Insurance and Banking Interconnectedness in Europe: the Opinion of Equity Markets.

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Abstract

Conditional expected shortfalls calculated for European insurance companies and banks under stressed market conditions are shown to be of similar magnitudes. Measured at 95% and 99% stress levels, on data covering the period from 1995 to 2011, the tail losses of insurance undertakings and banks are indistinguishable. Granger-causality analysis on all pairs of banks and insurance companies included in the sample shows that banks and insurance companies have equal propensity to cause each others price movements. Even though the business model of insurance undertakings is different from the business model typically applied by banks, and even though insurance companies are not depending to a similar degree on short term funding as banks are, the empirical results indicate that the equity markets in Europe do not differentiate their trading of banks and insurance companies in periods of stress.

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1 Introduction

Insurance companies perform an important task in the economy by ensuring that economic agents can buy protection against risks that otherwise cannot be hedged. In this way they complement financial markets by making risk-hedging instruments available. A traditional insurance company will build its business model around the collection of premiums over time, from households and firms, and by the implementation of an appropriate asset allocation as a storage of wealth, whereby premiums and investment returns are accumulated and grown with the help of financial market instruments. The aim of such investment activities is to build an asset base that will enable the company to cover future insurance claims, that are uncertain in amount and timing. A traditional bank also serves a central role in the economy by providing credit intermediation for agents with lending and borrowing needs. Traditional banking operations reduce the search costs, and potentially creates better prised and organised markets for credit intermediation, to the benefit of agents with surplus and deficit cash positions. Economic agents can thus turn to the a bank to deposit funds and obtain loans, respectively, rather than searching for bilateral agreements in the markets.

These different roles played by insurance companies and banks in the economy naturally leads to differences in their balance sheet composition, and to differences in their risk profiles and potential business-cycle vulnerabilities. An insurance company can relatively freely determine its asset composition, and will inherently strive to minimise the shortfall risk stemming from states of the world where its assets do not provide adequate funding of the liabilities. Consequently, the insurance company balance sheet will typically show limited exposure to market risk. However, long-term market trends can adversely affect the solvency position of insurance companies: for example, a prolonged period of low interest rates will reduce (re)investment income on the asset side, and increase the present value of the liabilities. Also, structural changes in mortality rates, birth rates, crime rates, and natural disaster frequencies and severities, can erode the profitability of insurance companies on the longer time-horizon. Compared to balance sheet risks existing in traditional banking business, which comprise, among other things, an inherent duration mismatch between assets and liabilities, liquidity and credit risk, the insurance business seem to constitute a type of financial activity that is relatively safe and chiefly affected by long-term secular trends.

This is the conclusion reached when analysing and comparing the intrinsic and fundamental features of the banking and insurance businesses: by construction, banking carries an amount of systematic risk, while insurance business is more safe and not necessarily of systemic importance. Understandably, and rightly so, such views are advanced by insurance companies, insurance industry associations and think-tanks, when issues are discussed pertaining to whether insurance companies qualify as being Systemically Important Financial Institutions (SIFIs), and whether insurance and banking is interconnected.[1]

The current paper does not dispute this. Clearly, there is merit to the argument that insurance business is different from banking business. However, in the reality of today's economic setup, it is not the business model, in itself, that determine whether a given company is considered to be interconnected and systemically important for the stability of financial markets.

[1] See, for example, various publication from the Geneva Association (http://www.genevaassociation.org). To exemplify, Liedtke (2011) states: "Core insurance activities are not a source of threat to the financial and economic system. There are however two potentially systemically risky activities that require further assessment (derivatives speculation/financial guarantees and mis-managing short-term funding) as contained in an earlier report by the Geneva Association".

These issues are rather determined by the empirical behaviour of financial markets: If equity prices of insurance companies and banks move in lock-step in crisis situations, then banking and insurance are de-facto interconnected, and both would be of systemic relevance to regulators, since their equity capital would be equally eroded in such states of the world.

In the light of this reality the current paper sets out to analyse the degree of interconnectedness that exist between exchange traded European insurance and banking companies. This is done by two derived measures: the conditional tail dependance, and Granger-causality tests.

2 The Modeling Approach

To investigate the degree of interconnectedness that may exist between European insurance companies and banks, I rely on the frameworks and ideas presented by Acharya, Pedersen, Philippon and Richardson (2010), Xin, Zhou and Zhu (2010) and Adrian and Brunnermeier (2011). These papers outline measures of system risk that are quantified on the basis of the conditional expected shortfall of individual companies' equity distributions, where the conditioning information set is the evolution of a general market index. Within in this line of reasoning, a company is systemically important if it experiences large negative returns at the same time as the market as a whole is experiencing large price drops. Loosely speaking, the derived measures for systemic risk are then effectively a gauge for the degree of tail dependency between the general market movement and groups of individual companies.

As an extension of this frame of thought, I suggest to measure interconnectedness between companies, in the current case between banks and insurance undertakings, simply by the size of their conditional expected shortfall (CES), and by their ranking the in the distribution of conditional tail losses. In addition to the CES analysis, I also perform Granger-causality tests, as suggested by among others, Billio, Getmansky and Lo (2010), to identify any possible direction of the interconnectedness in pair of banks and insurance companies covered by the sampled data.[2]

2.1 Conditional Expected Shortfall

The used CES measure is defined in the following way: Let R_t^m denote the return of the chosen equity market index m at date t, and denote by R_t^i and by R_t^b the return of a particular insurance company $i \in \{1, 2, \ldots, I\}$, and the return of a particular bank $b \in \{1, 2, \ldots, B\}$, respectively. Superscripts i and b span the insurance companies and banks included in the analysis, with I and B being the total number of insurance companies and banks in the data sample. The conditional tail loss measure is then defined as:

$$CES^j \equiv \frac{1}{n} \sum_t^n \left(R_t^j | R_t^m < VaR_\alpha^m \right), \tag{1}$$

where VaR_α^m is the Value-at-Risk return of the market index measured at the α-level of significance; n denotes the number of days (observations) for which the return of the market index R^m is lower than the VaR^m, ie the number of observation that fall in the loss tail of R^m at the used level of significance; the superscript j refers to the individual companies where $j \in \{i, b\}$.

Based on this, interconnected insurance companies and banks, as judged by the equity markets, are defined by the set of companies fulfilling equation (2), where $f(\cdot)$ represents a function providing a relevant summary statistics,

[2] If tick-by-tick data sets were available, it would be equally interesting to extend this idea to approximate interconnectedness by a conditional draw-down measure, where the draw-down calculation would follow, for example, Sornette (2003) and the conditioning would be a well defined equity market index.

for example, the average, the minimum the maximum, the average of the five worst CESs, and so on.

$$f(CES^i) \approx f(CES^b) \quad \forall \{i, b\} \in \{\{1, 2, \ldots, I\}, \{1, 2, \ldots, B\}\}\,, \qquad (2)$$

It is of course possible to construct a portfolio of non-financial equities that fulfills Equation (2): a portfolio of industrials that have market factor loadings, in the sense of Ross (1976), comparable to firms included in the market index, would constitute such a portfolio. However, this does not necessarily mean that industrials are interconnected with bank and insurance companies. The premise for Equations (1) and (2), as a test for the degree of interconnectedness that exist between European banking and insurance sectors, is that: (a) it is commonly accepted that banks are systemically important, and exhibit close interconnectedness internally as a group[3]; (b) insurance companies and banks are subject to specific regulatory requirements, as well as to tough scrutiny at national and European levels by competent national supervisors, the European Banking Authority and the European Insurance and Occupational Pension Authority; (c) the business model applied by insurance companies are often highlighted as being particularly prudent and not subject to the same level of riskiness as banks, as outlined in Section 1. Since industrials do not fulfill premises (b) and (c), the, admittedly ad-hoc and loosely formulated requirement in Equation (2), is seen as applicable to insurance companies and banks alone, and not to industrials. In addition, it follows tautologically that most industrials will have CESs that are similar to, or worse, than banks - otherwise, the "Market index" concept would loose its meaning.

[3] As documented by, amongst others, the work of the Basel Committee on Banking Supervision and the Financial Stability Board.

2.2 Granger-causality

I follow Billio et al. (2010) and employ Granger-causality tests (Granger (1969)) to explore the direction of interconnectedness in all pairs of banks and insurance companies covered by the data sample. The test is implemented as described in Hamilton (1994) by estimating the unrestricted (3) and the restricted (4) regressions:

$$
\begin{aligned}
R^x_t &= k + \sum_{j=1}^{p} a_j * R^x_{t-j} + \sum_{j=1}^{p} b_j * R^y_{t-j} + u_t, &(3)\\
R^x_t &= k + \sum_{j=1}^{p} a_j * R^x_{t-j} + e_t, &(4)
\end{aligned}
$$

where $x = \{b\}$ and $y = \{i\}$ will test whether insurance Granger-cause banks, and where where $x = \{i\}$ and $y = \{b\}$, conversely, will test whether banks Granger-cause insurance. The corresponding F test is calculated by:

$$S = \frac{(e'e - u'u)/p}{u'u/(T - 2p - 1)} \quad \sim \quad F(p, T - 2p - 1), \tag{5}$$

with T being the number of observations. The lag length is determined by the $p = \{1, \ldots, 8\}$ that minimises the bic criterion:

$$bic = T * log\left(\frac{e'e}{T}\right) + k * log(T), \tag{6}$$

with k being the number of estimated parameters.

3 Related Literature

A number of recent papers have proposed alternative ways to define and quantify the concept interconnectedness, with applications primarily to the banking sector. The common denominator of these papers is that they rely, in one way or the other, on traditional statistical methods. Billio et al. (2010) put forth five measures to estimate the systemic risk in financial firms. These measures comprise correlations, cross-autocorrelations, principle component methods, regime-switching models and Granger causality tests. A variance decomposition methodology is proposed by Diebold and Yilmaz (2011) where the variance contributions from other variables in the VAR system are interpreted as the degree of connectedness. The authors propose different connectedness measures on this basis, and also allude to the possibility of relying on a factor VAR structure in the case where high-dimension systems are analysed. Network analysis, as presented and summarised by, among others, Adamic, Brunetti, Harris and Kirilenko (2011), Allen, Babus and Carletti (2010) and Bech and Atalay (2011), is also a line of thought that has gained traction in the finance literature over the past years, in the treatment and estimation of interconnectedness among financial intermediaries.

The purpose of the current paper is not to compare and contrast different measures of systemic risk or interconnectedness. Rather, the paper sets out to investigate the more narrowly defined topic of whether insurance and banking industries are interconnected. And, for this purpose, as mentioned above, I rely on the frameworks and ideas outlined by Acharya et al. (2010), Xin et al. (2010), and Adrian and Brunnermeier (2011), as well as traditional Granger-causality tests, as used by Billio et al. (2010).

4 Data

Daily equity market data are used in the CES analysis, and weekly return data are used in the Granger-causality test.[4] European insurance companies and banks are included in the data sample on the basis of two criteria: the company should (1) be a member of the EuroStoxx600 Insurance or Banking Index at the time when the data were collected, or otherwise be considered as an relevant sized company on the European market; (2) have equity prices available on a reasonable high frequency for the majority of days covered by the sampling window, which covers 1 January 1995 to 26 August 2011.[5] The resulting companies included in the analysis are shown in Table 1.

[...Table 1 around here...]

In the CES analysis it is necessary to identify the exact dates at which markets are deemed to be stressed. Two different indices are used for this purpose. One is the German equity market index, the DAX, and the other is a US market index, the Dow Jones industrial average. These two indices are hence used as the conditioning information set in the calculation of Equation (1). The DAX is included because it is a major European equity index, and therefore a good proxy of the general market movements in relation to the European insurance and banking sectors. However, one caveat pertaining to the DAX is that some of the individual companies included in the analysis are also members of the DAX universe.[6] It is therefore potentially possible, although highly unlikely, that spurious effects are induced into the analysis, of some of the individual companies that are included in the data sample, if

[4]Weekly data are used in the Granger-causality tests to optimise data availability on all dates of the data panel. Daily data for the CES analysis is used and here data coverage on the 'crisis days' is of importance.

[5]All data are downloaded from Bloomberg.

[6]This is the case for Allianz, Deutsche Bank, and Muenchener Rueckversicherung.

these are also members of the DAX index. To avoid this potential source of error, the CES results are also generated by using the DOW index. In this context it is worth noting that since the DOW is US based, its trading day only partly overlaps with the European trading day. As such, the results generated with the DOW index are likely to be more robust, compared to those generated by the DAX, since only truly 'world-wide' financial market down turns will be recorded.

5 Results

5.1 Conditional Expected Shortfall

Two sets of results are produced on the basis of the analysis framework outlined in Section 2. First, Table 2 shows CES summary statistics for the insurance companies and banks included in the sample. Second, Tables 3-6 displays individual company specific CES rankings.

[...Table 2 around here...]

Table 2 presents the results that emerge when applying equation (1) to the sampled data. Results are presented for the two market indices, that are used as conditioning information sets, the Dow Jones Industrial Average (DOW) and the German equity market index (DAX), as well as for five different levels of significance, with $\alpha = \{0.01, 0.02, 0.03, 0.04, 0.05\}$. In order to assess the fulfillment of Equation (2) a number of summary statistics are reported. No formal statistical testing is performed for the sample differences between insurance companies and banks: given that there are twenty one insurance companies and thirty one banks, such statistics would anyway have low power. Instead, conclusions are drawn on the basis of common sense and visual inspection of the results.[7] The produced summary statistics are the average, the minimum, and the maximum CES. In addition, averages are computed for ranked CESs, from worst to best, within each group of companies.

A casual look at the calculated differences between summary statistics for insurance and banks clearly indicates that there is no material economical difference between these two groups of financial firms. This is true across all produced summary statistics, and across all confidence levels, as well as for both of the used market indices. It is noted that conditional tail loss are smaller when using the DOW as a conditioning information set, as compared to the DAX. However, this result is consistent for both insurance companies and banks.

As shown in the first line of the two panels contained in Table 2, under the heading 'Average' for R^m =dow and R^m =DAX, respectively, the CES figures produced for the two groups of financial firms, insurance companies and banks, are very similar across the tested levels of significance. Differences in the magnitude of -0.02 to 0.07 are observed for the DOW, and differences between -0.37 and -0.57 are observed for the DAX. Note in this context that a negative difference means that the average CES for the group of insurance companies is lower than that of banks. Similar conclusions are reached for the other calculated summary statistics.

It could (perhaps) be argued, since the sample of banks is larger, measured by the total number of included firms, compared to the sample of

[7] As an statistical yard-stick, for the generated results when $\alpha = 0.01$ and R^m =DOW, a difference in the mean of the CES between insurance companies and banks, equal to 2.05, ie $\overline{CES}^i - \overline{CES}^b = 2.05$, would correspond to 95% level of confidence. In other words, if the mean differences between the CES of insurance and banking is roughly 2.00 of less, one can distinguish statistically the means of the two samples, at a 5% level of significance.

insurance companies[8], that the banking results are muted by a higher degree of 'portfolio' diversification effects, compared to the insurance results, and that this distorts the reported average CES figures. However, this is not the case. When looking at portfolio results including the same number of entities, the referred conclusion remain unchanged. Table 2 also shows the results for the composition of portfolios containing the five, ten and twenty worst CES^i and CES^b, and the average figures for these portfolios show patterns similar to that of the full samples. Naturally, the average CESs drop as the quality of the analysed portfolio is worsened, that is, the portfolio of the five worst performers is lower than the average of the twenty worst performers. But again, the differences between the average CES of insurance companies and banks are negligible, for all tested portfolios and confidence levels.

In summary, the results displayed in Table 2 strongly suggest that equity markets under stressed conditions do not distinguish between the trading of insurance companies and banks, despite the obvious business model and balance sheet compositions of these two groups of financial firms. It is therefore conjectured that when equity markets are stressed, the capacity to see nuances is lost, and it trades one group of 'financials' rather than trading 'insurance companies' and 'banks' separately. Consequently, seen through the lens of financial markets, insurance companies and banks are interconnected and thus equally systemically important.

As a supplement to this conclusion Tables 3 and 4 show the ranking of CES values calculated for the insurance companies included in the analysis. Similarly, Tables 5 and 6 show the CES ranking for the included banks. It is interesting to observe that there is consistency in the ranking of both

[8]The former containing thirty one entities and the latter twenty one entities.

insurance companies and banks across the conditioning information sets and across significance levels. For example, the composition of the group of the ten worst insurance companies, except for one or two companies, is stable with respect to the tested R^m and α values. A similar conclusion can be drawn for banks.

[...Tables 3, 4, 5, and 6 around here...]

5.2 Granger-Causality Analysis

The Granger-causality between all pairs of banks and insurance companies are tested at a 99% level of confidence. Results are presented in Table 7. It is observed that of the 651 possible pairs there are 55 instances of banks Granger-causing Insurance companies, 46 instances where insurance companies granger cause banks, and 5 instances of joint Granger-causality between banks and insurance companies. There seem to be a slightly higher relative propensity for insurance companies to Granger-cause banks, than the other way around. However, measured in terms of economic relevance, this relative difference seems to be insignificant.[9]

[...Table 7 around here...]

6 Conclusion

While the business models and the core functions performed by insurance companies and banks in the economy are very different, this paper concludes

[9] Qualitatively identical results are obtained when applying the Granger-causality tests to the full set of banks (46 entities) and insurance companies (29 entities) included in the respective STOXX indices for data covering 2000 to 2011. Here the same proportion of Granger-causality between all pairs of banks and insurance companies are found.

that according to the trading behaviour of European Equity markets, insurance companies and banks are tightly interconnected, and equally systemically important.

An empirical analysis is presented of the conditional expected shortfall (CES) of European insurance companies and banks. Daily equity return data covering the period from January 1995 to August 2011 form the basis of the analysis. Expected shortfalls are calculated for individual firms, conditional on the worst trading-day returns of the Dow Jones Industrial Average (DOW) and the German Equity Index (DAX). Summary statistics for different portfolio compositions of insurance companies and banks fail to document any material difference between the equity market trading of insurance companies and banks, when markets are under stress. The performed Granger-causality tests on all pairs of banks and insurance companies fail to detect any systematic structure of one particular group Granger-causing the other. One might have conjectured at the outset that there would be a greater propensity for banks to Granger-cause insurance company equity movements. However, this conjecture is not supported by the empirical results. In fact, measured at a 99% confidence level, there equally many instances of banks being Granger-caused by insurance comapnies, as there are instances of insurance companies being Granger-caused by banks.

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Tables

Table 1: Entities Included in the Analysis

Bloomberg Ticker	Name	Country	Market Cap (mill)	Number of Employees
Insurance				
AGN NA Equity	Aegon Nv	Netherlands	5204	30092
AGS BB Equity	Ageas	Belgium	3222	12000
ALV GY Equity	Allianz Se-Reg	Germany	28084	150170
AML LN Equity	Amlin Plc	Britain	1403	1249
AV/ LN Equity	Aviva Plc	Britain	7970	45341
CS FP Equity	Axa Sa	France	20047	102957
FSA IM Equity	Fondiaria-Sai Spa	Italy	604	7833
G IM Equity	Assicurazioni Generali	Italy	17608	85019
INGA NA Equity	Ing Groep Nv-Cva	Netherlands	17823	107305
JLT LN Equity	Jardine Lloyd Thompson Group	Britain	1384	6212
LGEN LN Equity	Legal & General Group Plc	Britain	5437	8662
MUV2 GY Equity	Muenchener Rueckver Ag-Reg	Germany	14595	47039
RSA LN Equity	Rsa Insurance Group Plc	Britain	3793	22078
SAMAS FH Equity	Sampo Oyj-A Shs	Finland	9738	6928
SCR FP Equity	Scor Se	France	2797	1822
SLHN VX Equity	Swiss Life Holding Ag-Reg	Switzerland	2915	7483
SREN VX Equity	Swiss Re Ag	Switzerland	14447	10448
STB NO Equity	Storebrand Asa	Norway	12188	2163
TOP DC Equity	Topdanmark A/S	Denmark	12609	2523
VIG AV Equity	Vienna Insurance Group Ag	Austria	3300	24968
ZURN VX Equity	Zurich Financial Services Ag	Switzerland	25522	54934

Bloomberg Ticker	Name	Country	Market Cap (mill)	Number of Employees
Banks				
ALPHA GA Equity	Alpha Bank A.E.	Greece	695	14673
BARC LN Equity	Barclays Plc	Britain	17873	146100
BCP PL Equity	Banco Comercial Portugues-R	Portugal	1319	21365
BES PL Equity	Banco Espirito Santo-Reg	Portugal	2197	9858
BNP FP Equity	Bnp Paribas	France	32331	205348
BPE IM Equity	Banca Popol Emilia Romagna	Italy	2012	11647
BPSO IM Equity	Banca Popolare Di Sondrio	Italy	1662	3014
CBK GY Equity	Commerzbank Ag	Germany	8688	58255
CRG IM Equity	Banca Carige Spa	Italy	2564	6177
CSGN VX Equity	Credit Suisse Group Ag-Reg	Switzerland	26473	50700
DANSKE DC Equity	Danske Bank A/S	Denmark	66433	21536
DBK GY Equity	Deutsche Bank Ag-Registered	Germany	22308	101694
DNBNOR NO Equity	Dnb Nor Asa	Norway	91783	13124
ETE GA Equity	National Bank Of Greece	Greece	2601	36588
GLE FP Equity	Societe Generale	France	13015	160704
HSBA LN Equity	Hsbc Holdings Plc	Britain	88135	302327
ISP IM Equity	Intesa Sanpaolo	Italy	17440	101169
KBC BB Equity	Kbc Groep Nv	Belgium	5111	52949
LLOY LN Equity	Lloyds Banking Group Plc	Britain	24014	103859
MB IM Equity	Mediobanca Spa	Italy	4917	2567
PMI IM Equity	Banca Popolare Di Milano	Italy	589	8570
POH1S FH Equity	Pohjola Bank Plc-A Shs	Finland	2366	3083
RBS LN Equity	Royal Bank Of Scotland Group	Britain	25716	148300
SEBA SS Equity	Skandinaviska Enskilda Ban-A	Sweden	78698	17576

Bloomberg Ticker	Name	Country	Market Cap (mill)	Number of Employees
SHBA SS Equity	Svenska Handelsbanken-A Shs	Sweden	100891	11078
STAN LN Equity	Standard Chartered Plc	Britain	30144	85231
SWEDA SS Equity	Swedbank Ab - A Shares	Sweden	81943	17008
SYDB DC Equity	Sydbank A/S	Denmark	6980	2274
TPEIR GA Equity	Piraeus Bank S.A.	Greece	560	13135
UBSN VX Equity	Ubs Ag-Reg	Switzerland	39393	65707
UCG IM Equity	Unicredit Spa	Italy	13621	160562

This table shows the insurance companies and banks included in the sample. Displayed Market Cap values and Number of Employees, are recorded as of end August 2011.

Table 2: Results - CES for Insurance and Banking

		R^m = DOW				
		α =0.01	α =0.02	α =0.03	α =0.04	α =0.05
Average	Insurance	-3.83	-3.17	-2.48	-2.17	-2.02
	Banking	-3.81	-3.21	-2.55	-2.19	-2.03
	Difference	-0.02	0.04	0.07	0.02	0.01
Minimum	Insurance	-6.99	-5.62	-4.20	-3.59	-3.37
	Banking	-6.18	-4.78	-3.91	-3.30	-2.99
	Difference	-0.81	-0.84	-0.28	-0.29	-0.38
Maximum	Insurance	-0.60	-0.68	-0.62	-0.62	-0.58
	Banking	-0.61	-0.64	-0.54	-0.57	-0.59
	Difference	0.01	-0.04	-0.08	-0.05	0.01
Average worst 20	Insurance	-3.99	-3.3	-2.58	-2.25	-2.09
	Banking	-4.62	-3.91	-3.13	-2.71	-2.47
	Difference	0.63	0.61	0.55	0.46	0.38
Average worst 10	Insurance	-5.19	-4.23	-3.24	-2.82	-2.64
	Banking	-5.25	-4.41	-3.54	-3.03	-2.76
	Difference	0.06	0.18	0.3	0.21	0.13
Average worst 5	Insurance	-5.88	-4.74	-3.60	-3.14	-2.97
	Banking	-5.63	-4.58	-3.74	-3.19	-2.90
	Difference	-0.26	-0.16	0.14	0.05	-0.07
		R^m = DAX				
		α =0.01	α =0.02	α =0.03	α =0.04	α =0.05
Average	Insurance	-5.59	-4.39	-3.76	-3.35	-3.11
	Banking	-5.02	-3.86	-3.32	-2.95	-2.75
	Difference	-0.57	-0.53	-0.44	-0.40	-0.37
Minimum	Insurance	-9.67	-7.55	-6.11	-5.25	-4.93
	Banking	-7.80	-6.36	-5.45	-4.88	-4.47
	Difference	-1.88	-1.19	-0.66	-0.37	-0.46
Maximum	Insurance	-1.37	-0.93	-0.82	-0.74	-0.67
	Banking	-1.55	-0.98	-0.81	-0.78	-0.67
	Difference	0.17	0.05	-0.01	0.03	0.00
Average worst 20	Insurance	-5.80	-4.56	-3.91	-3.48	-3.24
	Banking	-6.12	-4.74	-4.08	-3.60	-3.37
	Difference	0.32	0.18	0.18	0.12	0.13
Average worst 10	Insurance	-7.42	-5.97	-5.03	-4.48	-4.15
	Banking	-6.99	-5.49	-4.68	-4.14	-3.84
	Difference	-0.43	-0.48	-0.35	-0.35	-0.31
Average worst 5	Insurance	-8.13	-6.49	-5.48	-4.85	-4.53
	Banking	-7.44	-5.96	-5.04	-4.48	-4.15
	Difference	-0.69	-0.53	-0.43	-0.37	-0.38

This table shows summary statistics: average, minimum, maximum, and average CES for portfolios containing the 20, 10 and 5 worst entities ranked according to their individual CES figures. The CES is calculated according to Equation (1): $CES^j \equiv \frac{1}{n}\sum_t^n \left(R_t^j | R_t^m < VaR_\alpha\right)$, where VaR_α is the Value-at-Risk return of the market index measured at the α-level of significance; n denotes the number of days (observations) for which the return of the market index R^m is lower than the VaR, ie the number of observation that fall in the loss tail of R^m at the used level of significance; two market indices are used: DOW and DAX, and the superscript j refers to the individual companies where $j \in \{(i)nsurance, (b)anks\}$.

Table 3: Results - Insurance ranked by CES (1)

$\alpha = 0.01$			
$R^m = DOW$		$R^m = DAX$	
CES	Name	CES	Name
-6.99	Ing Groep Nv-Cva	-9.67	Ing Groep Nv-Cva
-6.15	Ageas	-7.94	Aegon Nv
-5.99	Aegon Nv	-7.80	Axa Sa
-5.38	Aviva Plc	-7.73	Allianz Se-Reg
-4.91	Storebrand Asa	-7.48	Ageas
-4.72	Axa Sa	-7.10	Zurich Financial Services Ag
-4.64	Legal & General Group Plc	-6.91	Swiss Re Ag
-4.42	Swiss Life Holding Ag-Reg	-6.84	Aviva Plc
-4.41	Swiss Re Ag	-6.39	Storebrand Asa
-4.32	Allianz Se-Reg	-6.33	Muenchener Rueckver Ag-Reg
-4.22	Zurich Financial Services Ag	-6.16	Swiss Life Holding Ag-Reg
-3.25	Fondiaria-Sai Spa	-5.96	Legal & General Group Plc
-3.18	Sampo Oyj-A Shs	-5.24	Rsa Insurance Group Plc
-3.06	Vienna Insurance Group Ag	-4.81	Scor Se
-2.87	Scor Se	-4.28	Assicurazioni Generali
-2.86	Muenchener Rueckver Ag-Reg	-3.67	Fondiaria-Sai Spa
-2.72	Rsa Insurance Group Plc	-3.64	Sampo Oyj-A Shs
-2.69	Assicurazioni Generali	-3.01	Topdanmark A/S
-1.72	Topdanmark A/S	-2.73	Vienna Insurance Group Ag
-1.36	Amlin Plc	-2.29	Amlin Plc
-0.60	Jardine Lloyd Thompson Group	-1.37	Jardine Lloyd Thompson Group

This table shows CES ranking, from worst to best, of the individual insurance companies included in the analysis. The CES is calculated according to Equation (1): $CES^j \equiv \frac{1}{n}\sum_t^n \left(R_t^j | R_t^m < VaR_\alpha\right)$, where VaR_α is the Value-at-Risk return of the market index measured at the α-level of significance; n denotes the number of days (observations) for which the return of the market index R^m is lower than the VaR, ie the number of observation that fall in the loss tail of R^m at the used level of significance; two market indices are used: DOW and DAX, and the superscript j refers to the individual companies where $j \in \{(i)nsurance\}$.

Table 4: Results - Insurance ranked by CES (2)

$\alpha = 0.05$			
$R^m = DOW$		$R^m = DAX$	
CES	Name	CES	Name
-3.37	Ing Groep Nv-Cva	-4.93	Ing Groep Nv-Cva
-3.27	Aegon Nv	-4.64	Allianz Se-Reg
-2.83	Axa Sa	-4.54	Aegon Nv
-2.72	Ageas	-4.49	Axa Sa
-2.67	Allianz Se-Reg	-4.03	Muenchener Rueckver Ag-Reg
-2.43	Aviva Plc	-3.99	Ageas
-2.36	Swiss Life Holding Ag-Reg	-3.89	Zurich Financial Services Ag
-2.35	Zurich Financial Services Ag	-3.80	Swiss Life Holding Ag-Reg
-2.20	Swiss Re Ag	-3.66	Aviva Plc
-2.16	Storebrand Asa	-3.55	Swiss Re Ag
-2.08	Muenchener Rueckver Ag-Reg	-3.45	Legal & General Group Plc
-1.98	Legal & General Group Plc	-3.25	Rsa Insurance Group Plc
-1.93	Rsa Insurance Group Plc	-3.13	Storebrand Asa
-1.67	Assicurazioni Generali	-2.58	Assicurazioni Generali
-1.66	Sampo Oyj-A Shs	-2.56	Scor Se
-1.59	Fondiaria-Sai Spa	-2.41	Fondiaria-Sai Spa
-1.53	Scor Se	-1.96	Sampo Oyj-A Shs
-1.28	Vienna Insurance Group Ag	-1.63	Vienna Insurance Group Ag
-1.11	Topdanmark A/S	-1.39	Topdanmark A/S
-0.60	Amlin Plc	-0.87	Amlin Plc
-0.58	Jardine Lloyd Thompson Group	-0.67	Jardine Lloyd Thompson Group

This table shows CES ranking, from worst to best, of the individual insurance companies included in the analysis. The CES is calculated according to Equation (1): $CES^j \equiv \frac{1}{n}\sum_t^n \left(R_t^j | R_t^m < VaR_\alpha\right)$, where VaR_α is the Value-at-Risk return of the market index measured at the α-level of significance; n denotes the number of days (observations) for which the return of the market index R^m is lower than the VaR, ie the number of observation that fall in the loss tail of R^m at the used level of significance; two market indices are used: DOW and DAX, and the superscript j refers to the individual companies where $j \in \{(i)nsurance\}$.

Table 5: Results - Banking Ranked by CES (1)

$\alpha = 0.01$			
$R^m = DOW$		$R^m = DAX$	
CES	Name	CES	Name
-6.18	Kbc Groep Nv	-7.80	Commerzbank Ag
-6.02	Commerzbank Ag	-7.56	Deutsche Bank Ag-Registered
-5.47	Deutsche Bank Ag-Registered	-7.45	Societe Generale
-5.39	Barclays Plc	-7.35	Barclays Plc
-5.09	Royal Bank Of Scotland Group	-7.03	Credit Suisse Group Ag-Reg
-4.96	Ubs Ag-Reg	-6.69	Bnp Paribas
-4.96	Credit Suisse Group Ag-Reg	-6.64	Kbc Groep Nv
-4.92	Intesa Sanpaolo	-6.55	Unicredit Spa
-4.86	Societe Generale	-6.55	Intesa Sanpaolo
-4.63	Standard Chartered Plc	-6.28	Dnb Nor Asa
-4.59	Skandinaviska Enskilda Ban-A	-6.17	Royal Bank Of Scotland Group
-4.34	Swedbank Ab - A Shares	-6.15	Ubs Ag-Reg
-4.34	Lloyds Banking Group Plc	-5.91	Skandinaviska Enskilda Ban-A
-4.13	Dnb Nor Asa	-5.63	Lloyds Banking Group Plc
-4.07	Unicredit Spa	-5.37	Standard Chartered Plc
-3.82	National Bank Of Greece	-4.97	Swedbank Ab - A Shares
-3.79	Hsbc Holdings Plc	-4.90	Hsbc Holdings Plc
-3.65	Bnp Paribas	-4.54	Svenska Handelsbanken-A Shs
-3.63	Banca Popolare Di Milano	-4.45	National Bank Of Greece
-3.49	Danske Bank A/S	-4.38	Danske Bank A/S
-3.28	Sydbank A/S	-4.18	Alpha Bank A.E.
-3.16	Alpha Bank A.E.	-3.91	Banca Popolare Di Milano
-2.90	Pohjola Bank Plc-A Shs	-3.78	Banco Comercial Portugues-R
-2.86	Svenska Handelsbanken-A Shs	-3.63	Mediobanca Spa
-2.80	Piraeus Bank S.A.	-3.48	Sydbank A/S
-2.34	Banco Comercial Portugues-R	-3.45	Piraeus Bank S.A.
-2.30	Mediobanca Spa	-2.76	Banco Espirito Santo-Reg
-2.14	Banco Espirito Santo-Reg	-2.50	Pohjola Bank Plc-A Shs
-1.71	Banca Carige Spa	-2.27	Banca Carige Spa
-1.55	Banca Popol Emilia Romagna	-1.75	Banca Popol Emilia Romagna
-0.61	Banca Popolare Di Sondrio	-1.55	Banca Popolare Di Sondrio

This table shows CES ranking, from worst to best, of the individual banks included in the analysis. The CES is calculated according to Equation (1): $CES^j \equiv \frac{1}{n}\sum_t^n \left(R_t^j | R_t^m < VaR_\alpha\right)$, where VaR_α is the Value-at-Risk return of the market index measured at the α-level of significance; n denotes the number of days (observations) for which the return of the market index R^m is lower than the VaR, ie the number of observation that fall in the loss tail of R^m at the used level of significance; two market indices are used: DOW and DAX, and the superscript j refers to the individual companies where $j \in \{(b)anks\}$.

Table 6: Results - Banking Ranked by CES (2)

$\alpha = 0.05$			
$R^m = DOW$		$R^m = DAX$	
CES	Name	CES	Name
-2.99	Deutsche Bank Ag-Registered	-4.47	Deutsche Bank Ag-Registered
-2.92	Credit Suisse Group Ag-Reg	-4.33	Commerzbank Ag
-2.88	Royal Bank Of Scotland Group	-4.15	Credit Suisse Group Ag-Reg
-2.88	Commerzbank Ag	-3.96	Societe Generale
-2.85	Kbc Groep Nv	-3.83	Barclays Plc
-2.78	Societe Generale	-3.66	Bnp Paribas
-2.63	Ubs Ag-Reg	-3.62	Intesa Sanpaolo
-2.61	Barclays Plc	-3.59	Royal Bank Of Scotland Group
-2.56	Standard Chartered Plc	-3.46	Ubs Ag-Reg
-2.53	Intesa Sanpaolo	-3.35	Skandinaviska Enskilda Ban-A
-2.51	Skandinaviska Enskilda Ban-A	-3.30	Unicredit Spa
-2.51	Unicredit Spa	-3.30	Lloyds Banking Group Plc
-2.46	Lloyds Banking Group Plc	-3.25	Kbc Groep Nv
-2.34	Bnp Paribas	-3.24	Standard Chartered Plc
-2.18	Hsbc Holdings Plc	-2.80	Dnb Nor Asa
-2.15	Swedbank Ab - A Shares	-2.77	Swedbank Ab - A Shares
-2.10	Banca Popolare Di Milano	-2.72	Hsbc Holdings Plc
-2.02	Dnb Nor Asa	-2.66	Banca Popolare Di Milano
-1.83	Mediobanca Spa	-2.54	Mediobanca Spa
-1.74	Danske Bank A/S	-2.45	National Bank Of Greece
-1.71	National Bank Of Greece	-2.25	Danske Bank A/S
-1.63	Svenska Handelsbanken-A Shs	-2.22	Alpha Bank A.E.
-1.42	Alpha Bank A.E.	-2.19	Svenska Handelsbanken-A Shs
-1.42	Banco Comercial Portugues-R	-2.03	Banco Comercial Portugues-R
-1.40	Piraeus Bank S.A.	-1.93	Piraeus Bank S.A.
-1.37	Sydbank A/S	-1.61	Banco Espirito Santo-Reg
-1.16	Banco Espirito Santo-Reg	-1.50	Pohjola Bank Plc-A Shs
-1.15	Pohjola Bank Plc-A Shs	-1.38	Sydbank A/S
-0.97	Banca Carige Spa	-1.14	Banca Carige Spa
-0.71	Banca Popol Emilia Romagna	-0.84	Banca Popol Emilia Romagna
-0.59	Banca Popolare Di Sondrio	-0.67	Banca Popolare Di Sondrio

This table shows CES ranking, from worst to best, of the individual banks included in the analysis. The CES is calculated according to Equation (1): $CES^j \equiv \frac{1}{n}\sum_t^n \left(R_t^j | R_t^m < VaR_\alpha\right)$, where VaR_α is the Value-at-Risk return of the market index measured at the α-level of significance; n denotes the number of days (observations) for which the return of the market index R^m is lower than the VaR, ie the number of observation that fall in the loss tail of R^m at the used level of significance; two market indices are used: DOW and DAX, and the superscript j refers to the individual companies where $j \in \{(b)anks\}$.

Table 7: Granger Causality between Banks and Insurance - 99% confidence level

Bank \ Insurance	Aegon	Ageas	Allianz	Amlin	Generali	Aviva	Axa	Fondiaria	ING	Jardine Lloyd	Legal & General	Muenchener Re	RSA Insurance	Sampo	Scor	Storebrand	Swiss Life Holding	Swiss Re	Topdanmark	Vienna Insurance	Zurich Fin.
Alpha Bank						⤴					⤴			↩		⤴					
Banca Carige																	⤴				
Banca Pop. Emi. Romagna		↩									⤴							⤴			
Banca Pop. Di Milano		↩⤴																			
Banca Pop. Di Sondrio																		⤴			
Banco Com. Portugues		⤴				⤴					⤴			⤴		⤴					
Banco Espirito Santo	↩	↩			↩			↩			↩						↩	↩			
Barclays		↩				⤴	↩				⤴							↩			
Bnp Paribas		↩														↩					
Commerzbank																				⤴	
Credit Suisse Group						⤴					⤴									↩	
Danske Bank		⤴				⤴															
Deutsche Bank						⤴					↩					↩					
Dnb Nor Asa						⤴			↩			↩		↩			↩	↩			
Hsbc Holdings																					
Intesa Sanpaolo																					
Kbc Groep		⤴				⤴	↩				⤴										
Lloyds Banking						⤴															
Mediobanca														⤴							
Nat. Bank of Greece		↩														⤴					
Piraeus Bank																⤴				⤴	
Pohjola Bank																		↩		⤴	
RBS		↩⤴														↩					
Skandinaviska Enskilda	↩	↩	⤴			↩⤴	⤴		↩		↩							↩			↩
Societe Generale							↩									↩					
Standard Chartered	⤴	⤴				⤴			⤴		⤴					⤴				↩	
Svenska Handelsbanken							↩										↩				
Swedbank	↩				↩						↩						↩	↩			↩
Sydbank	⤴	↩	⤴		⤴	⤴	⤴		↩				⤴	↩			⤴	↩⤴			⤴
UBS		⤴						⤴			⤴					⤴		⤴		↩⤴	
Unicredit						⤴		⤴													

This table shows the direction of Granger-causality between banks and insurance companies measured at a 99% level of confidence. The calculations follow the setup presented in section 2.2. The direction of granger-causality is indicated by arrows in the table: $\lefthookarrow\!\!\uparrow$ indicates that Granger-causality runs from a particular bank (left most column) to a particular insurance company (top row), while $\hookrightarrow$ indicate that Granger causality runs from a given insurance company (top row) to a given bank (left most column). It is seen, that in a few cases there is a joint effect where Granger-causality runs in both directions, as indicated by both arrows being printed in a given cell.