowing for this two-stage estimation procedure:

$$l_t(\omega,\theta) = \left[-\frac{1}{2}\sum_{t=1}^{T}(N\log(2\pi) + \log|D_t|^2 + \varepsilon'_t D_t^{-2}\varepsilon_t) \right] + \left[-\frac{1}{2}\sum_{t=1}^{T}(\log(|R_t|) + z'_t R_t^{-1} z_t - z'_t z_t) \right]$$

Where the volatility component is first maximized in respect to the univariate GARCH parameters, and second, the correlation part is maximized to estimate θ_1 and θ_2.

The necessary and sufficient conditions for positive definiteness of the conditional covariance matrix are the same for the DCC model as for a univariate GARCH process with the following specification:

$$h_{it} = \omega_i + \sum_{j=1}^{r}\alpha_{ij}\varepsilon_{i,t-j}^2 + \sum_{j=1}^{s}\beta_{ij}h_{i,t-j} \text{ , where } \sum_{j=1}^{r_i}\alpha_{ij} + \sum_{j=1}^{s_i}\beta_{ij} < 1.$$

Finally we are interested in testing whether CDS returns series exhibit constant correlations. We follow Engle and Sheppard's (2001) constant correlation test procedure[12], which generalizes well to the multivariate case, as opposed to Bera's (1996) bivariate constant correlation test and Tse's (1998) LM test for constant correlation. We test the following null versus alternative hypothesis:

$$H_0 : R_t = \bar{R} \ \forall t \in T$$
$$H_A : vech(R_t) = vech(\bar{R}) + \beta_1 vech(R_{t-1}) + \beta_2 vech(R_{t-2}) + ... + \beta_p vech(R_{t-p})$$

The implementation of such hypotheses testing requires the estimation and testing of a restricted VAR. The following equation gives the unrestricted form of the model:

[12] We are grateful to Mr. Abdelaziz Rouabah from Banque Centrale du Luxembourg for his guidance in implementing the test's code on Eviews.

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + ... + \beta_p Y_{t-p} + \eta_t$$

where Y_t is a kx1 vector such as $Y_t = vech^u\left[(\bar{R}^{-1/2} D_t^{-1} r_t)(\bar{R}^{-1/2} D_t^{-1} r_t)' - I_k\right]$ and $\bar{R}^{-1/2} D_t^{-1} r_t$ is a kx1 vector of residuals standardized by both estimated standard deviations and the symmetric square root decomposition of their unconditional correlation matrix. $vech^u$ denotes a modified *vech* that only selects elements above the diagonal.

Under the null, the VAR's constant and lagged parameters should be equal to zero. The test statistic is equal to the VAR's restricted residual sum of squares over the unrestricted model residual sum of squares and is asymptotically distributed as χ^2_{p+1}.

4 Empirical Findings

We fitted a diagonal DCC-GARCH (1,1) model to all CDS returns samples[13]. The model was estimated by quasi-maximum likelihood (QML), with robust t ratios (Bollerslev and Wooldridge, 1992) used for the estimates statistical significance. Table 1 in Appendix 2.a shows the diagonal DCC-GARCH (1,1) estimates[14] for the 9 CDS samples. As reported, all estimates of the lagged variance and squared innovations terms are highly significant denoting time-varying volatilities in CDS returns. Moreover, all variance equations satisfy the stationarity assumption as the sum of ARCH and GARCH coefficient for each issuer is less, yet very close to unity, implying considerable persistence in the volatilities of CDS returns. The correlation equations are also stationary over time with positive and highly significant DCC parameters, which makes it clear that the assumption of a constant conditional correlation is empirically challenged for financial institutions CDS returns. Our suggestions are further validated by Engle and Sheppard (2001) constant correlation tests' results. For each of the estimated DCC-GARCH(1,1) models, we apply Engle and Sheppard (2001) proposed test. The results are reported in Table 2. For each sample, we reject the null hypothesis of constant correlation. Moreover, our DCC parameters estimates suggest that, over the period spanning December 31st, 2004 to November 13th, 2008, changes in correlations are predominantly driven by past realizations of conditional correlations as denoted by coefficients on θ_2 close to 1. Even in the case of the German banking and UK insurance sectors for which estimates of θ_2 are lower, the impact of past standardized shocks on dynamic conditional correlations is mitigated by higher estimates of the DCC's own lagged effect. Estimates of selected pair-wise correlations for each country's both Insurance and Banks samples are depicted in Appendix 2.b.

[13] The DCC-GARCH model assumes conditionally multivariate returns with zero expected value and covariance matrix Ht (Engle, 2002). To the extent that we performed a zero mean hypothesis test and found that all our CDS returns series' means are statistically not different from zero, we did not need to de-mean our series by estimating a VAR- like mean process prior the DCC-GARCH estimation. The lags order p and q are equal to 1 as the analysis of squared returns autocorrelation and partial autocorrelation functions evidenced a significant first-order lag. See the autocorrelation and partial autocorrelation functions of selected CDS squared returns, Appendix 1.d. The choice of a first order ARCH and GARCH lag also made sense due to the intrinsic difficulty in estimating higher order models as the number of parameters increases.

[14] Diagonal DCC-GARCH were computed as no significant spill-over effects were found to allow for extended multivariate DCC-GARCH models estimation. ω_i, α_i, β_i are the constant, the one order ARCH parameter and the one order GARCH parameter respectively for each of the $i,\ldots,N$ entities comprised in each sample.

The simulations results for the US and European banking and insurance sectors are presented in Tables 1 to 9 in Appendix 2.c. The tables report both the constant correlation and dynamic conditional correlation scenarios for all sectors. Within the constant correlation framework, the asymptotic independence scenario generates a significantly lower average number than the actual number of maximum simultaneous bottom and top tails returns for financial institutions (p-value < 0.05). In the case of UK Banks (Table 3), the simulation's p-value for four co-exceedances is 0.115, yet it is obvious when looking at the actual and simulated counts of extreme synchronised co-movements, that the multivariate normal distribution is not able to replicate the actual number of 3 co-exceedances in the top tails (p-value = 0.007). Those results suggest asymptotic tail dependence, which is found to be asymmetrical in the case of UK Insurance companies (Table 4) and Spanish banks (Table 9) as the low kurtosis scenario is able to explain all lower tails co-exceedances. Simulations based on the high co-kurtosis scenario, i.e., when allowing for a strong dependence structure in the tails, yield mixed results. In the case of UK Banks, German and French insurance companies as well as Spanish banks, the multivariate Student distribution generates an average count of maximum positive co-exceedances that is comparable with the true data generating process, hence validating the hypothesis of strong dependence in the tails for those four samples. In the case of Spanish banks and French insurance companies, dependence in the tails is symmetrical as negative co-exceedances are also accounted for by the high co-kurtosis scenario. Asymmetry is on the other hand found for the German insurance sector (Table 6) and the UK banks (table 3) as the high co-kurtosis hypothesis is rejected in the lower tails at a 10% and 5% significance level (p-value of 0.098 and 0.006 respectively). Overall, those results suggest that over the period of interest, an increased tail dependence seems to characterize banking and insurance sectors in specific countries (US banks and insurers, UK insurers, French Banks and German banks) as both the hypothesis of constant correlation and tail dependence aren't satisfactory in explaining their CDS returns extreme, notably positive, co-movements.

Compared to the time-varying correlation scenario results, those findings are nuanced. The DCC-GARCH with normal distributed innovations models fail in explaining the observed number of maximum extreme co-movements of CDS for the majority of sectors. Exception made for the Spanish banks for which the lower and upper tails p-values are 0.34 and 0.13 respectively, there seems to be no evidence that tail dependence found in the first stage of our simulation experiment can be entirely accounted for a by a changing correlation structure. When allowing for t-distributed innovations, our simulation results easily replicate the maximum number of co-exceedances for the insurance sectors in the US, Germany and France (respectively 0.84, 0.76, 0.88 in the lower tails and 0.59, 0.88, 0.82 in the upper tails), suggesting evidence of asymptotic dependence and time-varying correlations for Insurance companies. Finally, the results on banks in the US, France and Germany, as well as insurance companies in the UK are noteworthy. For those samples, DCC-GARCH based simulations, even when allowing for Student-t distributed innovations do not generate a comparable count of extreme co-movements neither in the top nor lower tails for US and German Banks, while the p-values are lower then the 10% significance level in the lower tails for French banks and UK insurers (0.069 for three co-exceedances of UK insurers and 0.057 for four co-exceedances of French banks), so that even in the lower tails, the hypothesis of a stable tail dependence structure is debatable. Those results suggest that tail dependence of those financial institutions exhibit breaks and that those breaks aren't reflected in the CDS returns distribution's overall dynamic correlation structure given by the estimated time-varying correlation coefficients.

Our empirical findings have two implications. First, while it is well known among economists that there are inherent difficulties in predicting systemic crises- both it their scope and intensity- rather then merely identifying them *ex post*, the current financial crisis proved one more time that it is also difficult to recognise the risks associated with events as they take place or rise in severity during a crisis. This *Disaster-myopia*[15] driven behaviour directly relates to the inclination of economic agents to underestimate the probability of occurrence of adverse events, notably when those events last took place in the very distant past. This readiness not to recognize or estimate stress events and associated risks as they occur, especially after prolonged periods of stability, makes it difficult for both policy-makers and market participants to gauge the marginal contribution of a particular distressed financial institution in the disruption of the entire banking or financial system. Because it is based on daily observations and on a joint tail risk measure, our analytical model can help capture systemic risk as it occurs, since it is capable of differentiating and hence pointing out to non linearities in tail dependence, or in other words, increasing risk that multiple financial institutions become simultaneously distressed.

Increased tail dependence was found to characterise major economies' banking sectors (the US, France and Germany) and to less extent insurance companies (only UK insurers' DCC-GARCH model simulations with t-distributed innovations couldn't generate a comparable count of positive extreme co-movements at the 5 % significance level, see Table 4, Appendix 2.c). This result suggests that the financial crisis was rather of a systemic nature in banking sectors with stress events such as the Lehman Brothers bankruptcy and the near failure of Bear Sterns, as opposed to being a rather contained crisis in global insurance sectors. In sum, the analysis presented here could be jointly used with other approaches such as early warning signals/financial soundness and market indicators in order to determine when a financial institution, given the state of global capital and liquidity markets, is increasingly contributing to the whole sector or system's fragility, in other words, when systemic risk becomes apparent.

A second implication of our results pertains to the inevitable interaction of credit and counterparty risks in the CDS markets. Counterparty risk directly relates to the probability of the counterparty of a CDS contract to fail to meet its payment obligations if the reference entity were to default. If a CDS seller defaults, the protection buyer will look to replace the trade with a different counterparty at a price often different (higher) than the original contract price. The defaulted counterparty is legally bound to pay the additional cost of trade replacement. Those costs, if unpaid by the defaulted counterparty, can incur significant losses to the protection buyer. The Lehman debacle proved that the actual losses due to trade novation costs when a financial institution defaults as a counterparty can be much greater than the losses on its debt instruments, i.e, when the same defaulted financial institution is the reference entity in the contract. In the days following Lehman Brothers' default and the resulted increase in CDS volatility, several market participants suffered losses in novating their trades with other financial institutions on account of simultaneous jumps in CDS spreads across the board[16].

[15] See Haldane (2009) for a presentation of the concept of "Distaster Myopia "resulting in Banks' failures in risk management practices prior and during the 2007 financial crisis.
[16] ECB, page 33.

The Lehman episode was consequently able to reveal at least two structural features in CDS trading that played in favour of increased counterparty risk and, as we believe, increased systemic risk. The over-concentration of CDS markets since the start of the crisis in 2007 led a few dealers to account for a big share of traded volumes. More importantly, concentration risk in the market resulted in greater systemic risk as both counterparty risk and exposure by the major CDS dealers increased. In 2008, the five largest CDS dealers were JP Morgan, Goldman Sachs, Morgan Stanley, Deutsche bank and Barclays. According to the Depository Trust and Clearing Corporation (DTCC) data, the five largest CDS dealers were, as of April 2009, counterparties to almost 50% of the total outstanding notional trades[17]. Despite the fact that our simulation study was conducted over samples of banks and insurance companies selected on a national scale, and given that three out of the five names were included in this study, we believe, that this concentration risk, resulting in greater systemic risk, might have been apparent in the case of Germany and the US.

A second factor which we believe contributed to increased tail dependence in Banks CDS returns is the stronger interconnectivity of the CDS market as a network over the past two years. Stronger interconnectivity resulted in an increase in correlation between financial institutions CDS spread movements since the start of the crisis in July 2007 (see Appendix 2.b selected DCC-GARCH estimated pair-wise correlation coefficients). Those stronger linkages resulted primarily from both the over-concentration of the CDS markets and the increase in demand for protection against the failure of financial institutions that were hit by the crisis. This, in turn further deteriorated their CDS spreads levels, as they turned out to be counterparties to other financial institutions. Counterparty risk thus emerged to add a layer to credit risk as financial institutions became both counterparties and underlying reference entities to CDS transactions, and mechanically fed into successive rounds of spread decompression when market participants realized that the potential impact of a financial institution's default as both an obligor and a counterparty needed to be hedged against.

Those findings are in line with those of financial markets structure research. Cont et al. (2009) have shown that CDS networks' complexity constitutes a channel for the diffusion of systemic risk within a network of financial institutions. The enhanced complexity of the trading network, in the aftermath of the 2007 sub-prime crisis, increased the potential impact of a financial institution's default, which in turn resulted in a synchronised increase in financial institutions' CDS spreads. It is in that sense that tail dependence breaks can be viewed as a key feature of contagion that ought to be particularly assessed for systematically important financial institutions.

[17] ECB, page 21.

5 Summary

This paper provides evidence that the dependence structure between CDS returns of financial institutions in the US and Europe changed since the start of the financial crisis in 2007. Changes in dependence adjusted for high volatility on CDS markets- as denoted by statistically significant DCC parameters- are captured by DCC-GARCH (1,1) models. We also evidence different patterns of tail dependence for financial institutions CDS returns. Based on numerically simulated extreme co-movements, we demonstrate the increased fragility of the banking sectors in the US, France, Germany as well as the UK insurance sector and point out to a changing dependence structure in the tails. More importantly, we show that, for those sectors, changes in tail dependence aren't revealed through changes in correlation. Those results seem to characterize the extreme co-movements of the largest CDS dealers evidencing that counterparty risk might have possibly contributed to the increased fragility of those sectors. More broadly, our findings provide a basis for a better understanding of CDS market dynamics and extreme dynamics which are both of growing importance to policymakers and risk management practitioners. Future research is needed to control for fundamentals and market structure variables for a deeper understanding of CDS returns extreme co-movements.

6 References

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Appendix 1.a: Descriptive statistics on CDS returns (31/12/2004 – 13/11/2008)

	US Banks Sample					US Insurance Sample			
	Wells Fargo	Citigroup	BoA	Wachovia	JP Morgan	GenworthFin.	LincolnNat.	Ace	Metlife
Mean	0.0018	0.0025	0.0022	0.0021	0.0015	0.0038	0.0034	0.0005	0.0032
Maximum	0.412	0.437	0.299	0.839	0.295	0.374	0.691	0.436	0.538
Minimum	-0.395	-0.431	-0.362	-1.269	-0.383	-0.312	-0.411	-0.235	-0.353
Std. Dev.	0.064	0.065	0.060	0.081	0.057	0.054	0.062	0.052	0.053
Skewness	0.063	-0.155	-0.201	-3.213	-0.264	1.14	1.53	0.90	0.96
Excess Kurtosis	8.81	11.23	6.23	74.40	7.56	9.73	19.40	9.86	17.67
Excess Robust Kurtosis	0.70	0.66	0.88	0.70	0.87	0.90	0.58	0.63	0.48
Jarque-Bera	3261*	5301.9*	1641.1*	234435.4*	2416.8*	4199.9*	16208.8*	4219.8*	13273.0*
ADF	-30.7*	-30.5*	-31.1*	-33.3*	-28.9*	-18.4*	-34.0*	-19.7*	-28.3*
L-B(35)	31.5	49.1	39.4	203.6	59.4*	75.1*	69.9*	65.3*	93.6*

* denotes significance at the 5% level

	UK Banks Sample				UK Insurance Sample			
	RBS	Barclays	HSBC	Lloyds TSB	Old Mutual	Aviva	Legal & General	Royal & Sun
Mean	0.0025	0.0026	0.0023	0.0021	0.0029	0.0024	0.0028	0.0009
Maximum	0.455	0.452	0.487	0.496	0.282	0.582	0.362	0.339
Minimum	-0.707	-0.443	-0.381	-0.424	-0.317	-0.323	-0.210	-0.402
Std. Dev.	0.082	0.070	0.065	0.074	0.047	0.057	0.046	0.061
Skewness	-0.552	-0.226	0.527	0.050	0.074	1.224	0.948	0.109
Excess Kurtosis	8.01	6.42	7.35	5.41	6.72	14.36	8.44	7.41
Excess Robust Kurtosis	0.67	0.68	1.25	0.70	1.19	1.14	1.32	0.70
Jarque-Bera	2750.1*	1743.1*	2317.8*	1229.5*	1897.9*	8916.5*	3143.6*	2309*
ADF	-34.7*	-30.4*	-33.1*	-34.68151*	-33.4*	-32*	-30.9*	-35.4*
L-B(35)	46.7**	38.9	36.1	48.3**	98.7*	62.1*	50*	73.7*

* denotes significance at the 5% level, ** denotes significance at the 10% level

	Germany Banks Sample					Germany Insurance Sample		
	HVB	Deutsche Bank	Commerzbank	Dresdner Bank	WestLB	Allianz	Hannover Re	Munich Re
Mean	0.0015	0.0021	0.0013	0.0014	0.0018	0.0017	0.0013	0.0012
Maximum	0.655	0.537	0.599	0.496	0.772	0.613	0.532	0.545
Minimum	-0.381	-0.476	-0.464	-0.281	-0.478	-0.359	-0.255	-0.358
Std. Dev.	0.071	0.070	0.069	0.068	0.080	0.064	0.056	0.063
Skewness	0.95	0.27	0.81	0.59	1.17	0.592	1.173	0.845
Excess Kurtosis	12.45	8.86	15.51	8.08	18.67	14.66	13.04	11.58
Excess Robust Kurtosis	0.49	0.61	0.73	0.43	3.32	0.95	0.96	0.99
Jarque-Bera	6663.4*	3309.9*	10219.8*	2801.7*	14878.1*	9091.5*	7382.4*	5755.9*
ADF	-37.7*	-32.1*	-24*	-32.7*	-35*	-18.3*	-29.9*	-31.3*
L-B(35)	73.8*	33.3	53.1*	42.9	60*	60.9*	38.9	45.7

* denotes significance at the 5% level

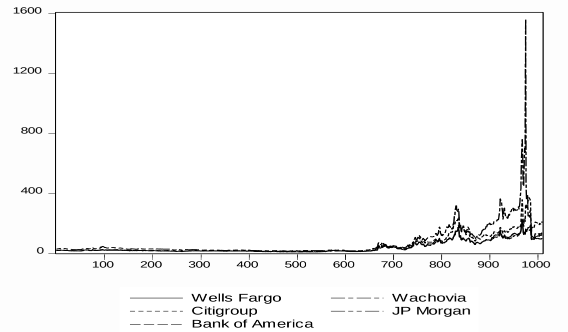
	France Banks Sample				France Insurance Sample	
	Crédit Agricole	Natixis	Société Générale	BNP Paribas	AXA	SCOR
Mean	0.0021	0.0030	0.0022	0.0018	0.0021	0.0005
Maximum	0.365	0.774	0.38	0.627	0.626	0.345
Minimum	-0.270	-0.509	-0.273	-0.315	-0.319	-0.236
Std. Dev.	0.064	0.062	0.065	0.071	0.055	0.049
Skewness	0.01	1.37	0.34	0.80	1.65	0.47
Excess Kurtosis	3.88	33.03	4.04	8.61	21.19	6.37
Excess Robust Kurtosis	0.88	1.89	0.86	1.13	0.73	0.88
Jarque-Bera	631.6*	46181*	704.1*	3226.6*	19342.1*	1741.9*
ADF	-33.8*	-37.8*	-33.9*	-35.2*	-31.8*	-31.6*
L-B(35)	34.7	58.8*	51.3*	56.4*	66.6*	47.9*

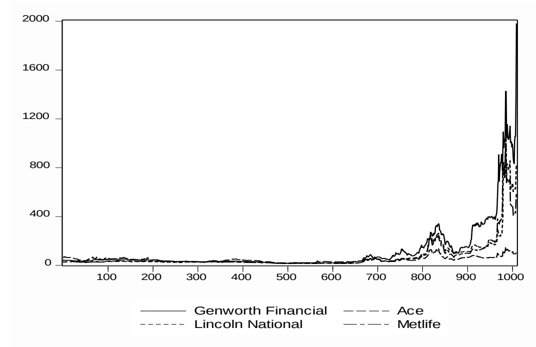
* denotes significance at the 5% level

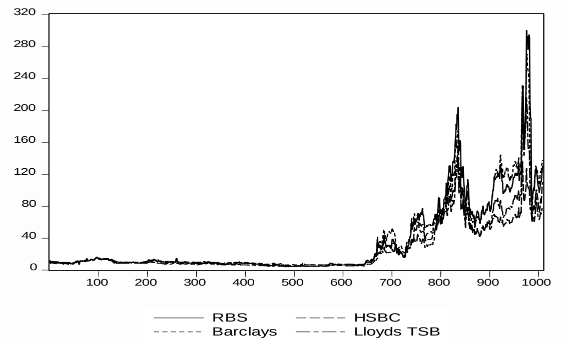
	Spain Banks Sample		
	BBVA	Santander	Bancaja
Mean	0.0020	0.0020	0.0035
Maximum	0.315	0.325	0.831
Minimum	-0.322	-0.335	-0.388
Std. Dev.	0.061	0.062	0.069
Skewness	0.32	0.14	2.76
Excess Kurtosis	5.08	4.47	34.98
Excess Robust Kurtosis	0.910	0.682	na
Jarque-Bera	1103.6*	843.1*	52718.3*
ADF	-31.5*	-31.5*	-35.3*
L-B(35)	42.1	36	75.5*

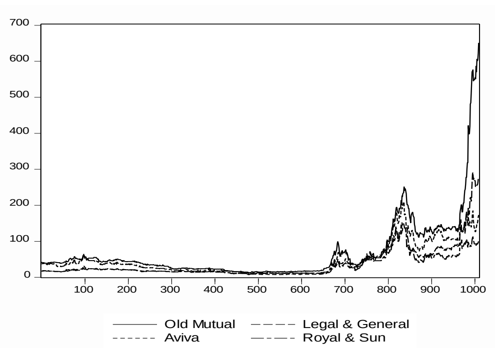
* denotes significance at the 5% level

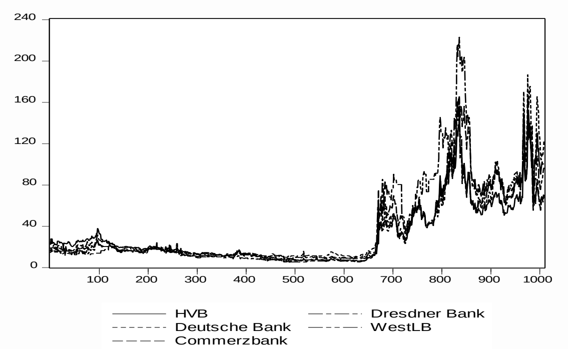
Appendix 1.b: US and Europe financial institutions CDS prices (31/12/2004 – 13/11/2008)

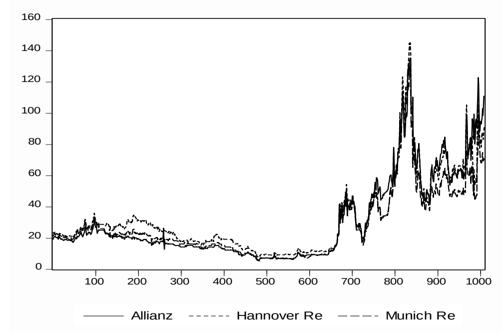


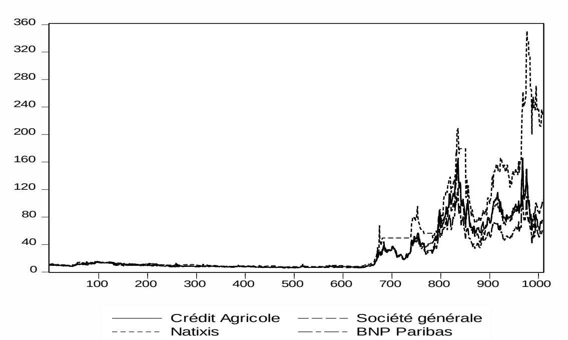


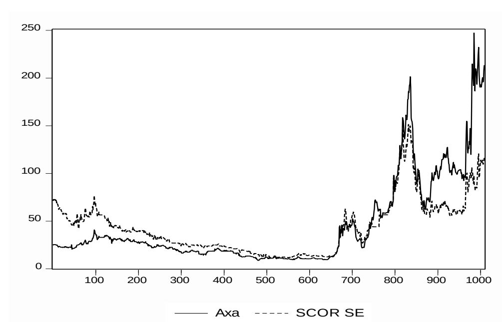


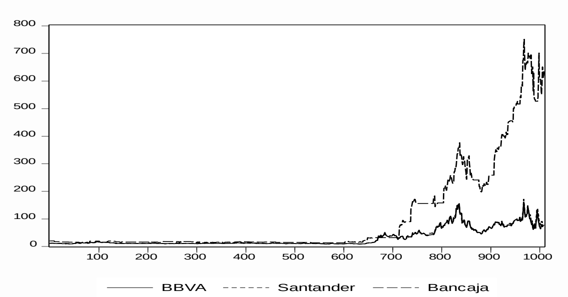




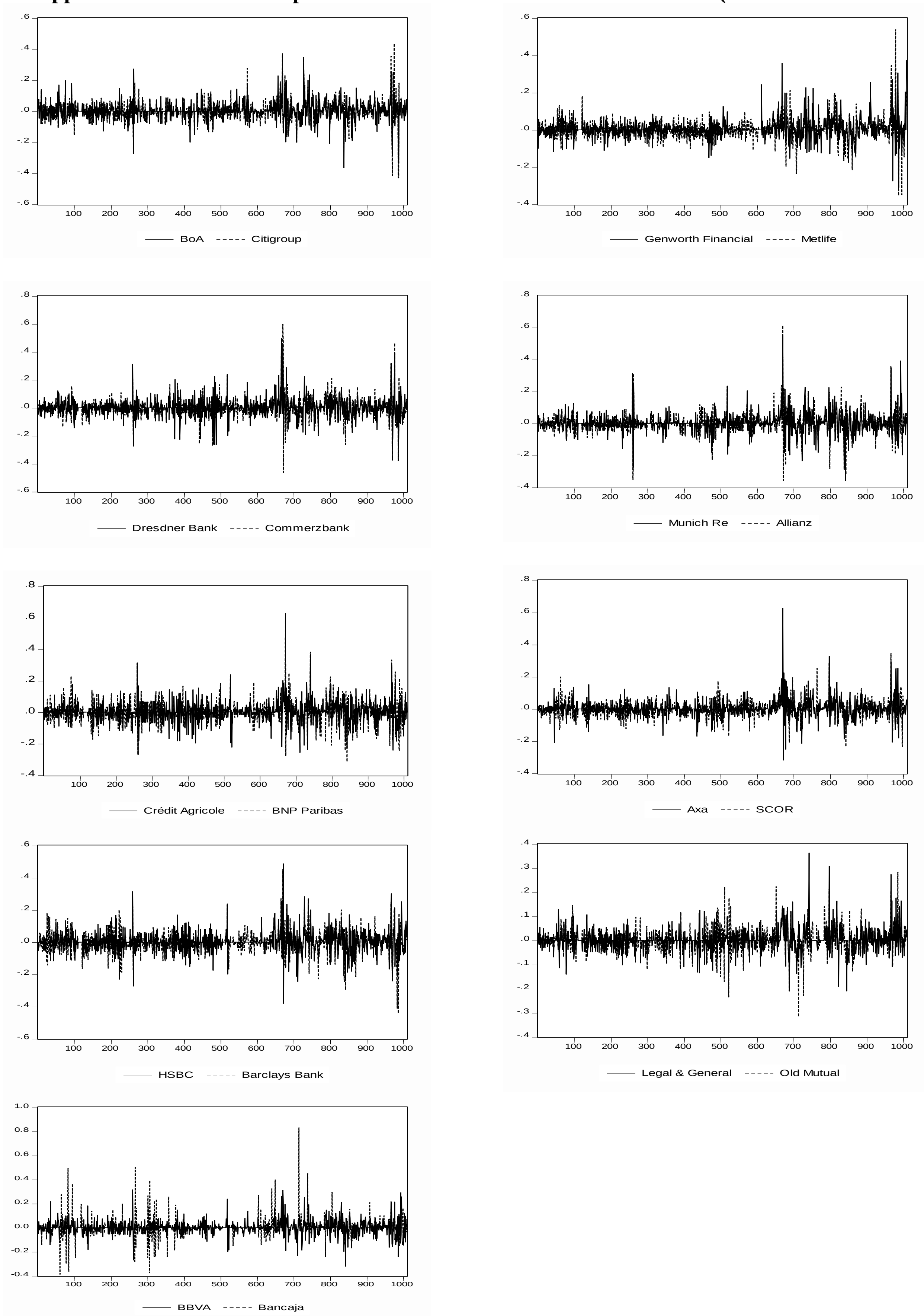




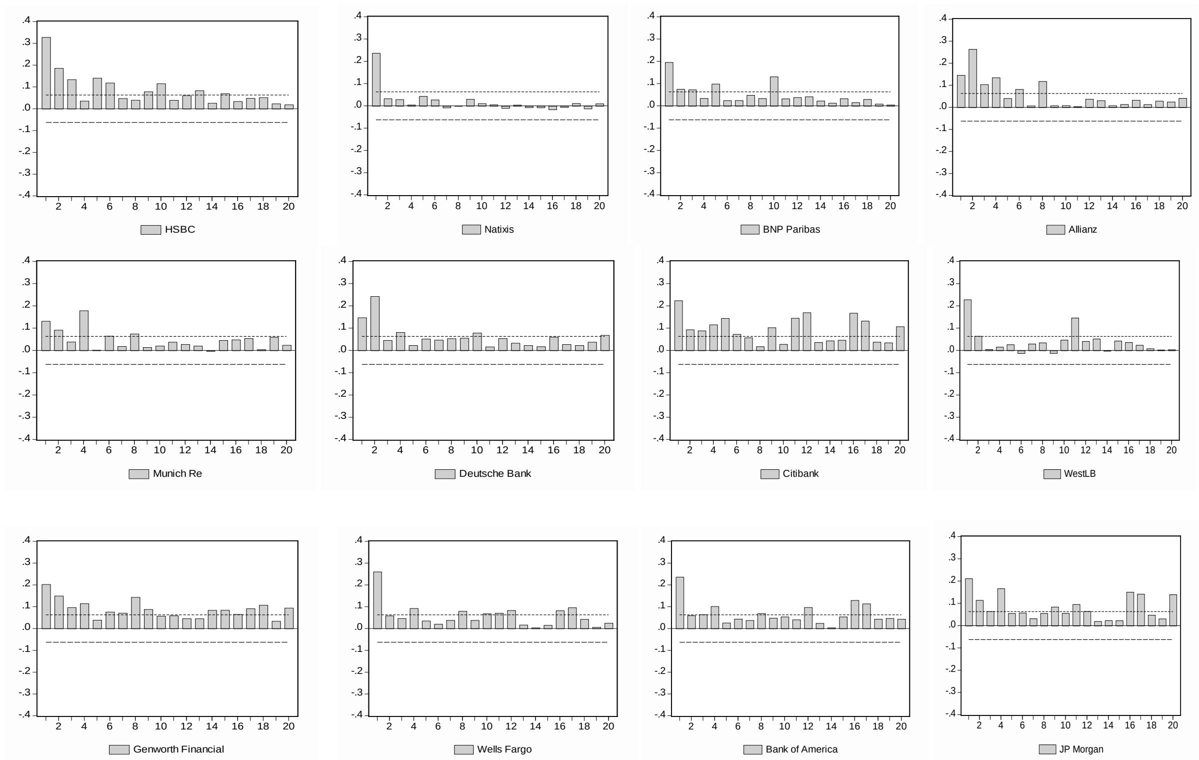




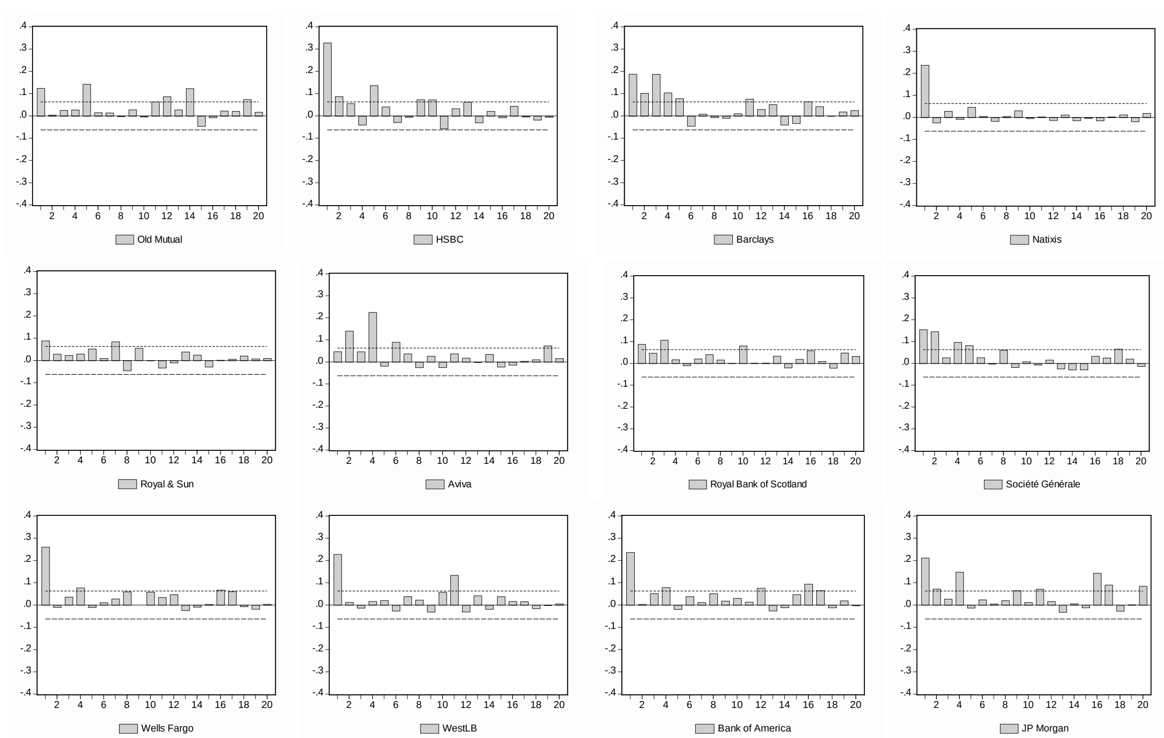
Appendix 1.c: US and Europe selected financial institutions CDS returns (31/12/2004 – 13/11/2008)



Appendix 1.d: selected US and Europe financial institutions CDS squared returns autocorrelation functions



Selected US and Europe financial institutions CDS squared returns partial autocorrelation functions



Appendix 2.a: Multivariate DCC-GARCH models estimates

	Banks					Insurance			
	US	Germany	France	UK	Spain	US	UK	Germany	France
ω_1	0.0002* (0.0001)	0.0004* (0.0002)	0.0003* (0.0002)	0.0004* (0.0002)	0.00017* (0.0001)	0.0001 (0.0001)	0.0009* (0.0002)	0.0002* (0.0001)	0.0003** (0.0002)
ω_2	0.0002 (0.0605)	0.0004 (0.06)	0.0005 (0.0409)	0.0004 (0.0448)	0.0002 (0.05)	0.0002 (0.0456)	0.0002 (0.0838)	0.0001 (0.0601)	0.0003 (0.0594)
ω_3	0.0001 (0.063)	0.0003 (0.05)	0.0003 (0.0584)	0.0001 (0.0448)	0.001 (0.054)	0.0001 (0.0677)	0.0003 (0.1479)	0.0002 (0.043)	-
ω_4	0.0002 (0.0001)	0.0004* (0.0001)	0.0003 (0.0002)	0.0003 (0.0002)	-	0.0001 (0.0001)	0.0009* (0.0001)	-	-
ω_5	0.0005 (0.0473)	0.0012 (0.059)	-	-	-	-	-	-	-
α_1	0.208* (0.052)	0.118* (0.049)	0.174** (0.095)	0.166* (0.038)	0.246* (0.0001)	0.214* (0.069)	0.389* (0.066)	0.237* (0.00004)	0.276* (0.105)
α_2	0.184* (0.0001)	0.221* (0.0001)	0.203* (0.082)	0.175* (0.055)	0.195* (0.038)	0.247* (0.063)	0.309* (0.054)	0.197* (0.054)	0.168* (0.0002)
α_3	0.147* (0.04)	0.15* (0.045)	0.324* (0.0001)	0.197* (0.00007)	0.108* (0.041)	0.16* (0.00005)	0.354* (0.0001)	0.208* (0.039)	-
α_4	0.233* (0.046)	0.205* (0.043)	0.191* (0.052)	0.167* (0.039)	-	0.151* (0.042)	0.158* (0.076)	-	-
α_5	0.565* (0.00004)	0.097* (0.0002)	-	-	-	-	-	-	-
β_1	0.771* (0.045)	0.807* (0.045)	0.764* (0.067)	0.791* (0.039)	0.746* (0.001)	0.771* (0.052)	0.294* (0.057)	0.747* (0.0001)	0.671* (0.046)
β_2	0.797* (0.035)	0.743* (0.055)	0.711* (0.0001)	0.749* (0.00009)	0.771* (0.065)	0.743* (0.00005)	0.688* (0.0004)	0.795* (0.063)	0.727* (0.084)
β_3	0.832* (0.0001)	0.795* (0.002)	0.66* (0.059)	0.799* (0.033)	0.696* (0.179)	0.83* (0.063)	0.608* (0.06)	0.787* (0.041)	-
β_4	0.745* (0.17)	0.712* (0.078)	0.77* (0.053)	0.793* (0.036)	-	0.83* (0.054)	0.622* (0.147)	-	-
β_5	0.414* (0.086)	0.71* (0.219)	-	-	-	-	-	-	-
θ_1	0.067* (0.009)	0.151* (0.002)	0.066* (0.025)	0.064* (0.009)	0.052* (0.009)	0.013* (0.006)	0.162* (0.012)	0.06* (0.011)	0.081* (0.008)
θ_2	0.887* (0.022)	0.523* (0.007)	0.873* (0.067)	0.901* (0.018)	0.94* (0.011)	0.98* (0.016)	0.419* (0.029)	0.895* (0.03)	0.85* (0.024)

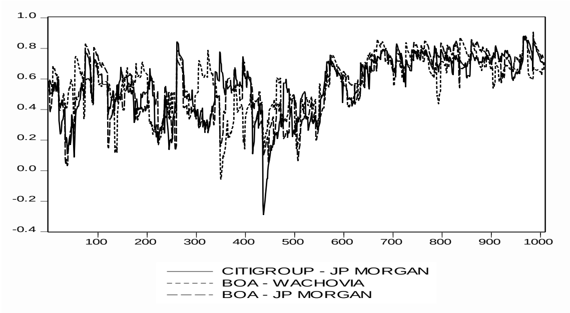
* denotes significance at the 5% level. ** denotes significance at the 10% level. Numbers in parentheses are robust standard errors.

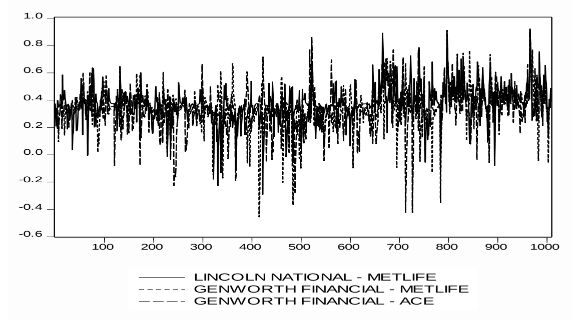
Table 1: Multivariate DCC-GARCH estimation results

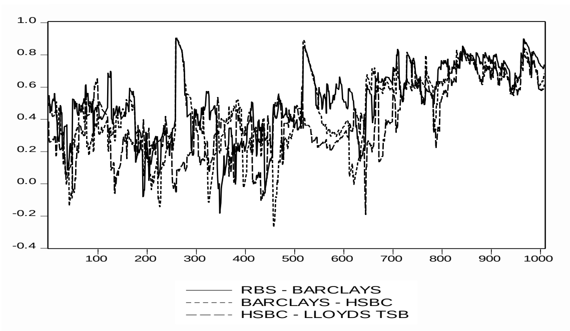
DCC-GARCH : Constant correlation test	test statistic	p-value
Banks		
US	0.145	0.000
Germany	0.218	0.001
France	0.072	0.000
UK	0.152	0.000
Spain	0.101	0.000
Insurance		
US	0.215	0.001
Germany	0.098	0.000
France	0.044	0.000
UK	0.095	0.000

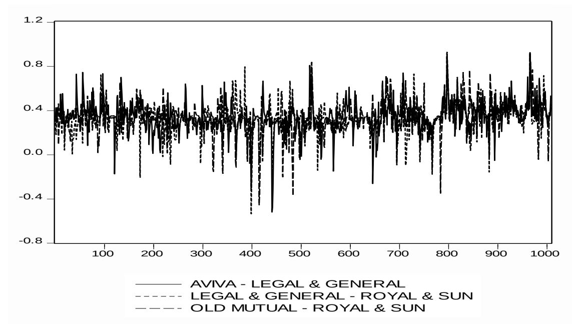
Table 2: Constant Correlation test results

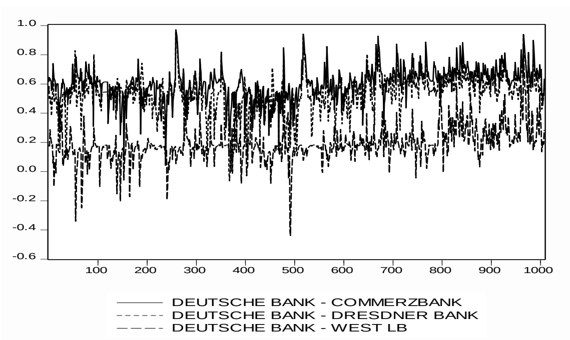
Appendix 2.b: DCC estimates – Selected pair-wise correlations

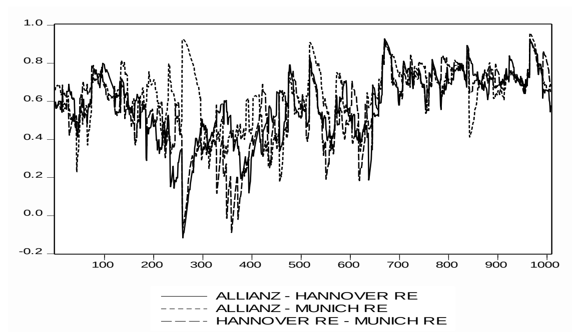


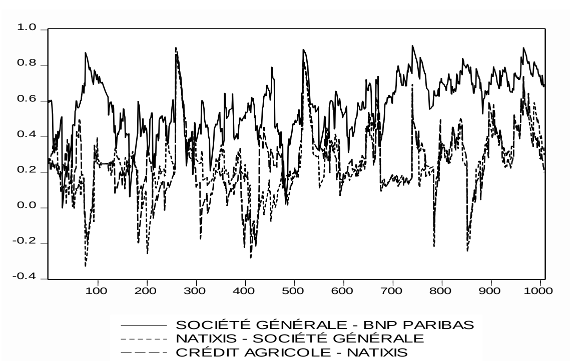


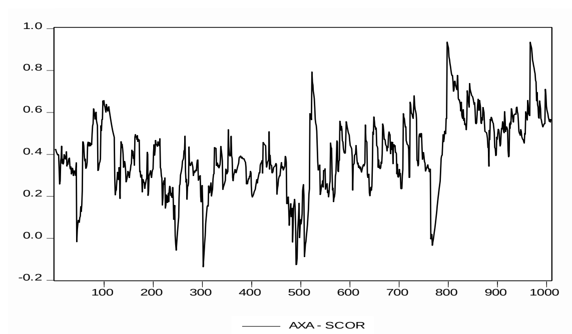


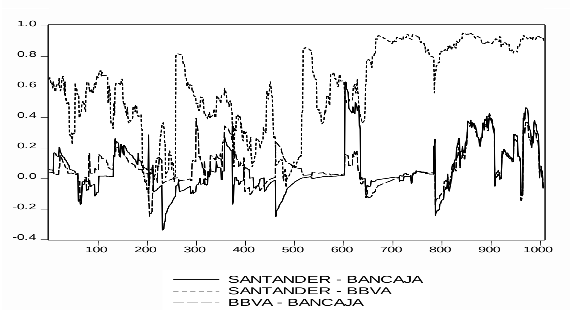












Appendix 2.c: Monte Carlo simulations results

	Number of negative (co-)exceedances						Number of positive (co-)exceedances					
Low Kurtosis Scenario	0	1	2	3	4	5	0	1	2	3	4	5
Actual	**887**	**69**	**19**	**7**	**8**	**19**	**884**	**71**	**16**	**15**	**8**	**15**
Multivariate Normal distribution												
Simulated Mean	868	79	31	17	10	5	868	79	31	16	10	5
Standard Deviation	6.36	8.35	4.92	3.59	2.75	2.06	6.4	8.31	4.99	3.56	2.73	2.08
Min	845	49	15	5	1	0	845	47	14	6	2	0
Max	896	110	50	30	19	13	891	108	49	34	21	14
p-value	0.001	0.902	0.995	0.999	0.807	0.000	0.006	0.845	0.999	0.709	0.807	0.000
High Kurtosis Scenario												
Multivariate t-distribution (df=5)												
Simulated Mean	881	64	28	17	12	8	881	64	27	17	12	8
Standard Deviation	6.44	8.1	4.89	3.66	2.9	2.41	6.34	7.89	4.9	3.58	2.92	2.41
Min	860	37	11	6	3	0	857	36	14	5	2	0
Max	903	95	46	30	22	17	905	94	48	31	23	17
p-value	0.196	0.300	0.977	0.999	0.924	0.000	0.355	0.206	0.996	0.718	0.923	0.004
DCC GARCH- Normal distributed innovations												
Simulated Mean	862	86	32	16	9	4	861	86	32	16	9	4
Standard Deviation	9.44	11.58	5.61	3.71	2.94	2.53	9.65	11.92	5.72	3.71	2.91	2.53
Min	832	41	10	5	0	0	828	45	12	4	0	0
Max	912	126	49	29	22	18	905	129	54	30	22	18
p-value	0.007	0.941	0.989	0.998	0.649	0.000	0.016	0.912	1.000	0.684	0.670	0.002
DCC GARCH- t distributed innovations (df=5)												
Simulated Mean	852	99	31	16	8	2	852	99	31	16	8	2
Standard Deviation	22.8	26.7	9.89	5.34	6.09	3.86	22.8	26.79	9.75	5.3	5.98	3.86
Min	788	15	4	0	0	0	795	10	6	0	0	0
Max	933	191	70	35	33	27	933	180	69	36	30	27
p-value	0.081	0.873	0.904	0.964	0.501	0.009	0.097	0.851	0.957	0.607	0.499	0.022

Table 1: Monte Carlo simulation results for US Banks

	Number of negative (co-)exceedances					Number of positive (co-)exceedances				
Low Kurtosis Scenario	0	1	2	3	4	0	1	2	3	4
Actual	**864**	**102**	**31**	**8**	**4**	**873**	**95**	**22**	**11**	**8**
Multivariate Normal distribution										
Simulated Mean	855	116	29	9	1	855	116	29	9	1
Standard Deviation	5.09	8.32	4.29	2.58	1.09	5.08	8.31	4.17	2.5	1.06
Min	838	85	12	0	0	837	88	14	1	0
Max	875	146	43	20	6	874	145	46	20	7
p-value	0.026	0.848	0.996	0.136	0.001	0.000	0.999	0.511	0.507	0.000
High Kurtosis Scenario										
Multivariate t-distribution (df=4)										
Simulated Mean	873	89	30	13	4	873	89	30	13	4
Standard Deviation	5.74	8.67	4.46	2.97	1.9	5.71	8.56	4.55	3.07	1.92
Min	851	60	14	2	0	851	57	17	3	0
Max	896	120	48	25	12	894	119	49	29	13
p-value	0.957	0.071	0.469	0.962	0.653	0.552	0.242	0.976	0.752	0.057
DCC GARCH- Normal distributed innovations										
Simulated Mean	851	122	28	7	1	851	122	28	7	1
Standard Deviation	8.13	12.87	4.65	2.92	1.35	8.05	12.79	4.63	2.9	1.34
Min	822	60	9	0	0	824	51	12	0	0
Max	895	172	47	20	12	906	168	46	21	14
p-value	0.059	0.944	0.319	0.393	0.060	0.011	0.980	0.936	0.113	0.003
DCC GARCH- t distributed innovations (df=4)										
Simulated Mean	898	55	28	18	10	898	55	29	18	10
Standard Deviation	16.13	20.06	6.99	4.71	5.91	16.31	20.27	7.17	4.69	6.02
Min	841	9	6	0	0	843	9	6	0	0
Max	946	139	58	35	39	946	133	65	35	39
p-value	0.972	0.026	0.375	0.980	0.849	0.929	0.046	0.834	0.942	0.590

Table 2: Monte Carlo simulation results for US Insurance companies

	Number of negative (co-)exceedances					Number of positive (co-)exceedances				
Low Kurtosis Scenario	0	1	2	3	4	0	1	2	3	4
Actual	**880**	**88**	**19**	**10**	**12**	**874**	**94**	**18**	**18**	**5**
Multivariate Normal distribution										
Simulated Mean	863	104	30	10	3	863	104	30	10	3
Standard Deviation	5.38	8.45	4.41	2.75	1.54	5.46	8.65	4.44	2.7	1.51
Min	845	76	15	1	0	843	71	13	2	0
Max	884	134	47	21	11	882	138	44	20	11
p-value	0.001	0.973	0.996	0.588	0.000	0.027	0.877	0.998	0.007	0.115
High Kurtosis Scenario										
Multivariate t-distribution (df=4)										
Simulated Mean	879	81	29	14	6	879	81	30	14	6
Standard Deviation	5.79	8.59	4.64	3.15	2.12	5.73	8.4	4.61	3.2	2.15
Min	856	51	14	3	0	860	52	12	4	0
Max	900	113	48	25	15	899	109	50	28	15
p-value	0.450	0.233	0.994	0.918	0.006	0.829	0.075	0.997	0.123	0.690
DCC GARCH- Normal distributed innovations										
Simulated Mean	862	105	30	10	3	862	106	30	10	2
Standard Deviation	7.84	11.78	4.78	3.14	1.96	7.9	11.87	4.66	3.17	1.92
Min	839	60	15	0	0	836	68	13	1	0
Max	892	141	48	22	14	890	146	48	24	14
p-value	0.015	0.935	0.992	0.516	0.002	0.070	0.842	0.997	0.013	0.135
DCC GARCH- t distributed innovations (df=4)										
Simulated Mean	860	107	29	10	2	860	107	29	10	2
Standard Deviation	21.04	30.51	8.08	6.87	4.33	21.18	30.72	8.18	6.92	4.35
Min	807	16	2	0	0	808	14	3	0	0
Max	939	200	67	36	36	939	198	64	38	32
p-value	0.178	0.737	0.914	0.471	0.054	0.249	0.677	0.928	0.147	0.171

Table 3: Monte Carlo simulation results for UK Banks

	Number of negative (co-)exceedances					Number of positive (co-)exceedances				
Low Kurtosis Scenario	0	1	2	3	4	0	1	2	3	4
Actual	**850**	**123**	**27**	**9**	**0**	**870**	**102**	**19**	**8**	**10**
Multivariate Normal distribution										
Simulated Mean	849	125	28	6	1	849	125	28	6	1
Standard Deviation	5.18	8.69	4.22	2.3	1.01	5.16	8.69	4.19	2.3	0.97
Min	829	91	11	0	0	833	95	12	0	0
Max	868	157	45	16	6	868	152	44	17	6
p-value	0.447	0.598	0.630	0.167	1.000	0.000	0.997	0.990	0.292	0.000
High Kurtosis Scenario										
Multivariate t-distribution (df=4)										
Simulated Mean	867	98	31	11	3	867	97	31	11	3
Standard Deviation	5.68	8.86	4.52	2.82	1.66	5.62	8.67	4.51	2.87	1.66
Min	845	63	13	3	0	848	67	15	1	0
Max	888	132	47	23	10	888	126	52	22	11
p-value	0.999	0.002	0.814	0.799	1.000	0.316	0.315	0.998	0.888	0.001
DCC GARCH- Normal distributed innovations										
Simulated Mean	846	130	27	6	1	846	130	27	6	1
Standard Deviation	5.83	9.77	4.35	2.33	0.97	5.81	9.73	4.29	2.32	0.97
Min	824	94	12	0	0	827	95	10	0	0
Max	867	168	42	17	6	867	162	44	16	6
p-value	0.270	0.766	0.539	0.120	1.000	0.000	0.998	0.977	0.199	0.000
DCC GARCH- t distributed innovations (df=4)										
Simulated Mean	843	134	28	4	0	843	134	28	4	0
Standard Deviation	9.14	15.79	6.08	2.59	0.95	9.13	15.8	6.08	2.53	0.98
Min	819	75	11	0	0	818	71	7	0	0
Max	882	176	54	19	12	884	181	59	18	10
p-value	0.226	0.765	0.536	0.069	1.000	0.007	0.970	0.949	0.113	0.000

Table 4: Monte Carlo simulation results for UK Insurance companies

	Number of negative (co-)exceedances						Number of positive (co-)exceedances					
Low Kurtosis Scenario	0	1	2	3	4	5	0	1	2	3	4	5
Actual	**842**	**119**	**23**	**13**	**9**	**3**	**844**	**112**	**28**	**17**	**4**	**4**
Multivariate Normal distribution												
Simulated Mean	827	131	35	13	3	0	826	131	35	13	3	0
Standard Deviation	5.84	9.03	4.82	3.05	1.71	0.65	5.79	8.89	4.82	3.03	1.73	0.65
Min	808	98	19	4	0	0	806	95	18	3	0	0
Max	849	163	53	23	10	6	850	162	53	24	11	4
p-value	0.005	0.910	0.995	0.544	0.005	0.009	0.002	0.987	0.939	0.114	0.454	0.001
High Kurtosis Scenario												
Multivariate t-distribution (df=5)												
Simulated Mean	845	105	34	16	6	2	846	105	34	16	6	2
Standard Deviation	6.38	9.14	5.07	3.39	2.23	1.2	6.34	9.01	5.04	3.38	2.28	1.19
Min	820	76	16	5	0	0	824	70	19	5	0	0
Max	868	144	52	30	15	7	871	135	51	29	18	7
p-value	0.736	0.075	0.991	0.847	0.168	0.195	0.624	0.25	0.907	0.436	0.906	0.061
DCC GARCH- Normal-distributed innovations												
Simulated Mean	826	131	35	13	3	0	826	131	35	13	3	0
Standard Deviation	6.76	10.15	5.06	3.14	1.84	0.71	6.68	10.1	4.95	3.06	1.81	0.74
Min	803	97	18	2	0	0	805	96	18	4	0	0
Max	847	167	54	26	12	4	852	164	52	24	12	4
p-value	0.016	0.89	0.9958	0.482	0.007	0.014	0.005	0.98	0.933	0.107	0.447	0.004
DCC GARCH- t distributed innovations (df=5)												
Simulated Mean	825	132	37	12	3	0	825	132	37	12	3	0
Standard Deviation	11.15	16.18	5.93	3.94	2.23	0.83	11.31	16.3	5.78	3.93	2.24	0.87
Min	788	79	16	0	0	0	791	60	19	0	0	0
Max	867	193	59	28	16	7	878	190	59	26	15	8
p-value	0.073	0.802	0.991	0.389	0.022	0.030	0.056	0.900	0.943	0.115	0.360	0.013

Table 5: Monte Carlo simulation results for German Banks

	Number of negative (co-)exceedances				Number of positive (co-)exceedances			
Low Kurtosis Scenario	0	1	2	3	0	1	2	3
Actual	**923**	**40**	**25**	**21**	**917**	**48**	**27**	**17**
Multivariate Normal distribution								
Simulated Mean	903	69	25	11	903	70	25	11
Standard Deviation	4.38	7.2	3.97	2.67	4.42	7.25	3.92	2.67
Min	885	44	12	3	888	43	11	3
Max	919	99	41	22	921	95	42	21
p-value	0.000	1.000	0.532	0.001	0.001	0.999	0.330	0.027
High Kurtosis Scenario								
Multivariate t-distribution (df=3)								
Simulated Mean	914	53	25	17	914	53	25	17
Standard Deviation	4.44	7	4.04	2.97	4.51	7.07	4.06	3.04
Min	897	31	10	5	900	31	10	6
Max	929	81	39	28	929	78	40	29
p-value	0.029	0.977	0.517	0.098	0.311	0.79	0.315	0.533
DCC GARCH- Normal-distributed innovations								
Simulated Mean	900	75	25	10	900	75	25	10
Standard Deviation	7.55	11.9	4.59	4.1	7.5	11.83	4.61	4.1
Min	874	25	9	0	874	24	10	0
Max	936	118	41	32	934	118	41	33
p-value	0.004	0.997	0.498	0.012	0.020	0.987	0.334	0.060
DCC GARCH- t-distributed innovations (df=3)								
Simulated Mean	930	31	23	26	930	31	23	25
Standard Deviation	9.15	11.8	6.49	7.17	9	11.57	6.53	7.11
Min	882	6	3	0	880	5	6	0
Max	951	103	45	44	950	106	45	44
p-value	0.793	0.217	0.380	0.761	0.921	0.086	0.279	0.882

Table 6: Monte Carlo simulation results for German Insurance companies

	Number of negative (co-)exceedances					Number of positive (co-)exceedances				
Low Kurtosis Scenario	0	1	2	3	4	0	1	2	3	4
Actual	**865**	**108**	**18**	**12**	**6**	**873**	**91**	**29**	**9**	**7**
Multivariate Normal distribution										
Simulated Mean	855	116	29	9	1	855	116	29	9	1
Standard Deviation	5.09	8.32	4.29	2.58	1.09	5.08	8.31	4.17	2.5	1.06
Min	838	85	12	0	0	837	88	14	1	0
Max	875	146	43	20	6	874	145	46	20	7
p-value	0.026	0.848	0.996	0.136	0.001	0.000	0.999	0.511	0.507	0.000
High Kurtosis Scenario										
Multivariate t-distribution (df=4)										
Simulated Mean	871	91	30	13	4	871	91	30	13	4
Standard Deviation	5.6	8.54	4.43	3.01	1.75	5.62	8.55	4.48	3.02	1.78
Min	848	57	14	4	0	851	62	14	3	0
Max	893	125	49	24	10	891	122	48	24	11
p-value	0.893	0.030	0.999	0.682	0.133	0.415	0.541	0.601	0.935	0.056
DCC GARCH- Normal distributed innovations										
Simulated Mean	854	118	28	8	1	854	118	28	8	1
Standard Deviation	6.89	10.85	4.51	2.93	1.28	6.8	10.76	4.56	2.93	1.27
Min	827	79	12	0	0	833	81	12	0	0
Max	883	162	44	23	13	879	154	46	24	11
p-value	0.060	0.819	0.994	0.131	0.008	0.006	0.992	0.489	0.435	0.004
DCC GARCH- t distributed innovations (df=4)										
Simulated Mean	852	119	30	7	1	852	119	30	7	1
Standard Deviation	17.18	26.24	7.72	6.27	2.46	17.19	26.29	7.81	6.24	2.48
Min	811	24	4	0	0	812	24	5	0	0
Max	930	193	69	34	26	928	191	67	34	24
p-value	0.215	0.678	0.953	0.232	0.057	0.123	0.859	0.538	0.357	0.044

Table 7: Monte Carlo simulation results for French Banks

	Number of negative (co-)exceedances			Number of positive (co-)exceedances		
Low Kurtosis Scenario	0	1	2	0	1	2
Actual	**922**	**72**	**15**	**925**	**66**	**18**
Multivariate Normal distribution						
Simulated Mean	918	81	11	918	81	11
Standard Deviation	2.71	5.42	2.71	2.66	5.32	2.66
Min	909	60	2	909	60	2
Max	928	98	21	928	98	21
p-value	0.083	0.96	0.083	0.006	0.997	0.006
High Kurtosis Scenario						
Multivariate t-distribution (df=2)						
Simulated Mean	926	63	19	926	63	19
Standard Deviation	3.06	6.12	3.06	3.13	6.27	3.13
Min	916	40	9	916	42	9
Max	938	84	31	937	84	30
p-value	0.938	0.111	0.938	0.731	0.390	0.731
DCC GARCH- Normal-distributed innovations						
Simulated Mean	918	80	11	918	80	11
Standard Deviation	3.27	6.54	3.27	3.31	6.62	3.31
Min	909	56	2	909	54	2
Max	930	98	23	931	98	24
p-value	0.138	0.918	0.138	0.027	0.984	0.027
DCC GARCH- t-distributed innovations (df=2)						
Simulated Mean	933	50	26	933	50	26
Standard Deviation	8.99	17.97	8.99	9.01	18.02	9.01
Min	907	6	0	907	8	0
Max	955	102	48	954	102	47
p-value	0.887	0.134	0.887	0.819	0.208	0.819

Table 8: Monte Carlo simulation results for French Insurance companies

	Number of negative (co-)exceedances				Number of positive (co-)exceedances			
Low Kurtosis Scenario	0	1	2	3	0	1	2	3
Actual	**896**	**76**	**34**	**3**	**894**	**82**	**28**	**5**
Multivariate Normal distribution								
Simulated Mean	884	98	25	1	884	98	25	1
Standard Deviation	3.47	6.51	3.21	1.16	3.47	6.51	3.22	1.16
Min	872	74	14	0	873	75	11	0
Max	897	121	38	7	896	122	36	7
p-value	0.000	1.000	0.005	0.175	0.003	0.996	0.224	0.014
High Kurtosis Scenario								
Multivariate t-distribution (df=3)								
Simulated Mean	896	79	29	5	896	78	29	5
Standard Deviation	3.97	6.8	3.5	2.1	4.08	6.95	3.49	2.14
Min	881	56	15	0	881	51	19	0
Max	911	105	42	14	911	105	41	14
p-value	0.528	0.677	0.115	0.920	0.719	0.336	0.679	0.642
DCC GARCH- Normal-distributed innovations								
Simulated Mean	884	99	24	2	884	99	24	2
Standard Deviation	6.73	12.23	5.16	2.09	6.71	12.16	5.12	2.1
Min	860	60	3	0	863	51	7	0
Max	909	145	41	13	913	139	42	13
p-value	0.052	0.974	0.026	0.341	0.082	0.923	0.251	0.130
DCC GARCH- t-distributed innovations (df=3)								
Simulated Mean	893	82	32	2	893	82	32	2
Standard Deviation	11.4	21.11	9.29	3.18	11.31	20.99	9.29	3.15
Min	857	26	1	0	856	32	0	0
Max	934	151	50	32	929	153	51	28
p-value	0.476	0.526	0.518	0.314	0.539	0.428	0.710	0.171

Table 9: Monte Carlo simulation results for Spanish Banks