

Research Article

Insurance and Banking Interconnectedness in Europe: The Opinion of Equity Markets

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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 equity-return 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, the empirical results indicate that the financial equity markets in Europe do not differentiate their trading of banks and insurance companies in periods of stress.

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 priced and organised markets for credit intermediation, to the benefit of agents with surplus and deficit cash positions. Economic agents can thus turn to 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 lead to differences in their balance sheet compositions 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 its 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 investment assets 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.

The conclusion reached by analysing and comparing the intrinsic and fundamental features of the banking and insurance businesses is therefore that, by construction, banking business entails an amount of systematic risk, while insurance business is more safe. (See among others, publication from the Geneva Association (<http://www.genevaassociation.org/>), and for example, Liedtke [1] who 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)”.) The current paper does not dispute this conclusion, in principle. Clearly, there is merit to the argument that insurance business should be less risky compared to banking business. However, in the reality of today’s economic setup and the role played by fast pacing financial markets, it is not the business model, in itself, that determine whether a given company is considered to be risky, and of particular importance to the stability of financial markets. These issues are rather determined by the empirical behaviour of agents buying and selling financial instruments, if the 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 importance to regulatory bodies, since their equity capital would be equally eroded in such adverse 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 companies and banks. 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 et al. [2], Huang et al. [3], and Adrian and Brunnermeier [4]. 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 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 in distribution of conditional tail losses. In addition to the CES analysis, I also perform Granger-causality tests, as suggested by, among others, Billio et al. [5], to identify any possible direction of the interconnectedness in pairs of banks and insurance companies covered by the sampled data. (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, Didier [6] and the conditioning would be a well-defined equity market index).

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 $i \in \{1, 2, \dots, I\}$, and the return of a particular bank $b \in \{1, 2, \dots, B\}$, 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

$$CES^j \equiv \frac{1}{n} \sum_t^n (R_t^j | R_t^m < \text{VaR}_\alpha^m), \quad (1)$$

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 , that is, the number of observations that fall in the loss tail of R^m at the used level of significance; the superscript j refers to the individual companies where $j \in \{i, b\}$. (The degree of “market crisis” reflected in the calculations therefore depends on the chosen confidence interval for the market index. In this way, the “crisis” periods are defined objectively by the confidence level and data, and are not decided exogenously by a predefined set of calendar dates).

Based on this, interconnected insurance companies and banks, as judged by the equity markets, are defined by the set of companies fulfilling (2), where $f(\cdot)$ represents a function providing a relevant summary statistics, for example, the average, the minimum, the maximum, the average of the five worst CESs, and so on.

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

It is of course possible to construct a portfolio of non-financial equities that fulfills (2): a portfolio of industrials that have market factor loadings, in the sense of Ross [7], 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 (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 (As documented by, amongst others, the work of the Basel Committee on Banking Supervision and the Financial Stability Board.); (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 Pensions 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 (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 lose its meaning.

2.2. Granger-Causality. I follow Billio et al. [5] and employ Granger-causality tests [8] 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 [9] by estimating the unrestricted (3) and the restricted (4) regressions

$$R_t^x = k + \sum_{j=1}^p a_j * R_{t-j}^x + \sum_{j=1}^p b_j * R_{t-j}^y + u_t, \quad (3)$$

$$R_t^x = k + \sum_{j=1}^p a_j * R_{t-j}^x + e_t, \quad (4)$$

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

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

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

$$\text{Bic} = T * \log\left(\frac{e'e}{T}\right) + k * \log(T), \quad (6)$$

with k being the number of estimated parameters. Once the lag-length has been identified on the basis of the Bic criterion, for each data series, the unrestricted and restricted regressions shown in (3) and (4) are performed, and finally the F-test is calculated according to (5).

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.

[5] 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 [10] 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 et al. [11], Allen et al. [12], and Bech and Atalay [13], 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. [2], Huang et al. [3], and Adrian and Brunnermeier [4], as well as traditional Granger-causality tests, as used by Billio et al. [5].

4. Data

Daily equity market data are used in the CES analysis, and weekly return data are used in the Granger-causality test. (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 are used and here data coverage on the “crisis days” is of importance.) 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 from 1 January 1995 to 26 August 2011. (All data are downloaded from Bloomberg.) The resulting companies included in the analysis are shown in Table 1.

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 (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. (This is the case for Allianz, Deutsche Bank, and Muenchener Rueckversicherung.) It is therefore

TABLE 1: Entities included in the analysis.

Bloomberg ticker	Name	Country	Market cap (mill)	Number of employees
Insurance				
AGN NA Equity	Aegon Nv	The 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	The 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
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
SHBA SS Equity	Svenska Handelsbanken-A Shs	Sweden	100891	11078
STAN LN Equity	Standard Chartered Plc	Britain	30144	85231

TABLE 1: Continued.

Bloomberg ticker	Name	Country	Market cap (mill)	Number of employees
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.

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 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 “worldwide” 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, individual company specific CESs are generated.

Table 2 presents the results that emerge when applying (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 (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. (As a statistical yard-stick, for the generated results when $\alpha = 0.01$ and $R^m = \text{DOW}$, a difference in the mean of the CES between insurance companies and banks, equal to 2.05, that is, $\overline{\text{CES}}^i - \overline{\text{CES}}^b = 2.05$, 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 or less, one can distinguish statistically the means of the two samples, at a 5% level of significance). 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 $R^m = \text{DOW}$ and $R^m = \text{DAX}$, 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 -0.57 and -0.37 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 insurance companies (The former containing thirty one entities and the latter twenty one entities.), 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 CESⁱ 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 differences in business models and balance sheet compositions between these two groups of financial firms. It is therefore conjectured that when equity markets are stressed, the capacity to see nuances is lost, and

TABLE 2: Results—CES for insurance and banking.

		$R^m = \text{DOW}$				
		$\alpha = 0.01$	$\alpha = 0.02$	$\alpha = 0.03$	$\alpha = 0.04$	$\alpha = 0.05$
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
		$R^m = \text{DAX}$				
		$\alpha = 0.01$	$\alpha = 0.02$	$\alpha = 0.03$	$\alpha = 0.04$	$\alpha = 0.05$
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 (1): $CES^j \equiv (1/n) \sum_i^n (R_i^j | R_i^m < VaR_\alpha)$, 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_α , that is; the number of observations 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 $j \in \{(i)nsurance, (b)anks\}$.

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. (To support this conclusion the ranking of insurance companies and banks is made on the basis of CES values. It is observed that there is consistency in the

ranking of both insurance companies and banks across the conditioning information sets and across significance levels. These calculations are available upon request to the author).

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 3.

TABLE 3: Granger causality between banks and insurance—99% confidence level.

Bank \ insurance	Aegon	Ageas	Allianz	AmIn	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: ↑ indicates that Granger-causality runs from a particular bank (left most column) to a particular insurance company (top row), while → indicates 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.

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. (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).

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

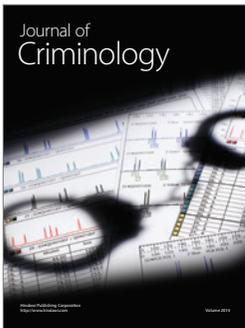
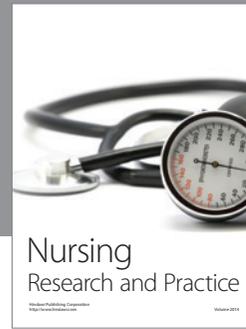
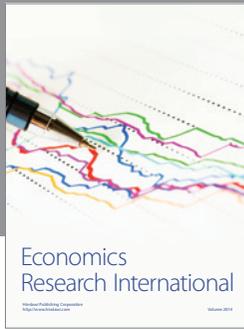
An empirical analysis is presented of the conditional expected shortfall (CES) of European insurance companies and banks. Daily equity return data covering the period from January 1995 to August 2011 form the basis of the analysis. Expected shortfalls are calculated for individual firms, conditional 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 are equally many instances of banks being Granger-caused by insurance companies, as there are instances of insurance companies being Granger-caused by banks.

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