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Systemic Risk in the European Insurance Sector*

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Abstract

This paper investigates the dynamic interdependencies between the European insurance sector and key financial markets—equity, bond, and banking—by extending the Generalized Forecast Error Variance Decomposition framework to a broad set of performance and risk indicators. Our empirical analysis, based on a comprehensive dataset spanning January 2000 to October 2024, shows that the insurance market is not a passive receiver of external shocks but an active conduit in the propagation of systemic risk, particularly during periods of financial stress such as the subprime crisis, the European sovereign debt crisis, and the COVID-19 pandemic. Significant heterogeneity is observed across subsectors, with diversified multiline insurers and reinsurance playing key roles in shock transmission. Moreover, our granular company-level analysis reveals clusters of systemically central insurance companies, underscoring the presence of a core group that consistently exhibits high interconnectivity and influence in risk propagation.

Keywords: insurance, systemic risk, GEFVD, CAViaR, CARES

1. Introduction

The insurance market is a crucial component in the architecture of financial markets. Beyond their traditional and key role in risk transfer and

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diversification, insurance companies operate as significant institutional investors, holding substantial portfolios of government and corporate bonds, equities, and alternative assets. In the aggregate, insurance companies in the European Union held approximately 10 trillion euro in assets at the end of 2024. The value of their portfolio holdings serves as the ultimate guarantee for their liabilities, which stood at approximately 8.5 trillion euro in the same period. In terms of market capitalization, the European insurance sector accounts approximately for 5% of the broad market cap, while the banking sector accounts for a further 10%. Given their size and interconnectedness, insurance companies are not only exposed to financial market fluctuations and systemic risks, but can also amplify or mitigate financial instability.¹

This paper quantifies the intricate interconnections between the insurance market and other financial markets from a systemic risk perspective. Specifically, we first examine the relationships between the insurance market as a whole and other key financial markets, such as the equity, bond, and banking ones. Next, we focus on the insurance market itself, identifying five key subsectors—insurance brokers, life and health, multiline, property and casualty, and reinsurance—and analyzing their interdependencies. Finally, we focus on the network of individual insurance companies. The empirical analysis builds on the classic framework of Diebold and Yilmaz (2008, 2014), and extends the investigation to a wide range of performance and risk measures. We leverage on this framework to identify channels of risk transmission, assess market resilience, and contribute to the ongoing debate on financial stability and regulation.

Extreme—but not uncommon—events such as the 2007–2009 subprime crisis, the European sovereign debt crisis, and the COVID-19 pandemic have demonstrated how vulnerabilities in one segment of the financial system can quickly propagate across multiple sectors. During these crises, insurance firms faced mounting pressures from declining asset values, liquidity strains, and increased claims, impacting their solvency and amplifying market stress. Moreover, the long duration of insurance liabilities makes these firms particularly sensitive to interest rate fluctuations, credit risk, and market volatility, further underscoring their systemic importance.

¹Data for the assets and liabilities of the European insurance companies is from the European Insurance and Occupational Pensions Authority (EIOPA), available at www.eiopa.europa.eu. Data for their market capitalization is from Bloomberg.

A striking example is the rapid and aggressive interest rate hikes implemented by central banks in response to surging inflation in 2022 and 2023, which contributed to the crisis of Eurovita, an Italian insurer. Although Eurovita was only a mid-sized financial institution, its distress had significant repercussions on the Italian insurance market and the banks distributing its life insurance products. The resulting financial turmoil was contained only after public authorities exerted moral suasion, reportedly urging the country’s five largest insurers and the distributing banks to coordinate efforts to prevent Eurovita’s disorderly collapse and mitigate investor losses. This intervention was driven by the imperative to preserve confidence in life insurance—one of the financial market’s most traditionally stable assets. The relatively small-scale shock caused by Eurovita’s distress highlights the significant risks posed by interconnectedness within the financial system. This underscores the importance of thoroughly assessing the systemic risk contributions of non-bank financial intermediaries, such as insurance companies, to ensure financial stability.

In this paper, we study the presence and propagation of spillovers by estimating the Generalized Forecast Error Variance Decomposition (GFEVD) model (Diebold and Yilmaz, 2014), which we extend to four indicators of risk and performance and apply to different degrees of granularity of the insurance market, and to interconnected markets, such as the equity, banking and bond market. The four indicators we consider are all based on equity prices and are stock returns and their volatility, the value-at-risk (VaR), and the expected shortfall (ES). For the volatility indicator, we estimate the conditional time-varying volatility of Bollerslev (1986). Also for the VaR and ES, we use conditional time-varying estimates following, respectively, the CAViaR model of Engle and Manganelli (2004) and the CARES model of Taylor (2007).

The GFEVD model is based on a vector autoregression model, and the construction of the h -step-ahead forecast error variance decomposition. The latter provides information about how much of the forecast error variance of each variable comes from shocks to itself, and from shocks to other variables. The GFVED model is a generalization of the forecast error variance decomposition model which allows for correlated shocks. By applying the GFEVD model to each of these four indicators, we provide a more comprehensive understanding of the dynamic interactions among the main financial markets and within the insurance market. Furthermore, these indicators are key components of either the current regulation, or the likely future changes

in regulation, of the insurance market.

We collect a comprehensive dataset to describe systemic risk and connectedness with a focus on the European insurance market. The sample goes from January 3, 2000 to October 22, 2024. First, we consider the Euro Stoxx Insurance Equity Index as proxy for the European insurance market. This is a capitalization-weighted index which includes insurance stocks from countries in the European Monetary Union (EMU). In addition, we use the Euro Stoxx Banks Index as representative of the Euro area banking sector, and the EMU Benchmark Government Bond 10-year Index as representative of the Eurozone government bond market. Moreover, to represent the overall European equity market, we rely on the Euro Stoxx Europe 600 ex Financials Index, which removes financial firms from the Stoxx Europe 600 Index. This exclusion prevents potential overlap with the indexes for the insurance and banking markets. We use these four indexes as proxies for the insurance, banking, bond, and equity markets, respectively. Second, we collect data for all publicly listed insurance companies in the Euro area, as well as geographically proximate regions, such as the UK, Switzerland and Turkey. We adopt the Bloomberg sectoral classification to assign insurance stocks to one of the following five subsectors: insurance brokers, life and health insurance, multiline, property and casualty, and reinsurance. We compute the daily log-return time series for each subsector as the average of the log-returns of the insurance companies within that subsector, weighted by market capitalization. From the log-return time series, we then obtain the time-varying conditional volatility, VaR, and ES of the five subsectors.

At the aggregate level, we find a strong comovement between the total spillover index and the insurance sector’s contribution to others across all four indicators. This result confirms the high interconnectedness of insurance companies with other markets. Furthermore, we find that all spillover indices increased markedly following the end of the 2001 recession, and have remained at structurally higher level since. Moreover, we find that, during the COVID-19 pandemic, the insurance sector’s contribution to systemic risk spiked sharply across all dimensions. While spillovers based on returns gradually declined after the pandemic, those derived from risk measures first declined, but then increased again as the ECB began raising interest rates in response to unexpectedly high inflation.

At the insurance subsector level, our results uncover significant heterogeneity. For instance, insurance brokers generally exhibit low “contribution to others,” meaning that while they are sensitive to shocks from other subsec-

tors, they do not transmit risk as strongly themselves. In contrast, multiline insurers, by virtue of their diversified business models, emerge as primary channels through which shocks are propagated. Life and health insurers and property and casualty insurers display moderate levels of interconnectedness, with both “to” and “from” contributions balancing out in a way that suggests mutual risk reinforcement. The reinsurance subsector, despite its risk-absorption function, is not immune; it plays a pivotal role during extreme events, as its contribution to overall spillovers rises significantly when market conditions deteriorate.

Next, we zoom in the insurance market with a granular analysis of interconnectedness at the individual stock level. By mapping the interconnections among individual insurance companies, we construct weighted and directed networks for each risk indicator. These networks reveal a core cluster of systemically important insurance firms that repeatedly emerge as central nodes across the log-return, volatility, VaR, and ES networks. Companies such as Aegon, Allianz, Generali, Zurich, Aviva, and Swiss Re are consistently identified as having high “contribution to others” scores. Their central positions imply that shocks affecting these firms are more likely to spread throughout the system. Additionally, the network topology uncovers both subsector and geographic clustering. For example, Turkish insurers tend to cluster together, suggesting that local market conditions or regulatory environments may lead to tighter risk interdependencies. Similarly, firms from certain regions (e.g., Slovenian companies) form isolated clusters, which might warrant focused regulatory attention. We extract from the four networks their respective central communities, by adopting an *ad hoc* algorithm. The intersection of the four central communities consists of only eight insurance companies, emphasizing their overall systemic relevance. Notably, the composition of this intersection is able to capture the list of the so-called Global Systemically Important Insurers (G-SIIs) provided by the Financial Stability Board from 2013 to 2016, when the designation of G-SIIs was officially suspended.

These results bear significant implications for both regulators and market participants. First, the identification of a core group of systemically important insurance companies suggests that supervisory frameworks should extend beyond traditional banking oversight. The increase of non-bank financial institutions (NBFI) in finance of the last twenty years is a strong motivation for increasing regulation and supervision attention to such institutions. For example, according to the latest Financial Stability Review by the ECB, 20% of Euro area banks’ funding is provided by the NBFI.

Regulators need to monitor not only aggregate market measures but also the detailed network structure within the insurance sector. Targeted stress tests that incorporate firm-level spillover metrics could help in preempting the amplification of shocks during periods of financial turmoil. Secondly, the varying spillover dynamics across different insurance subsectors suggest that a uniform regulatory framework may not be adequate. For instance, while multiline insurers act as major conduits of risk, the relatively muted interlinkages of insurance brokers imply that regulatory interventions might need to be calibrated differently across segments. In practice, policies that enhance transparency and encourage the sharing of risk-related information could mitigate the risk of contagion, particularly in times of heightened market stress. Finally, our integrated framework provides valuable guidance for risk managers. By simultaneously capturing the dynamics of performance (via log-returns) and tail risk (via VaR and ES), the proposed approach enables a more nuanced assessment of the vulnerabilities inherent in the insurance sector. This multi-dimensional view is particularly useful for designing stress-testing scenarios and for making informed decisions regarding capital allocation and risk mitigation.

This paper contributes to the literature on systemic risk. Diebold and Yilmaz (2008), Billio et al. (2012), Adrian and Brunnermeier (2016), Acharya et al. (2016), and Brownlees and Engle (2017) offer alternative theoretical frameworks to investigate and quantify systemic risk and market interconnectedness. Most of these studies focus on U.S. non-insurance financial institutions, although Billio et al. (2012) also considers U.S. insurance companies and finds that banks play a much more critical role in transmitting shocks. In addition, Engle et al. (2014) examines systemic risk among European financial companies using the SRISK model proposed by Brownlees and Engle (2017), revealing that the systemic risk of these firms is larger than that of their U.S. counterparts. Other contributions include Paulson and Rosen (2016), which focuses on the reduction of overall systemic risk through insurance companies' purchases of corporate bonds during periods of distress. Mühlnickel and Weiß (2015) investigates the impact of mergers between insurers on systemic risk, showing that larger firm sizes due to consolidation can lead to increased systemic risk. Bernal et al. (2014) employs the CoVAR measure introduced by Adrian and Brunnermeier (2016) to demonstrate that, while banks in the Eurozone are more systemically important than insurance companies, the opposite is true in the U.S. context. Borri and Di Giorgio (2022) and Bonaccolto et al. (2023) also use CoVAR

to estimate spillovers in the European sovereign debt and banking markets, respectively. Bierth et al. (2015) considers a large international sample, showing that the systemic risk contribution of insurance companies is generally modest but escalates substantially during financial crises. Foley-Fisher et al. (2020) theoretically examines self-fulfilling runs in the insurance sector. In contrast to these previous studies, our paper examines the European insurance market at different levels of granularity, measuring interconnectedness using a larger set of performance and risk indicators, thereby providing novel insights into the evolving role of insurance companies in the transmission of systemic risk.

The rest of the paper is organized as follows. Section 2.1 discusses the network model used to estimate the interconnection of financial intermediaries and the data. Section 3 presents the results of the empirical analysis. Section 4 concludes.

2. Methodology and data

This section first describes the model used to estimate spillovers in the insurance market. Next, it presents the data used in the empirical analysis.

We investigate spillovers by estimating the Generalized Forecast Error Variance Decomposition (GFEVD) model of Diebold and Yilmaz (2008, 2012, 2014). We extend the GFEVD model to four indicators of risk and performance, and apply it to different degrees of granularity of the insurance market, and to interconnected markets, such as the equity, banking and bond markets. The four indicators we consider are all based on equity prices and are the stock returns and their log-volatility, the value-at-risk (VaR), and the expected shortfall (ES). Specifically, volatility is estimated via the Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) model (Bollerslev, 1986), VaR via the Conditional AutoRegressive VaR (CAViaR) model (Engle and Manganelli, 2004), and ES via the Conditional AutoRegressive ES (CARES) model (Taylor, 2007). These four indicators offer a comprehensive framework to analyze the performance and risk in the insurance market. The methodological details regarding the construction of these indicators are provided in Section A of the Online Appendix.

2.1. Generalized Forecast Error Variance Decomposition

Let X_1, \dots, X_n be n real-valued variables, whose realizations at time t are the entries of the $n \times 1$ vector $\mathbf{x}_t = [x_{1,t} \cdots x_{n,t}]'$, with $t = 1, \dots, T$.

The Forecast Error Variance Decomposition (FEVD) builds on the following Vector AutoRegressive (VAR) model:

$$\mathbf{x}_t = \boldsymbol{\alpha} + \sum_{i=1}^p \boldsymbol{\beta}_i \mathbf{x}_{t-i} + \boldsymbol{\epsilon}_t, \quad (1)$$

where $\boldsymbol{\beta}_i$ is an $n \times n$ matrix of parameters that determine the VAR dynamics, $\boldsymbol{\alpha} = [\alpha_1 \cdots \alpha_n]'$ is an $n \times 1$ vector of intercepts, and $\boldsymbol{\epsilon}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma})$ is an $n \times 1$ vector of errors that follow a multivariate Gaussian distribution, such that $\mathbb{E}(\boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_s') = 0$ and $s \neq t$ (Lütkepohl, 2007; Pesaran and Shin, 1998).

The VAR model defined in Equation (1) has the following infinite moving average representation:

$$\mathbf{x}_t = \boldsymbol{\mu} + \sum_{i=0}^{\infty} \boldsymbol{\Phi}_i \boldsymbol{\epsilon}_{t-i}, \quad (2)$$

where $\boldsymbol{\mu}$ is the unconditional expected value of \mathbf{x}_t , and $\boldsymbol{\Phi}_i$ is obtained from the following recursions:

$$\boldsymbol{\Phi}_i = \boldsymbol{\beta}_1 \boldsymbol{\Phi}_{i-1} + \boldsymbol{\beta}_2 \boldsymbol{\Phi}_{i-2} + \cdots + \boldsymbol{\beta}_p \boldsymbol{\Phi}_{i-p}, \quad (3)$$

with $\boldsymbol{\Phi}_0$ being an $n \times n$ identity matrix, and $\boldsymbol{\Phi}_i = \mathbf{0}$ if $i < 0$ (Pesaran and Shin, 1998).²

In this paper, we use the Generalized FEVD (GFEVD), proposed by Pesaran and Shin (1998), that, in contrast to the FEVD resulting from orthogonalized impulse response functions, does not depend on the ordering of the variables in \mathbf{x}_t . In particular, given a forecast horizon h , we define the (i, j) -th entry of the $n \times n$ GFEVD matrix as follows:

$$\theta_{i,j}(h) = \frac{\sigma_{jj}^{-1} \sum_{l=0}^h (\mathbf{e}_i' \boldsymbol{\Phi}_l \boldsymbol{\Sigma} \mathbf{e}_j)^2}{\sum_{l=0}^h (\mathbf{e}_i' \boldsymbol{\Phi}_l \boldsymbol{\Sigma} \boldsymbol{\Phi}_l' \mathbf{e}_i)}, \quad (4)$$

where $[\sigma_{11} \cdots \sigma_{nn}] = \text{diag}(\boldsymbol{\Sigma})$, and \mathbf{e}_j is an $n \times 1$ selection vector whose entry j is equal to one, whereas its other elements are zeros (Diebold and Yilmaz, 2014).

$\theta_{i,j}(h)$ defined in Equation (4) is a measure of spillover from element j to element i . More precisely, it is the proportion of the h -step ahead

²In the empirical analysis, we determine the lag order p in Equation (1) by the Bayesian Information Criterion (BIC).

forecast error variance of variable i which is accounted for by the innovations in variable j , with $i, j = 1, \dots, n$. Note that $\sum_{j=1}^n \theta_{i,j}(h)$ is not necessarily equal to one for each row i (Lanne and Nyberg, 2016; Gross and Siklos, 2019; Bax et al., 2024). We then normalize $\theta_{i,j}(h)$ as follows:

$$\tilde{\theta}_{i,j}(h) = \frac{\theta_{i,j}(h)}{\sum_{j=1}^n \theta_{i,j}(h)} \cdot 100, \quad (5)$$

for $i = 1, \dots, n$. The coefficients $\tilde{\theta}_{i,j}$ are the central object of estimation and capture the spillovers in the system of equations in the VAR.

Following Diebold and Yilmaz (2014), Lanne and Nyberg (2016), Gross and Siklos (2019), and Bax et al. (2024), among others, we compute three different indicators from the $\tilde{\theta}_{i,j}(h)$ values. First, we refer to the contribution “from others” to node i :

$$\tilde{\theta}_{i \leftarrow \bullet}(h) = \sum_{\substack{j=1 \\ j \neq i}}^n \tilde{\theta}_{i,j}(h). \quad (6)$$

Second, we refer to the contribution “to others” of node j :

$$\tilde{\theta}_{\bullet \leftarrow j}(h) = \sum_{\substack{i=1 \\ i \neq j}}^n \tilde{\theta}_{i,j}(h). \quad (7)$$

Finally, we denote the “total” spillover index:

$$\tilde{\theta}(h) = \sum_{i=1}^n \sum_{\substack{j=1 \\ j \neq i}}^n \tilde{\theta}_{i,j}(h), \quad (8)$$

which captures the sum of all the spillovers across nodes, and thus is a measure of the interconnectedness of a market, or set of nodes, which we also refer to as a “system”.

We use the GFEVD model described above to study the presence and propagation of spillovers within three different systems. The first system includes the insurance, equity, banking and bond markets. The second system, which consists of five insurance subsectors (i.e., insurance brokers, life health, multiline, property and casualty, and reinsurance), allows the investigation of spillovers across the main subsectors of the insurance market. Because

of the relatively small number of variables in \mathbf{x}_t (4 and 5, respectively) in both the first and second system, we accurately estimate the parameters of the VAR model in Equation (1) using the Ordinary Least Squares (OLS) method.

In contrast, the number of estimates n significantly increases in the estimation of the third system, which is the system with the highest degree of granularity in our analysis. In this case, we investigate the network of individual insurance companies, and we address the curse of dimensionality using regularization methods applied to the GFEVD framework. These methods offer the benefit of balancing a slight increase in bias, with a significant reduction in variance (Bonaccolto et al., 2023). In the FEVD and GFEVD framework, Demirer et al. (2017) advocated the Least Absolute Shrinkage and Selection Operator (LASSO) introduced by Tibshirani (1996), and Gross and Siklos (2019), the Elastic Net (ELNET) introduced by Zou and Hastie (2005). We choose to apply LASSO, as it provides sparser solutions, allowing us to identify the most relevant links within the estimated network. However, as discussed by Fan and Li (2001), LASSO typically provides biased estimates, overshrinking the selected variables. We follow Bax et al. (2024), and address this issue by employing the post-LASSO approach described below.

In a first step of the post-LASSO method, we LASSO-select the relevant regressors of the j -th equation of the VAR model given in (1) by minimizing the following loss function:

$$\mathcal{L}_j = \sum_{t=p+1}^T \left(x_{j,t} - \alpha_j - \sum_{i=1}^p \beta_{i[j,:]} \mathbf{x}_{t-i} \right)^2 + \lambda_j \sum_{i=1}^p \|\beta_{i[j,:]}\|_1, \quad (9)$$

where $\beta_{i[j,:]}$ is the j -th row of β_i , $\|\beta_{i[j,:]}\|_1$ is the ℓ_1 -norm of $\beta_{i[j,:]}$, and $\lambda_j \geq 0$ is a tuning parameter that determines the sparsity of the solutions: the larger λ_j , the greater the number of coefficients set to zero (Hastie et al., 2009; Murphy, 2012), with $j = 1, \dots, n$.³

We select those regressors whose slope coefficients resulting from the minimization of the loss function in Equation (9) are different from zero. In a second step of the post-LASSO method, we estimate the slope coefficients of the LASSO-selected covariates using the standard OLS estimator, while the

³In our empirical analysis, the value of λ_j is determined using five-fold cross-validation.

slope coefficients of the regressors which are not LASSO-selected in the first step are set to zero.

2.2. Data

We collect a comprehensive dataset to investigate systemic risk and connectedness in the European insurance market. First, we use the Euro Stoxx Insurance Equity Index to proxy for the European insurance market. This is a capitalization-weighted index which includes insurance stocks from countries in the European Monetary Union (EMU). As of March 2025, the Euro Stoxx Insurance equity index has a total market capitalization of approximately 471 billion euro, about 5.6% of the market capitalization of the aggregate Euro Stoxx Equity Index. The median company in the index has a capitalization of approximately 12 billion euro, and Germany, France and Italy have the highest country weights, respectively equal to 56.5%, 18.6% and 10.2%. Moreover, we use the Euro Stoxx Banks Index, with a market capitalization of approximately 914 billion euro as of March 2025, as representative of the European banking market, and the EMU Benchmark Government Bond 10-year Index as representative of the European government bond market. Furthermore, we use the Stoxx Europe 600 ex Financials Equity Index, which removes financial firms from the Stoxx Europe 600 Index, to capture the residual part of the Euro equity market. This exclusion prevents a potential overlap with the indexes for the insurance and banking markets. We collect daily price data for these four indices from January 3, 2000 to October 22, 2024 and compute logged returns, which are then also used in the estimation of the conditional volatility, value-at-risk and expected shortfall.

Furthermore, we collect daily stock prices for all publicly listed insurance companies in the European Economic Area, as well as in geographically proximate countries such as the United Kingdom, Switzerland, and Turkey.⁴ From these prices, we compute daily logged returns. The resulting dataset is unbalanced, as some insurance companies entered the market after the beginning of our sample period (January 3, 2000), while others exited before its end (October 22, 2024).

We adopt the Bloomberg’s sectoral classification to assign insurance companies to one of the following five subsectors: insurance brokers, life and

⁴Specifically, we select our sample using the equity screening function in Bloomberg and applying filters to include all listed insurance companies in Eastern and Western Europe.

health insurance, multiline, property and casualty, and reinsurance. Table A.1 in Section B of the Online Appendix reports the complete list of the insurance companies included in our dataset along with their subsector classification. Figure A.1, also in Section B of the Online Appendix, plots the evolution in the number of insurance companies clustered by subsector for which daily logged returns are available. The figure indicates a general positive trend in the number of insurance companies. In particular, the number of companies in the insurance brokers subsector increases from 2 to 13, with a median value of 7. For the other subsectors, we observe the following initial and final number of insurance companies: 9 and 32 for life and health insurance; 20 and 47 for multiline; 8 and 37 for property and casualty; 4 and 10 for reinsurance.

Moreover, for each of the five subsectors of the insurance market, We compute the daily logged return as the weighted average of the logged returns of the insurance companies within that subsector. Specifically, the daily weight of each company within a given subsector is determined by its market capitalization on day t , divided by the total market capitalization of all companies in the same subsector on the same day. In case a given company presents missing values on a given day t , we set its daily logged return and weight equal to zero. From the logged return time series, we also estimate the time-varying conditional volatility, value-at-risk, and expected shortfall time series using the GARCH, CAViaR, and CARES models.

Table 1 reports descriptive statistics about the data used in the empirical analysis. Panel A refers to the main market indices, while Panel B to the insurance stock-level data. The summary statistics for the main market indices indicate differences in return characteristics across asset classes. The mean logged returns (in percentages) vary, with the Insurance Index (0.002) and Bank Index (-0.012) exhibiting lower values compared to Stocks ex-Financials (0.009) and Government Bonds (0.006). The standard deviation is highest for the banking (1.899) and insurance (1.731) equity indices, while government bonds exhibit the lowest volatility (0.370). The 5th and 95th percentiles highlight the extent of downside and upside risks, with the banking market displaying the widest dispersion (-2.927 to 2.777). For the insurance stock-level data in Panel B, the equally-weighted broad (All) mean return is high (0.012), and higher than the mean return on the main market indices. This indicates that small capitalization insurance stocks performed better than large capitalization insurance stocks, with the caveat that the Euro Stoxx Insurance Equity Index include only EMU stocks. For the insur-

ance sub-sectors, the highest return is for insurance brokers (0.047), followed by property and casualty. The insurance brokers subsector has also the highest volatility (1.882) among the five subsectors. Finally, for the insurance stock-level data, we also report the number of stocks in each sub-sector. The sub-sectors with the largest number of components, in our sample, are multiline (38) and property and casualty (26), while insurance brokers (7) and reinsurance (7) are the sub-sectors with the smallest number of components.

	Mean	Std	Q5	Q50	Q95	N	T
Panel A: main market indices							
Insurance Equity Index	0.002	1.731	-2.609	0.023	2.487	1	6472
Bank Equity Index	-0.012	1.899	-2.927	0.007	2.777	1	6472
Stocks ex Fin. Equity Index	0.009	1.119	-1.798	0.031	1.658	1	6472
Govt Bond Index	0.006	0.370	-0.596	0.007	0.560	1	6472
Panel B: insurance stock-level data							
Insurance Brokers	0.047	1.882	-2.319	0.000	2.493	7	6472
Life Health	0.010	1.528	-2.380	0.039	2.160	20	6472
Multiline	0.013	1.412	-2.097	0.039	1.961	38	6472
Property and Casualty	0.026	1.564	-2.295	0.053	2.175	26	6472
Reinsurance	0.012	1.626	-2.342	0.045	2.207	7	6472
All	0.012	2.375	-3.253	0.004	3.295	70	5584

Table (1) This table presents summary statistics for the logged return series (in percentages). Panel A refers to the main market indices: the equity indices for insurance, banking, non-financial stocks, and government bonds. Panel B refers to insurance stock-level data. Specifically, the table reports the mean, standard deviation, and the 5th, 50th, and 95th percentiles. For the insurance subsectors we consider value-weighted indices, while “All” refers to simple average across all the individual insurance stocks. The number of individual assets (N) and daily observations (T) are also reported. The sample period spans from January 3, 2000, to October 22, 2024. Data source: Datastream.

Figure 1 plots the daily log-return associated with the Euro Stoxx Insurance Equity Index (left subplot) and the cumulated returns of the main equity indices (right plot). The figure highlights two interesting stylized facts. First, the daily logged returns of the insurance equity index reveal heteroskedasticity and volatility clustering (Cont, 2001), and the frequency of large tail events, such as the COVID-19 pandemic, which produced the largest daily loss of -17.4% on March 12, 2020. This evidence motivates the construction, from the logged returns, of time-varying additional measures of risk, such as the conditional volatility, value-at-risk, and expected shortfall.

Second, the cumulated return series of the three main equity indices reveals the high co-movement, but also marked difference in performance over the sample considered. Moreover, the figure reveals the particularly high correlation, across these markets, of the largest tail events.

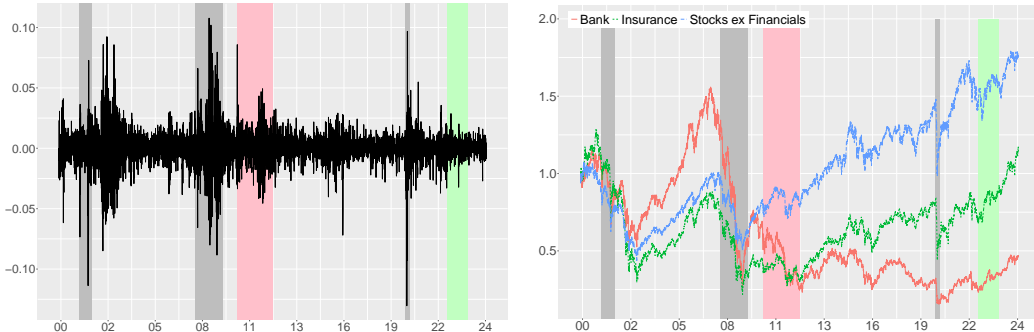


Figure (1) This figure plots the logged daily return time series for the Euro Stoxx Insurance equity index (left plot) and the cumulated return indices for the Euro Stoxx Insurance equity index (green line), together with the banking (red line) and equity ex-financial indices (blue line). The gray shaded bars correspond to NBER recessions, the pink shaded bar corresponds to the European sovereign debt crisis, from May 2010 to June 2012, and the green shaded bar refers to the ECB interest rate increase, from July 2022 to September 2023. The sample is from January 3, 2000 to October 22, 2024. Data are from Datastream.

3. Empirical analysis

This section presents the empirical results from the estimation of the GFEVD model. We first present the results for the insurance, banking, equity and government bond markets in Section 3.1. Section 3.2 considers spillovers across the insurance subsectors, while Section 3.3 contains the findings for the network of individual insurance companies. Finally, Section 3.4 presents additional results and extensions.

We estimate the model both unconditionally, using the full-sample, as well as conditionally, with dynamic estimates based on rolling windows. For the dynamic estimates, we consider a rolling window size of 250 daily observations (i.e., approximately one year) and a one-day forward step.

Following Gross and Siklos (2019) and Bax et al. (2024), we set the forecast horizon h in Equation (4) equal to 10, which is a reasonable choice from a risk management viewpoint (Diebold and Yilmaz, 2014). We determine the lag order p on the basis of the Bayesian Information Criterion (BIC)

computed on the underlying VAR model. The selected p values vary according to the system of interest and the performance or risk measure that is adopted to estimate the GFEVD model. Specifically, in the system comprising the insurance, banking, bond, and equity markets, the chosen values of p are 1 (GFEVD on log-return time series), 3 (conditional log-volatility), 1 (CAViaR), and 5 (CARES). In the case of the five insurance subsectors, the corresponding p values are 1, 1, 1, and 3, respectively. Finally, for individual insurance companies, p is always set to 1 across all estimations.

3.1. Insurance and other financial markets

In this section, we present the results obtained from the estimation of the GFEVD model at the most aggregated level, investigating spillovers across the insurance, banking, government bond, and equity markets. Specifically, we consider spillovers using the log-return, the conditional log-volatility, the CAViaR, and the CARES.

Figure 2 summarizes the results of the dynamic spillover estimates. It shows the evolution of the total spillover index (blue-dashed line, left vertical axis) across the insurance, banking, bond, and equity markets, for each of the four performance and risk indicators. In parallel, the figure plots the evolution of the insurance sector’s “contribution to others” index (red-solid line, right vertical axis), capturing the extent to which shocks originating in the insurance market spill over to the remaining markets. To support the interpretation, the figure includes vertical colored bands that highlight key economic episodes: gray bands correspond to NBER U.S. recession periods (specifically, the dot-com bubble, the subprime crisis, and the COVID-19 pandemic); the pink band marks the European sovereign debt crisis (May 2010 to June 2012); and the green band denotes the period of ECB monetary tightening (July 2022 to September 2023).

A first observation is the strong comovement between the total spillover index and the insurance sector’s contribution to others across all four indicators. The unconditional correlation coefficients are 0.90, 0.75, 0.81, and 0.92, respectively, pointing to a tight link between overall systemic risk and the insurance sector’s role in its propagation. Notably, all spillover measures tend to rise sharply during the major economic stress episodes highlighted in the figure, such as the NBER recessions.

Second, the figure shows that all spillover indices increased markedly following the end of the 2001 recession (associated with the dot-com bubble) and have remained at structurally higher levels since, with only a modest

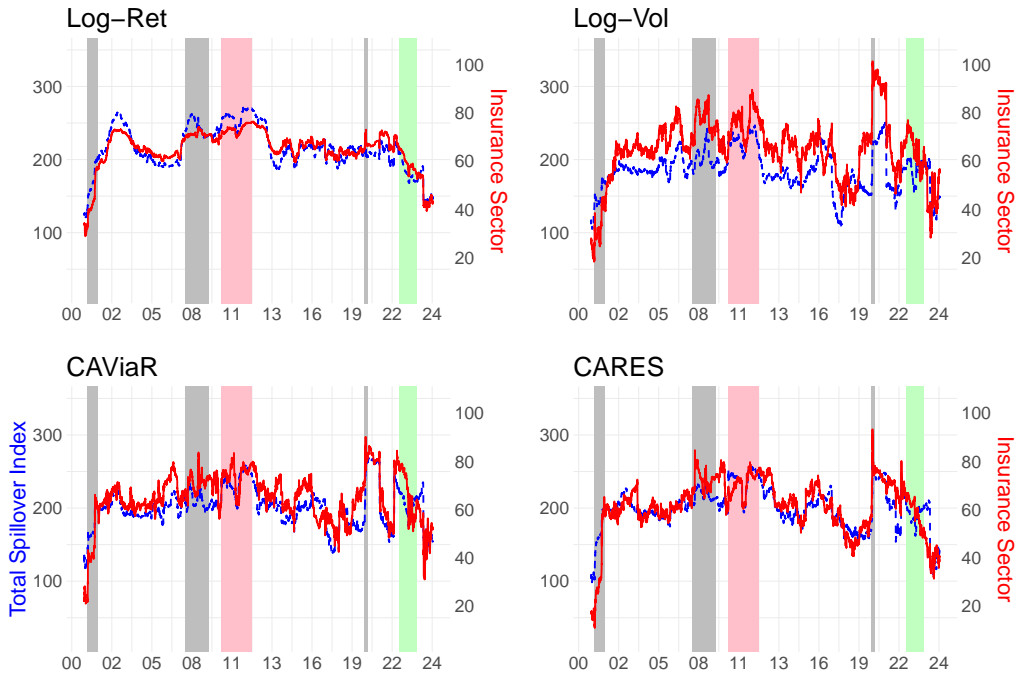


Figure (2) This figure plots the evolution of the contribution to others of the European insurance sector (red-solid line), as defined in Equation (7), and of the total spillover index (blue-dashed line), as defined in Equation (8), resulting from the estimation of the GFEVD model on the log-return (top-left panel), conditional log-volatility (top-right panel), CAViaR (bottom-left panel), and CARES (bottom-right panel) time series. The total spillover index is represented on the left vertical axis, while the contribution to others of the insurance sector is represented on the right vertical axis. The dynamic estimation is based on a 250-day rolling window and 1-day ahead forecast. The gray shaded bars correspond to NBER recessions, the pink shaded bar corresponds to the European sovereign debt crisis, from May 2010 to June 2012, and the green shaded bar refers to the ECB interest rate increase, from July 2022 to September 2023. The sample goes from January 3, 2000 to October 22, 2024.

decline toward the end of the sample. This suggests a long-term shift in the systemic interconnectedness of financial markets, which could be due to the relevant changes in technology, internet development and digitalization that made much more rapid the responses of agents and markets to new information.

A closer comparison between the total spillover index and the insurance sector spillover index reveals further insights. In relative terms, spillovers in returns remained lower for the insurance sector compared to the total

spillover index until the European sovereign debt crisis. Since then, however, the insurance sector’s spillovers have generally remained at higher levels. In contrast, for all risk indicators, the insurance sector index tends to exceed the total index throughout most of the sample, highlighting the sector’s relatively greater role in risk transmission. It is important to note, however, that in absolute terms, the total spillover index is always higher, as it captures contributions from all sectors, including insurance.

Toward the end of the sample, an interesting divergence emerges across the different spillover indicators. During the COVID-19 pandemic, the insurance sector’s contribution to systemic risk spiked sharply across all dimensions. While spillovers based on returns gradually declined after the crisis, those derived from risk measures—namely volatility, value-at-risk, and expected shortfall—exhibited a more complex and persistent pattern. Specifically, all three risk-based indicators show that both the total spillover index and the insurance sector index rose substantially during the pandemic, with the latter increasing relatively more. This elevated spillover from the insurance sector likely reflects the significant stress experienced by the industry, which, due to strong interconnections, transmitted financial instability to other markets.

Following the immediate pandemic shock, spillover indices for risk measures temporarily receded but surged again when the ECB began raising interest rates in response to unexpectedly high inflation. These rate hikes disproportionately affected the insurance sector, given its exposure to long-duration fixed-income assets, whose valuations declined as interest rates rose. As inflationary pressures later eased and market expectations shifted toward lower future rates, the spillover indices gradually declined, approaching levels observed at the start of the sample period.

These findings underscore the importance of looking beyond return-based measures when analyzing systemic risk. While return spillovers suggest a steady post-pandemic decline, risk-based indicators reveal a more nuanced and dynamic picture of financial contagion, highlighting the value of incorporating higher-order risk metrics in systemic risk assessments.

The evidence discussed above is summarized in Table 2, where we report the average values of the two indicators shown in Figure 2 across different periods of financial and economic stress. The table presents results for the different performance and risk indicators, namely log-returns (Panel A), log-volatility (Panel B), CAViaR (Panel C), and CARES (Panel D).

Several patterns emerge from the data. First, the total spillover index

Period	Start	End	Days	Total	Insurance
Panel A: Log-Return					
Dot-com bubble	01/03/2001	30/11/2001	197	171.36	44.83
Sub-prime crisis	03/12/2007	30/06/2009	412	245.35	71.17
EU Sovereign debt crisis	03/05/2010	01/06/2012	545	258.88	73.29
COVID-19	03/02/2020	30/04/2020	64	209.69	66.83
ECB interest rate increase	21/07/2022	21/09/2023	306	182.00	59.16
Normal times	03/01/2000	22/10/2024	4699	211.55	64.76
Panel B: Log-Volatility					
Dot-com bubble	01/03/2001	30/11/2001	197	151.07	33.45
Sub-prime crisis	03/12/2007	30/06/2009	412	203.05	76.89
EU Sovereign debt crisis	03/05/2010	01/06/2012	545	226.91	76.46
COVID-19	03/02/2020	30/04/2020	64	195.52	85.08
ECB interest rate increase	21/07/2022	21/09/2023	306	187.45	65.00
Normal times	03/01/2000	22/10/2024	4699	179.78	63.69
Panel C: CAViaR					
Dot-com bubble	01/03/2001	30/11/2001	197	174.29	45.78
Sub-prime crisis	03/12/2007	30/06/2009	412	211.43	70.87
EU Sovereign debt crisis	03/05/2010	01/06/2012	545	237.05	74.17
COVID-19	03/02/2020	30/04/2020	64	230.14	78.15
ECB interest rate increase	21/07/2022	21/09/2023	306	206.95	66.16
Normal times	03/01/2000	22/10/2024	4699	197.09	63.64
Panel D: CARES					
Dot-com bubble	01/03/2001	30/11/2001	197	163.92	35.70
Sub-prime crisis	03/12/2007	30/06/2009	412	218.67	72.27
EU Sovereign debt crisis	03/05/2010	01/06/2012	545	238.54	70.47
COVID-19	03/02/2020	30/04/2020	64	220.55	71.98
ECB interest rate increase	21/07/2022	21/09/2023	306	190.95	58.89
Normal times	03/01/2000	22/10/2024	4699	195.56	60.73

Table (2) This table reports summary statistics of systemic risk spillovers across sub-samples and different performance and risk indicators. Panel A to D refer to log-return, log-volatility, CAViaR and CARES, respectively. For each sub-sample, the table reports the start and end dates, the number of trading days within each period, the mean value of the total spillover index, and the mean contribution to others of the insurance sector. The dynamic GFEVD is estimated using a 250-day rolling window with a step of one day ahead.

exhibits significant increases during crisis periods relative to normal times across all four indicators. This confirms the heightened interconnectedness of financial markets during periods of systemic distress. Second, the insurance sector’s contribution to spillovers also rises substantially in these periods, particularly for risk-based indicators (Panels B to D). Notably, during the COVID-19 crisis, the insurance sector’s contribution to total spillovers reached its highest levels across all risk measures, underscoring the sector’s heightened vulnerability and systemic importance in times of severe financial turmoil.

The ECB’s interest rate hikes present a different dynamic. While the total spillover index increased compared to normal times, its rise was more contained than in previous crises, likely reflecting a more gradual market adjustment. However, the insurance sector’s contribution remained elevated, particularly for log-volatility and CAViaR, highlighting the sector’s sensitivity to interest rate changes due to its exposure to long-duration fixed-income assets. As financial conditions stabilized following the peak of inflationary pressures, spillover indices began to decline, nearing levels observed in normal times. Overall, these findings emphasize the need to analyze spillovers across multiple dimensions of risk beyond returns, as systemic stress can manifest more prominently through volatility, tail risk, and systemic fragility measures.

So far, we have compared the dynamics of the total spillover index and the impact of the insurance sector. We now directly contrast the systemic importance of the insurance sector with that of other financial markets—banking, bond, and equity markets—as illustrated in Figure 3. Once again, we observe pronounced spikes in systemic contributions during major financial crises, with these spikes becoming more pronounced as we shift from log-returns (top-left panel) to risk-based measures.

A key takeaway from the figure is that spillover measures based on log-returns exhibit more muted fluctuations compared to those based on risk indicators, underscoring the importance of looking beyond return-based spillovers to assess systemic risk. Across all periods, the insurance sector consistently maintains a high contribution to systemic risk, comparable to that of the banking and equity markets. The bond market, on the other hand, has a relatively lower systemic impact during stable periods but sees a sharp increase during financial crises, such as the US subprime crisis.

In the most recent period, characterized by the ECB’s interest rate hikes, we observe a divergence in systemic contributions across sectors. While the

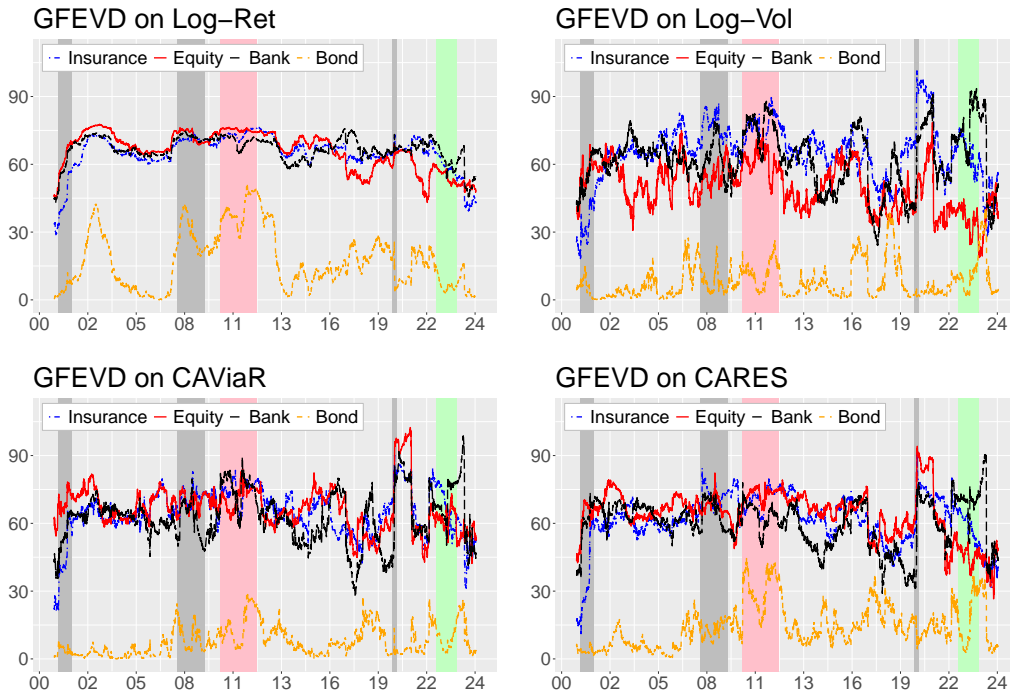


Figure (3) This figure plots the evolution of the spillover index for the broad equity, insurance, banking, and bond markets. The four panels correspond to estimation of the GFEVD model on logged returns (top left), conditional volatility (top right), CAViaR (bottom left) and CARES (bottom right). The dynamic estimation is based on a 250-day rolling window and 1-day ahead forecast. The gray shaded bars correspond to NBER recessions, the pink shaded bar corresponds to the European sovereign debt crisis, from May 2010 to June 2012, and the green shaded bar refers to the ECB interest rate increase, from July 2022 to September 2023. The sample goes from January 3, 2000 to October 22, 2024.

insurance, banking and government bond markets experienced a substantial increase in their contributions, reflecting the impact of tightening financial conditions, the contributions of the equity markets ex-financials declined. This divergence highlights sector-specific sensitivities to rising interest rates: while insurance companies, banks and bonds are directly affected by changes in monetary policy and yield curves, the rest of the equity market—despite being typically described as a long-duration asset—saw a relative decline in systemic impact. This further reinforces the importance of analyzing spillover dynamics across different market segments and risk dimensions.

3.2. The subsectors of the insurance market

In this section, we present the results from the estimation of the GFEVD model applied to the different insurance subsectors: insurance brokers, life and health, multiline, property and casualty, and reinsurance. For of each sector, we construct a value-weighted portfolio containing the insurance stocks using the sector-categorization from Bloomberg.

We start with the analysis of the results from the unconditional estimates, based on the full-sample, and summarized in Table 3. The four panels of the table refer to the spillovers in terms of returns (Panel A), conditional volatility (Panel B), CAViaR (Panel C) and CARES (Panel D).

A joint examination of the four spillover matrices in Table 3 shows distinct patterns in the transmission of systemic risk across insurance subsectors. A key finding is the dominant role of the multiline insurance subsector, which consistently generates high spillovers—measured by $\tilde{\theta}_{i,j}(h)$ —to all other subsectors except insurance brokers. Insurance brokers appear to be the most isolated segment, exhibiting low spillover values both in terms of contributions received and transmitted. Excluding brokers, the spillovers from multiline to other subsectors range from 22.24 (to property and casualty in Panel B) to 26.04 (to life and health in Panel C), significantly exceeding the spillovers originating from other subsectors.

The systemic relevance of the multiline subsector is further highlighted by its contributions to others, $\tilde{\theta}_{\bullet \leftarrow j}(h)$, where it is the only subsector consistently exceeding a value of 70. Notably, it reaches its peak at 81.22 in Panel C (CAViaR). The contrast between multiline and the other subsectors becomes even more pronounced when considering net contributions, calculated as the difference between contributions to and from others, $\tilde{\theta}_{\bullet \leftarrow j}(h) - \tilde{\theta}_{j \leftarrow \bullet}(h)$. While all other subsectors either exhibit negative values or remain close to zero, multiline consistently registers strongly positive net contributions, ranging from 11.97 in Panel A (log-returns) to 16.99 in Panel C (CAViaR). These results underscore the central role of the multiline subsector in the systemic risk dynamics of the insurance market.

Turning to the total spillover index, $\tilde{\theta}(h)$, the highest value of 278.74 is observed when estimating the GFEVD model on log-return time series (Panel A), indicating that return-based spillovers are more pronounced compared to risk-based measures.

After analyzing the unconditional estimates, we now focus on the dynamic estimates of the spillover for the five subsectors of the insurance market.

To	From					<i>Contr. from others</i>
	Ins.Bro.	Lif.Hea.	Mul.Lin.	Pro.Cas.	Reins.	
Panel A: Log-Return						
Ins.Bro.	79.23	4.39	7.24	4.13	5.01	<i>20.77</i>
Lif.Hea.	2.29	36.06	23.74	19.37	18.54	<i>63.94</i>
Mul.Lin.	3.13	21.32	32.73	20.48	22.34	<i>67.27</i>
Pro.Cas.	2.17	19.78	23.38	36.72	17.95	<i>63.28</i>
Reins.	2.47	18.60	24.89	17.52	36.52	<i>63.48</i>
<i>Contr. to others</i>	<i>10.07</i>	<i>64.09</i>	<i>79.24</i>	<i>61.50</i>	<i>63.84</i>	<i>Spillover Index:</i>
<i>Net Contribution</i>	<i>-10.70</i>	<i>0.15</i>	<i>11.97</i>	<i>-1.78</i>	<i>0.36</i>	<i>278.74</i>
Panel B: Log-Volatility						
Ins.Bro.	94.51	1.30	1.86	1.50	0.83	<i>5.49</i>
Lif.Hea.	0.59	42.43	24.04	16.81	16.13	<i>57.57</i>
Mul.Lin.	0.59	20.40	40.42	18.37	20.23	<i>59.58</i>
Pro.Cas.	0.53	16.92	22.24	45.27	15.04	<i>54.73</i>
Reins.	0.36	16.30	24.21	15.20	43.93	<i>56.07</i>
<i>Contr. to others</i>	<i>2.07</i>	<i>54.91</i>	<i>72.35</i>	<i>51.88</i>	<i>52.22</i>	<i>Spillover Index:</i>
<i>Net Contribution</i>	<i>-3.42</i>	<i>-2.66</i>	<i>12.77</i>	<i>-2.85</i>	<i>-3.85</i>	<i>233.44</i>
Panel C: CAViaR						
Ins.Bro.	87.44	2.88	4.51	2.61	2.56	<i>12.56</i>
Lif.Hea.	0.69	35.55	26.04	18.71	19.01	<i>64.45</i>
Mul.Lin.	0.76	20.98	35.77	20.26	22.23	<i>64.23</i>
Pro.Cas.	0.65	17.91	24.97	38.76	17.72	<i>61.24</i>
Reins.	0.37	17.91	25.70	17.45	38.57	<i>61.43</i>
<i>Contrib. to others</i>	<i>2.47</i>	<i>59.67</i>	<i>81.22</i>	<i>59.02</i>	<i>61.52</i>	<i>Spillover Index:</i>
<i>Net Impact</i>	<i>-10.09</i>	<i>-4.78</i>	<i>16.99</i>	<i>-2.22</i>	<i>0.09</i>	<i>263.90</i>
Panel C: CARES						
Ins.Bro.	84.24	3.16	4.28	5.51	2.81	<i>15.76</i>
Lif.Hea.	1.62	38.19	24.38	17.34	18.47	<i>61.81</i>
Mul.Lin.	1.92	20.24	36.17	20.28	21.39	<i>63.83</i>
Pro.Cas.	2.38	15.51	23.55	41.24	17.32	<i>58.76</i>
Reins.	1.43	17.16	24.82	18.38	38.21	<i>61.79</i>
<i>Contrib. to others</i>	<i>7.35</i>	<i>56.07</i>	<i>77.03</i>	<i>61.52</i>	<i>60.00</i>	<i>Spillover Index:</i>
<i>Net Impact</i>	<i>-8.41</i>	<i>-5.74</i>	<i>13.20</i>	<i>2.76</i>	<i>-1.79</i>	<i>261.95</i>

Table (3) This table summarizes the spillover matrix across the European insurance subsectors estimated by the GFEVD model. Furthermore, for each subsector, it reports the contribution to others, the contribution from others, and the net contribution. Finally, the table reports the total spillover index. Panel A to D refer to log-return, log-volatility, CAViaR and CARES, respectively. The model is estimated for the following subsectors: insurance brokers (Ins.Bro.), life health (Lif.Hea.), multiline (Mul.Lin.), property and casualty (Pro.Cas.), and reinsurance (Reins.). The sample goes from January 3, 2000 to October 22, 2024.

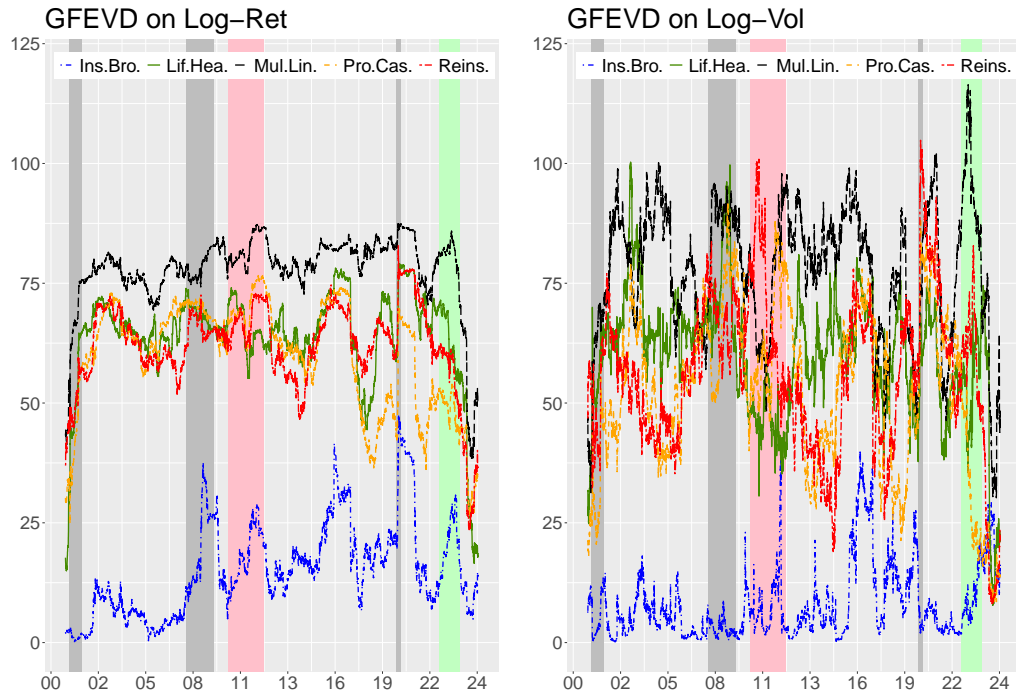


Figure (4) This figure plots the evolution of the impact (quantified by the contribution to others) of the insurance brokers (Ins.Bro.), life health (Lif.Hea.), multiline (Mul.Lin.), property and casualty (Pro.Cas.), and reinsurance (Reins.) subsectors, resulting from GFEVD estimated on the log-return (left panel) and conditional log-volatility (right panel) time series. The dynamic estimation is based on a 250-day rolling window and 1-day ahead forecast. The gray shaded bars correspond to NBER recessions, the pink shaded bar corresponds to the European sovereign debt crisis, from May 2010 to June 2012, and the green shaded bar refers to the ECB interest rate increase, from July 2022 to September 2023. The sample goes from January 3, 2000 to October 22, 2024.

Figure 4 summarizes the results, plotting the dynamic estimates for log-returns (left panel) and conditional log-volatilities (right panel).⁵

Figure 4 shows that the impacts of the subsectors are not constant over time, but are affected by the important events that occurred during the analyzed period, and that we cited above. The estimates obtained from log-returns appear more stable and smoothed, whereas those derived from log-volatilities are more volatile and exhibit significant spikes, which often

⁵The results obtained from the CAViaR and CARES time series are qualitatively similar and available upon request.

coincides with the relevant events highlighted with the colored bars.

The dynamic estimates confirm the earlier findings regarding the greater spillover impact of the multiline subsector (black line) of the insurance market. In fact, the contribution to others of the multiline subsector is persistently above the contribution to others of the remaining subsectors, and is the largest in the periods characterized by the US subprime financial crisis and the COVID-19 pandemic. Interestingly, during the COVID-19 pandemic related economic shock, the relative importance of the reinsurance sector increased sharply and, in the case of the spillovers in terms of log-volatility, reached a high-value above 100. Finally, the insurance brokers' sector contribution to risk is the lowest, although it also rises sharply in periods of financial and economic distress.

3.3. Insurance companies

In this section, we consider spillovers in the insurance market using a granular sample containing individual insurance stocks.

To address the issue of an unbalanced sample of insurance stocks, we implement a two-step strategy. First, we replace missing values with zeros, implicitly assuming that an insurance stock did not contribute to spillovers on those particular days. This assumption is consistent with the idea that if no data is available for a company on a given day, it had no significant market impact or did not trigger any notable events. Second, we filter time series by retaining only those in which nonzero log-returns exceed 30% of observations, corresponding to at least 1,941 trading days. This criterion ensures that the presence of zero log-returns does not unduly distort the results. A total of 70 companies meet this requirement, as indicated in Table 1 and by the value "1" in the fourth column of Table A.1 in B.

We first estimate the GFEVD model for the 70 companies we selected. Next, we investigate their interconnections and spillovers using a directed network. Note that, because of the large number of parameters of the model estimated on individual stocks, we estimate the VAR parameters using the post-LASSO regression method.

We construct four directed and weighted networks from the GFEVD estimation, each corresponding to a different variable: log-return (Figure 6), conditional log-volatility (Figure 7), CAViaR (Figure 8), and CARES (Figure 9). Each network consists of 70 nodes, representing the selected insurance companies, which are visually distinguished by color according to their

respective subsectors: insurance brokers (green), life and health insurers (orange), multiline insurers (blue), property and casualty insurers (red), and reinsurers (violet). The size of each node j is proportional to $\tilde{\theta}_{\bullet \leftarrow j}(h)$ from Equation (7), emphasizing companies with greater systemic impact. Similarly, the width of a directed link from node j to node i is proportional to $\tilde{\theta}_{i,j}(h)$ from Equation (5).

The estimated spillovers are densely clustered around zero, as illustrated in Figure 5, which presents the distributions of $\tilde{\theta}_{i,j}(h)$ in absolute value (excluding self-loops). The four boxplots reveal that a subset of spillovers is substantially larger, forming a right tail that deviates from the bulk of the data—indicating significant systemic interactions within the network. To enhance clarity and highlight the most relevant spillovers, we exclude from Figures 6–9 all links whose absolute value is below the third quartile of their respective distributions.

The networks in Figures 6–9 are visualized using the Fruchterman and Reingold (1991) force-directed algorithm, a widely used approach for network layout optimization. This algorithm simulates a physical system where nodes repel each other while edges act as attractive forces, pulling connected nodes together. As a result, highly interconnected companies form tightly clustered groups, whereas loosely connected firms are positioned toward the periphery (Bax et al., 2024).

Figures 6–9 reveal several key stylized facts. First, a well-defined core group of insurance companies consistently plays a central role across all four networks. Most of these firms belong to the multiline insurance sector, including Aegon, Ageas, Allianz, Unipol, and Zurich. Additionally, Aviva, Balaise, Generali, and Prudential emerge as central players within the life and health insurance industry. In the property and casualty sector, AXA, Coface, Topdanmark, and Tryg are prominent, with the latter three positioned at the periphery of the core cluster. The reinsurance subsector is also well represented, with Hannover Rück, Münchener Rück, and Swiss Re forming a central group. This core set of firms remains largely consistent across the networks, with only minor variations. For instance, Direct Line and Talanx appear centrally in Figure 6 but become more peripheral in Figure 7, where they are still interconnected but relatively isolated from the main cluster. Notably, AXA consistently stands out as the most systemically important company across all networks, maintaining a central position.

Another important pattern is the strong clustering of companies within the same subsector, reinforcing intra-sectoral interconnectedness. Addition-

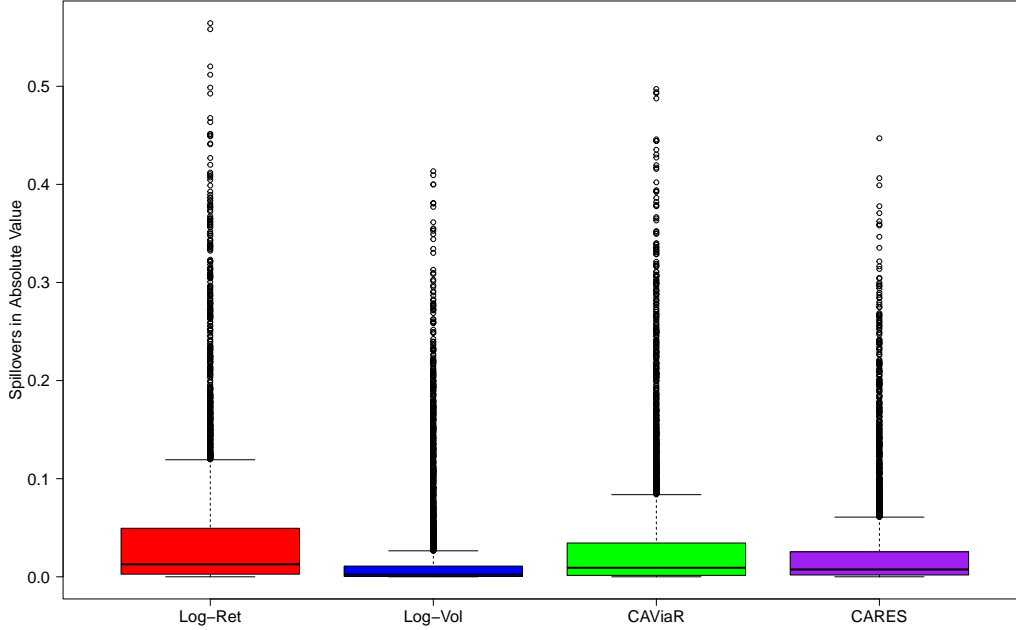


Figure (5) Boxplots of the absolute values of $\tilde{\theta}_{i,j}(h)$, with $i, j = 1, \dots, 70$ and $i \neq j$, resulting from the GFEVD estimation at the level of individual insurance companies on four different variables: log-returns (Log-Ret), conditional log-volatility (Log-Vol), conditional Value-at-Risk (CAViaR), and conditional Expected Shortfall (CARES). The boxes include companies above the bottom 5% and below the top 95% of the distribution. The horizontal lines denote the median.

ally, a significant “country effect” is evident. Turkish insurers—including Aksigorta, Anadolu Hayat Emeklilik, Anadolu Sigorta, Ray Sigorta, and Türkiye Sigorta—form a distinct, isolated cluster, exhibiting strong mutual interconnections across all four networks. A similar phenomenon is observed for the Slovenian insurers Pozavarovalnica Sava and Zavarovalnica Triglav, which are closely linked yet remain disconnected from the broader network. Although they belong to different subsectors—reinsurance and life and health insurance, respectively—their geographical proximity appears to drive their interconnectedness. This country-based clustering is particularly pronounced in Figure 6.

The identification of central insurance companies becomes even more precise through the application of the Louvain community detection algorithm

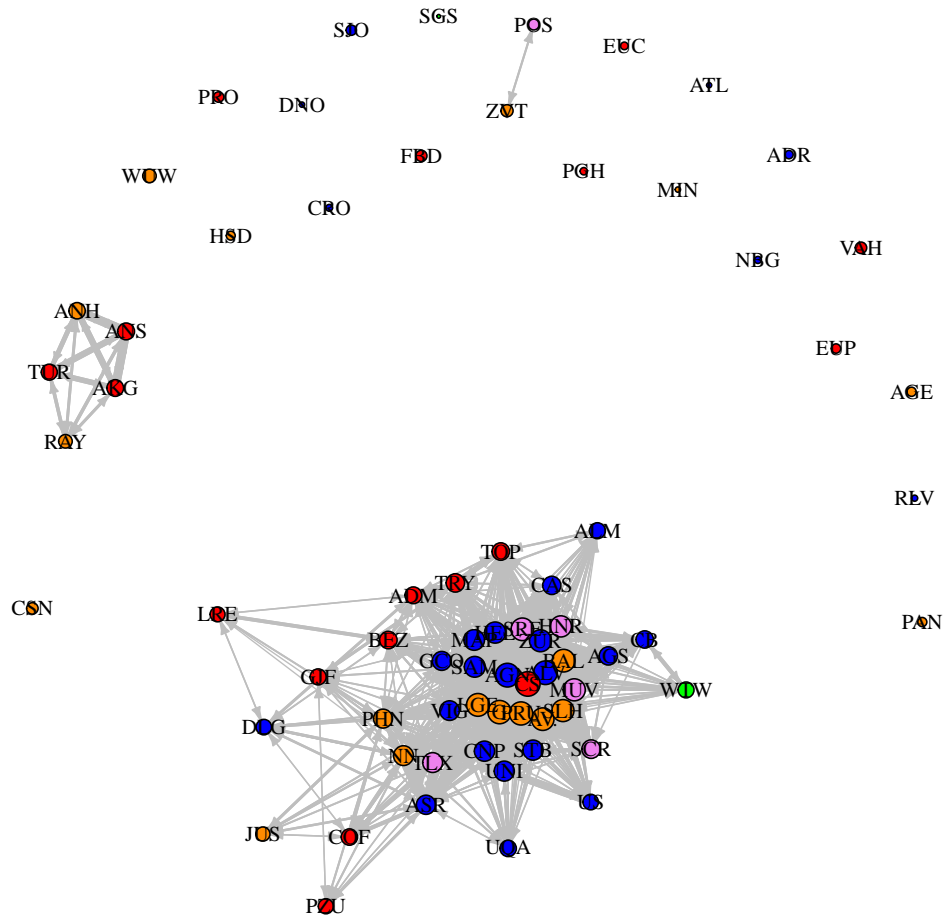


Figure (6) Network of insurance companies, color-coded by subsector—insurance brokers (green), life and health (orange), multiline (blue), property and casualty (red), and reinsurance (violet)—based on the GFEVD model estimated on the logged return time series.

(see, among others, Palowitch, 2019; Hegde et al., 2025). To implement this approach, we first convert each network in Figures 6—9 from directed to undirected, meaning that link direction is no longer considered. In the resulting

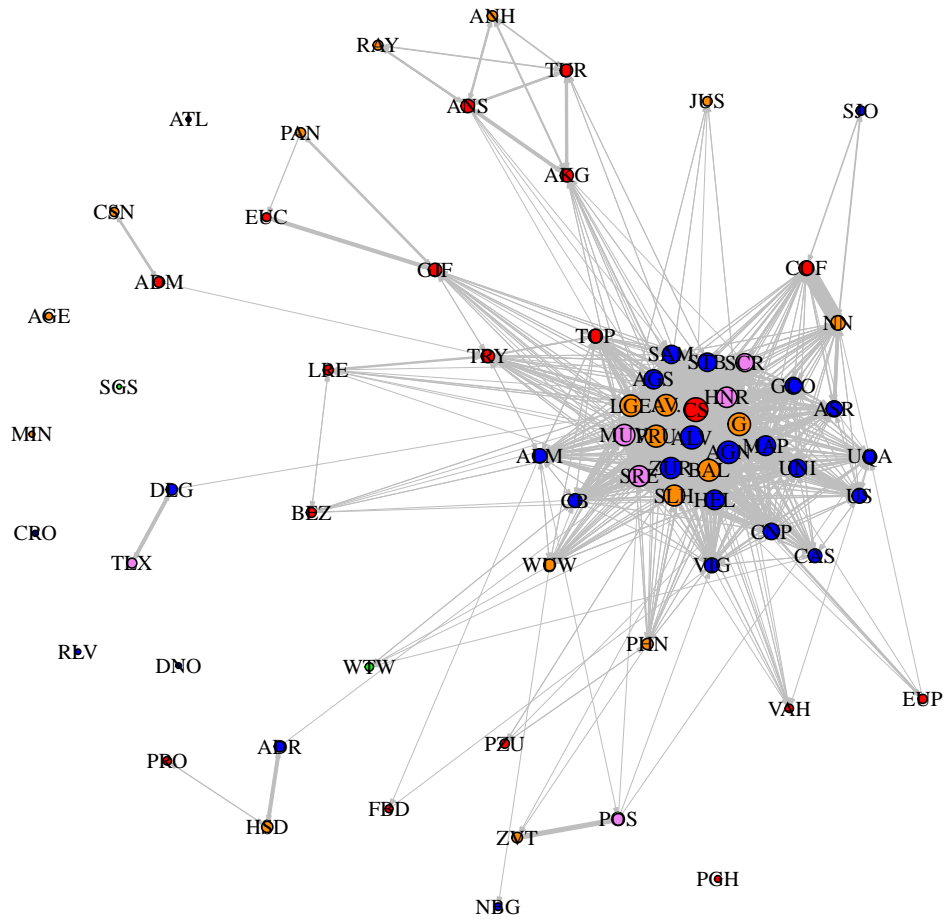


Figure (7) Network of insurance companies, color-coded by subsector—insurance brokers (green), life and health (orange), multiline (blue), property and casualty (red), and reinsurance (violet)—based on the GFEVD model estimated on the logged conditional volatility time series.

undirected networks, a link between nodes i and j exists if, in the original directed network, there is a link from i to j , from j to i , or both. The weight

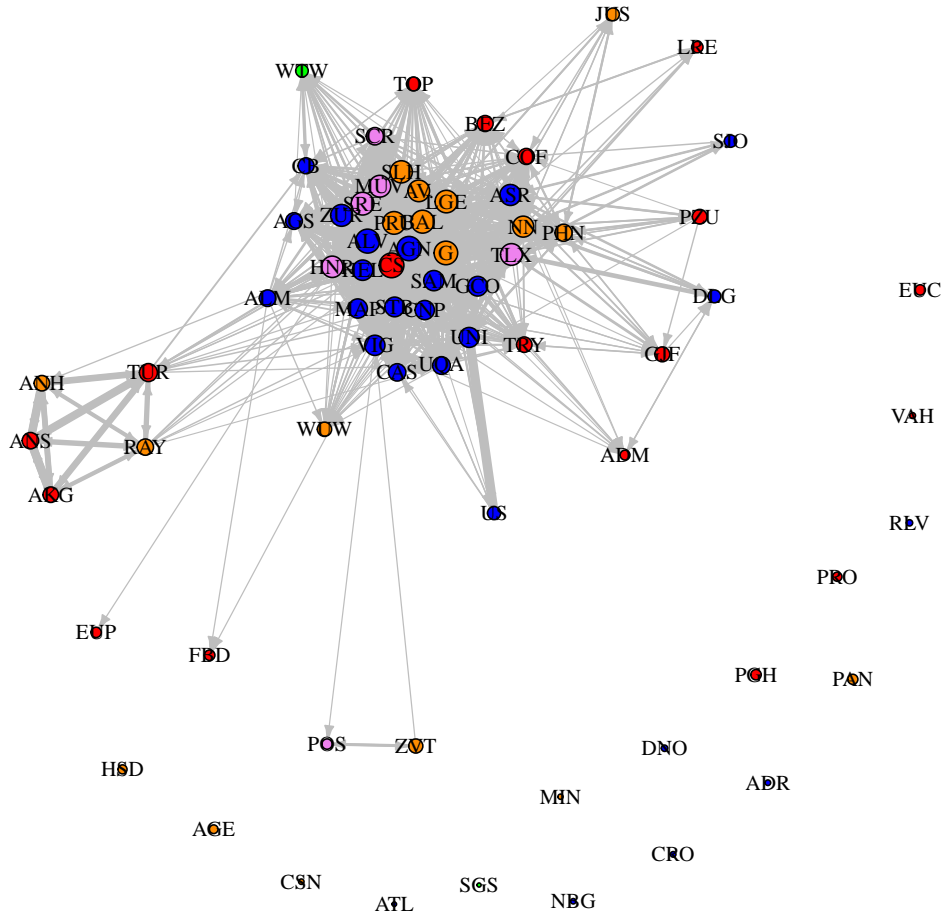


Figure (8) Network of insurance companies, color-coded by subsector—insurance brokers (green), life and health (orange), multiline (blue), property and casualty (red), and reinsurance (violet)—based on the GFEVD model estimated on the CAViaR time series.

of each undirected link is then computed as the sum $\left(\tilde{\theta}_{i \leftarrow j}(h) + \tilde{\theta}_{j \leftarrow i}(h)\right)$. We then apply the Louvain algorithm to identify communities within each network, focusing on the largest community (i.e., the one containing the

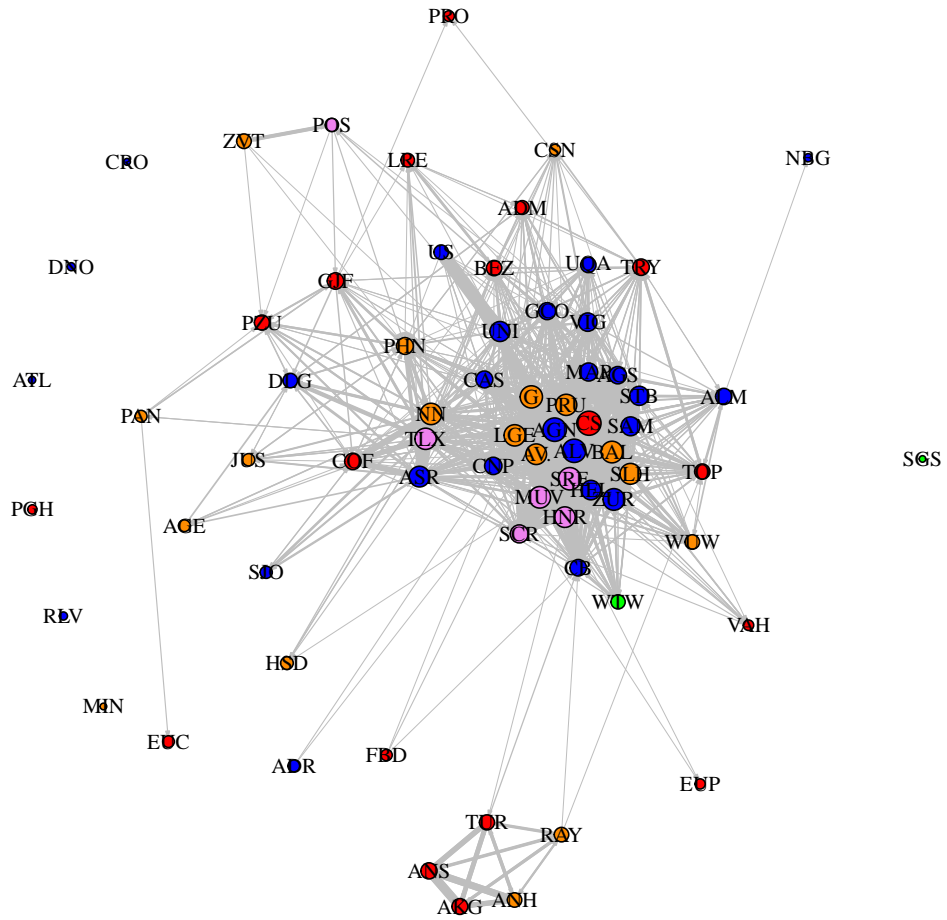


Figure (9) Network of insurance companies, color-coded by subsector—insurance brokers (green), life and health (orange), multiline (blue), property and casualty (red), and reinsurance (violet)—based on the GFEVD model estimated on the CARES time series.

most nodes). The intersection of the largest and most central communities detected across all four networks yields a core group of eight insurance companies: Aegon, Aviva, Ageas, Storebrand, Generali, AXA, Legal & General,

and Prudential.

This intersection of central communities highlights a subset of insurers with a pronounced systemic impact, consistently emerging as key players across all networks. Notably, this group aligns closely with the list of Global Systemically Important Insurers (G-SIIs) published by the Financial Stability Board (FSB) from 2013 to 2016, when the designation of G-SIIs was officially suspended, as reported in Table 4. In this table, European insurers are highlighted in bold and italic, while non-European firms—American International Group, MetLife, Prudential Financial, Inc., and Ping An Insurance (Group) Company of China Ltd.—are not present in our sample of insurance companies in Eastern and Western Europe. A key advantage of our methodology is that it relies solely on publicly available stock market data, whereas the FSB’s classification is based on a broad range of proprietary indicators, including firm-specific exposures, cross-jurisdictional activities, and off-balance-sheet positions. Despite these methodological differences, our results align remarkably well with the FSB’s multi-criteria assessment, demonstrating the effectiveness of our approach as a data-efficient alternative for systemic risk evaluation.

2013	2014	2015	2016
<i>Allianz</i>	<i>Allianz</i>	<i>Aegon</i>	<i>Aegon</i>
American Int.	American Int.	<i>Allianz</i>	<i>Allianz</i>
<i>Generali</i>	<i>Generali</i>	American Int.	American Int.
<i>Aviva</i>	<i>Aviva</i>	<i>Aviva</i>	<i>Aviva</i>
<i>AXA</i>	<i>AXA</i>	<i>AXA</i>	<i>AXA</i>
MetLife	MetLife	MetLife	MetLife
Ping An Ins.	Ping An Ins.	Ping An Ins.	Ping An Ins.
Prudential F.I.	Prudential F.I.	Prudential F.I.	Prudential F.I.
<i>Prudential Plc</i>	<i>Prudential Plc</i>	<i>Prudential Plc</i>	<i>Prudential Plc</i>

Table (4) This table reports the list of Global Systemically Important Insurers (G-SIIs) provided by the Financial Stability Board from 2013 to 2016; European companies are written in bold and italic text.

There are, however, some differences. For instance, Allianz, which appears in Table 4, is absent from our final intersection. However, it is worth noting that Allianz is part of three out of the four central communities identified by our method. Conversely, three companies in our intersection—Ageas, Storebrand, and Legal & General—are not included in the FSB’s list of G-

SIIs. Despite these discrepancies, our findings suggest that our approach provides a highly accurate proxy for systemic importance, successfully identifying most of the insurers classified by the FSB while relying solely on publicly available market data.

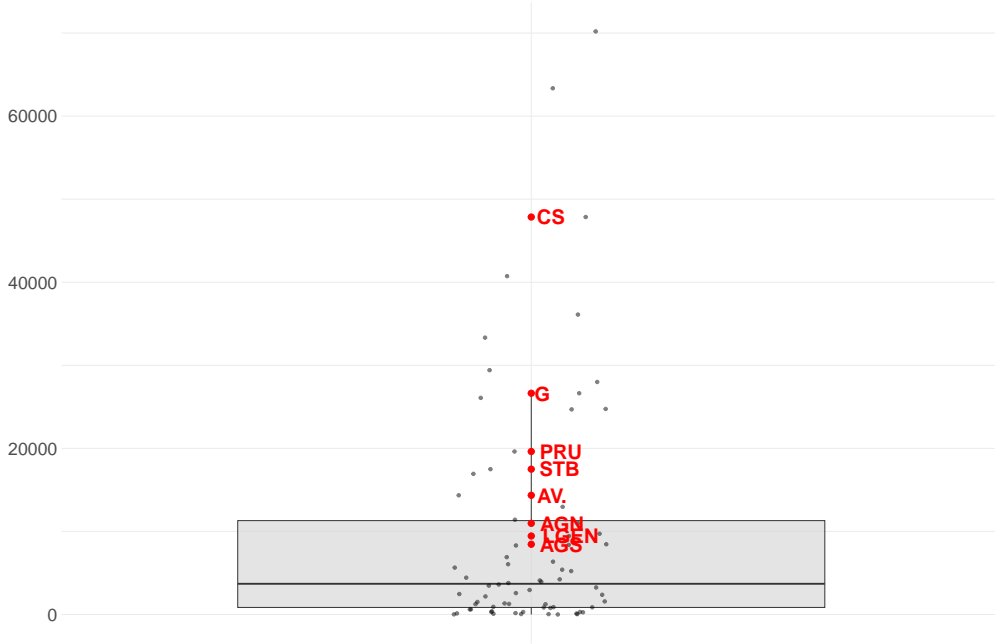


Figure (10) Distribution of the average market capitalization of the 70 insurance companies included in the networks given in Figures 6—9. Market capitalization is in millions of euros. The gray box includes companies with a market capitalization above the bottom 5% and below the top 95% of the distribution. The horizontal line is the median.

An important question is whether the systemic impact of the analyzed insurance companies is purely driven by their size. To investigate this, we use average market capitalization over the analyzed period as a proxy for firm size. Figure 10 presents a boxplot of these market capitalizations, highlighting in red the eight most systemically important companies identified through our intersection. While these firms are generally large (positioned above the median size), size alone does not fully explain their systemic relevance. Notably, although AXA is the most central institution in our analysis, other companies with comparable or even larger market capitalization do not necessarily exhibit the same systemic importance in the networks shown in Figures 6—9.

This finding underscores that being large is not sufficient to be systemically crucial. Instead, systemic importance is primarily determined by the degree of interconnectedness and the structure of financial dependencies within the insurance system. Firms with extensive linkages and central positions in the network can exert a greater impact on financial stability, regardless of their absolute size.

3.4. Robustness checks

In this section, we conduct a series of robustness checks to evaluate the stability of our results with respect to key parametric and empirical choices made in the previous sections. We focus on the individual insurance company level, which presents the greatest challenge among the three aggregation levels—financial markets, insurance subsectors, and individual firms—due to the significantly larger number of variables, potentially increasing result variability. To address the curse of dimensionality, we apply the post-LASSO method for estimating the VAR parameters, as discussed in Section 2.1.

Maintaining the same setup as in Section 3.3, we re-estimate the GFEVD model on the 70 insurance companies for the balanced sample. For simplicity, this section focuses on the GFEVD model estimated on log-return time series.⁶

We begin by assessing the impact of varying the forecast horizon h in Equation (4) on our estimates. While the previous sections adopted $h = 10$, we now extend the analysis to $h = 15$ and $h = 20$, keeping the lag order fixed at $p = 1$. The top panel of Figure 11 displays the values of $\tilde{\theta}_{\bullet \leftarrow j}(h)$, as defined in Equation (7), which measures the contribution of company j to others, for $j = 1, \dots, 70$ and $h = 10, 15, 20$. The bottom panel of Figure 11 presents the net contributions, computed as the difference between contributions to and from others, for the same set of companies.

The results remain remarkably stable across different values of h , with only minor variations among the three cases. This consistency reinforces the robustness of our approach, indicating that our methodology effectively isolates and quantifies systemic spillovers without being overly sensitive to the choice of forecast horizon.

⁶Estimates obtained from conditional log-volatility, CAViaR, and CARES time series, as well as those derived from aggregated financial markets and insurance subsectors, are available upon request.

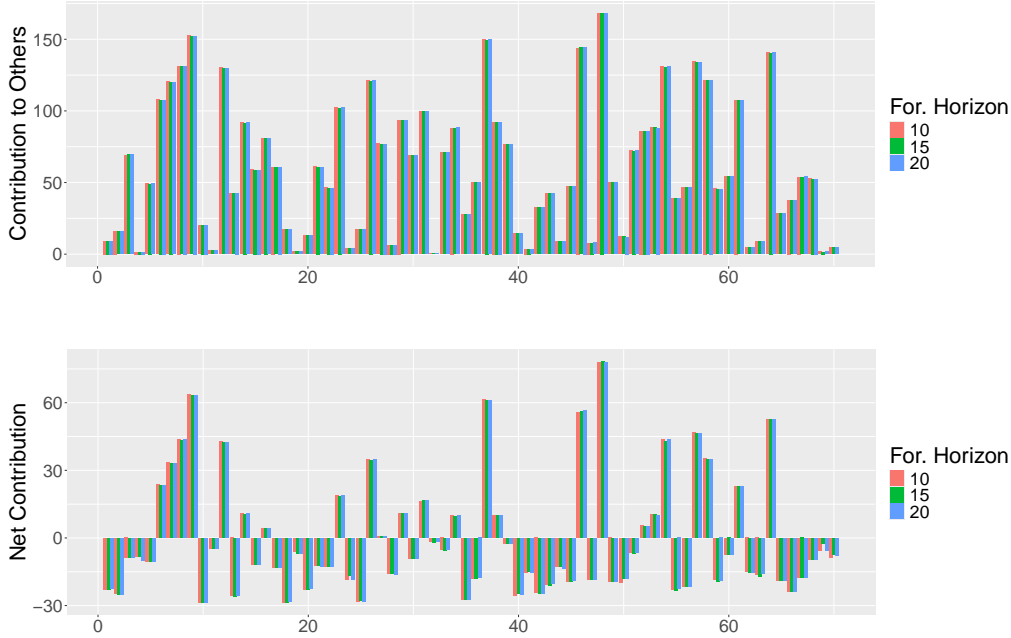


Figure (11) Contributions to others and net contributions of the 70 insurance companies identified with a value of “1” in the fourth column of Table A.1 in B. The results are derived from the GFEVD model estimated on daily log-return time series for different forecast horizons (h): 10, 15, and 20, with the underlying VAR model set to $p = 1$. The VAR parameters are estimated using the post-LASSO method.

We draw similar conclusions regarding the lag order. In particular, Figure 12 presents the estimates obtained from the GFEVD model with a forecast horizon of $h = 10$, based on VAR parameters estimated using lag orders $p = 1$, $p = 2$, and $p = 3$. The estimates remain nearly identical across the different values of p .

Our final robustness check examines the impact of data frequency. While our empirical analysis is based on daily log-returns, we now assess how the results change when the frequency is reduced to weekly log-returns. Figure 13 compares the contributions to others and net contributions of the selected insurance companies, obtained from estimating the GFEVD model using both daily and weekly log-returns.

Compared to Figures 11 and 12, the differences between the bars for each company in Figure 13 are relatively larger. However, these variations remain minimal, reinforcing the robustness of our methodology across different data

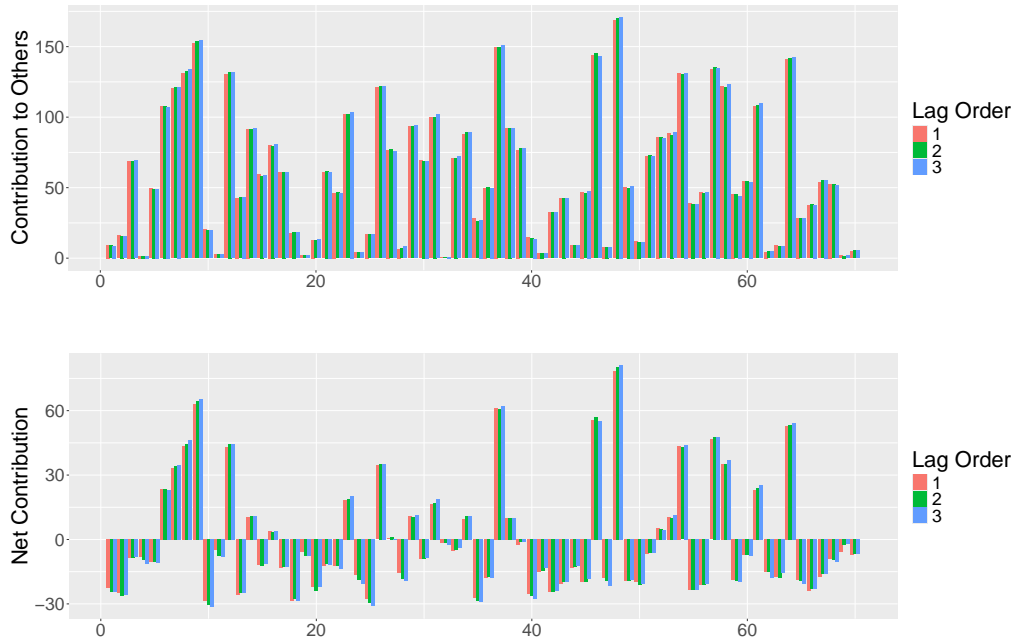


Figure (12) Contributions to others and net contributions of the 70 insurance companies identified with a value of “1” in the fourth column of Table A.1 in B. The results are derived from the GFEVD model with $h = 10$, estimated on daily log-return time series for different lag orders (p) in the underlying VAR model: 1, 2, and 3. The VAR parameters are estimated using the post-LASSO method.

frequencies.

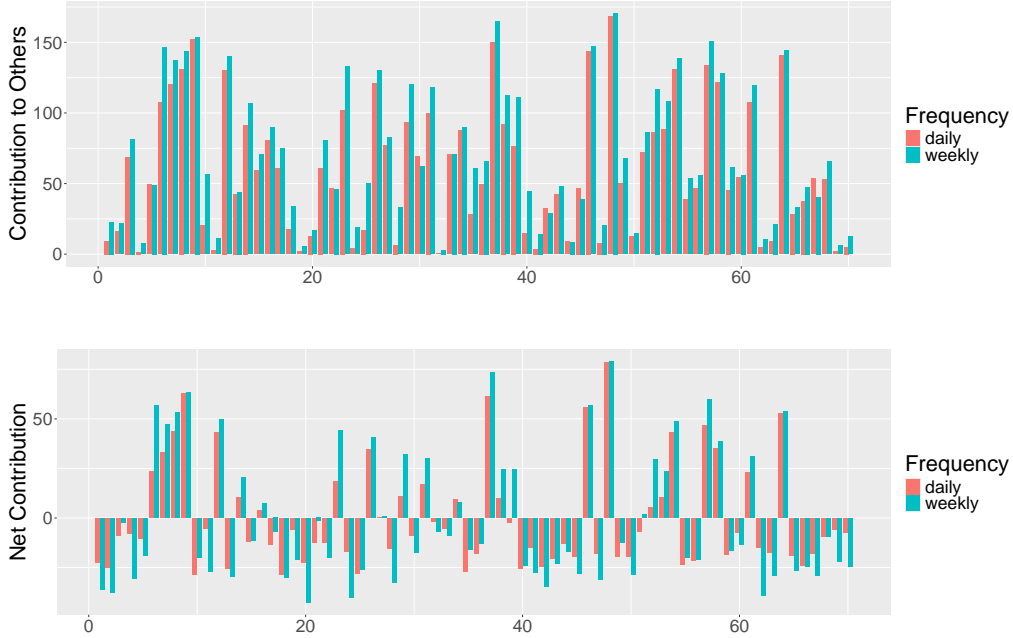


Figure (13) Contributions to others and net contributions of the 70 insurance companies marked with the value “1” in the fourth column of Table A.1 given in B. The results are obtained from the GFEVD model ($h = 10$) estimated on the weekly log-return time series, setting $p = 1$ in the underlying VAR model. The VAR parameters are estimated using the post-LASSO method.

4. Conclusions

Our analysis demonstrates that the European insurance market is not merely a passive recipient of external shocks; rather, it is an active participant in the propagation of systemic risk. The state-of-the-art econometric techniques applied in this study reveal that both sectoral and firm-level interdependencies play a critical role in shaping financial stability. As the financial landscape continues to evolve, the need for robust, data-driven methodologies to assess and manage systemic risk becomes ever more pressing. Future research may extend our framework by incorporating cross-border linkages and additional risk factors, thereby further elucidating the complex web of relationships that underpin financial stability in a globalized economy.

Furthermore, the recent Draghi report underscores the importance of the Capital Market Union while drawing attention to the challenges posed by

fragmented European capital markets and heterogeneous supervisory competences across members' countries. In light of our findings, it is increasingly vital to establish a unified supervisory framework able to address systemic spillover risks at the European level. This framework could be integrated within the European Systemic Risk Board's mandate or entrusted to a newly established European supervisory agency for insurance companies, tasked with overseeing the largest and most systemically significant institutions in the region, following the model already in place for banks.

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Appendix

A. Performance and risk indicators

We estimate the GFEVD model described in Section 2.1 using four indicators of performance and risk based on equity prices.

The first indicator is the log-return, a standard measure of market performance. Let $r_{j,t}$ be the log-return yielded by a given financial entity at time t , we estimate the GFEVD model by setting $\mathbf{x}_t = [x_{1,t} = r_{1,t} \cdots x_{n,t} = r_{n,t}]'$.

The second indicator is the conditional log-volatility, a standard measure of risk in financial markets, that we model using the Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) model (Bollerslev, 1986). We employ the following AutoRegressive Moving-Average (ARMA) process for the mean equation:

$$r_{j,t} = \phi_{j,0} + \sum_{i=1}^k \phi_{j,i} r_{j,t-i} + \sum_{i=1}^q \xi_{j,i} a_{j,t-i}, \quad (\text{A.1})$$

where $a_{j,t}$ is the innovation or shock of $r_{j,t}$ at time t (Tsay, 2010), defined as:

$$a_{j,t} = \tilde{\sigma}_{j,t} \tilde{\epsilon}_{j,t}, \quad (\text{A.2})$$

with $\{\tilde{\epsilon}_{j,t}\}$ being a sequence of independent and identically distributed random variables with mean zero and variance one.

The standard variance equation (Bollerslev, 1986) has the following specification:

$$\tilde{\sigma}_{j,t}^2 = \omega_0 + \sum_{i=1}^m \omega_{j,i} a_{j,t-i}^2 + \sum_{i=1}^s \nu_{j,i} \tilde{\sigma}_{j,t-i}^2, \quad (\text{A.3})$$

where $\omega_{j,i}$ and $\nu_{j,i}$ are referred to as ARCH and GARCH parameters, respectively (Tsay, 2010).

Starting from the specification in Equation (A.3) introduced by Bollerslev (1986), alternative variance equations have been proposed in the literature. In our study, we consider the EGARCH (Nelson, 1991), and the GJR GARCH (Glosten et al., 1993) models, in addition to the standard specification in (A.3). Moreover, we adopt six different distributions for the $\tilde{\epsilon}_{j,t}$ random variable: the Gaussian, Student-t, and Generalized Error distributions, and their respective skew variants based on the transformations described in Fernández and Steel (1998) and Ferreira and Steel (2006). We test the

AR and MA orders—i.e. k and q in Equation (A.1)—as well as the orders of the ARCH and GARCH effects—i.e. m and s in Equation (A.3), and in the alternative EGARCH and GJR GARCH variance equations—from zero to two. We combine all the aforementioned alternative choices, and select, for each individual time series, the best GARCH model based on the BIC. From the best GARCH specification, we then extract the time series of the estimated conditional volatility, denoted as $\tilde{\sigma}_{j,t}^*$, and estimate the GFEVD model on $\mathbf{x}_t = [x_{1,t} = \ln(\tilde{\sigma}_{1,t}^*) \cdots x_{n,t} = \ln(\tilde{\sigma}_{n,t}^*)]'$.

Next, we take the value-at-risk (VaR), a standard measure of tail risk, to build the third indicator of performance and risk. Specifically, we estimate the Conditional AutoRegressive VaR (CAViaR) model introduced by Engle and Manganelli (2004) to obtain a time series of time-varying VaR values. In contrast to other approaches that model entire return distributions to extract quantiles, the CAViaR model directly models quantiles on the basis of AR specifications. The underlying parameters are estimated through quantile regression (Koenker and Bassett, 1978). Let $f_t(\boldsymbol{\gamma}) \equiv f_t(\mathbf{z}_{t-1}, \boldsymbol{\gamma}_\tau)$ be the latent quantile at time t to estimate from a given return time series, where τ is the probability associated to VaR, and \mathbf{z}_t is a vector of time t observable variables.⁷ The generic CAViaR specification takes the following form:

$$f_t(\boldsymbol{\gamma}) = \gamma_0 + \sum_{i=1}^q \gamma_i f_{t-i}(\boldsymbol{\gamma}) + \sum_{j=1}^r \gamma_j \ell(\mathbf{z}_{t-j}). \quad (\text{A.4})$$

The AR terms $\gamma_1 f_{t-1}(\boldsymbol{\gamma}), \dots, \gamma_q f_{t-q}(\boldsymbol{\gamma})$ in Equation (A.4) ensure that the latent quantiles smoothly change over time. The role of $\ell(\mathbf{z}_{t-j})$ is to link $f_t(\boldsymbol{\gamma})$ to observable variables that belong to the information set (Engle and Manganelli, 2004). Among the alternative specifications proposed by Engle and Manganelli (2004), we adopt the asymmetric slope function to estimate the CAViaR of the j -th return time series:

$$f_t(\boldsymbol{\gamma}_j) = \gamma_{j,1} + \gamma_{j,2} f_{t-1}(\boldsymbol{\gamma}_j) + \gamma_{j,3} (r_{j,t-1})^+ + \gamma_{j,4} (r_{j,t-1})^-, \quad (\text{A.5})$$

where $(r_{j,t-1})^+ = \max(r_{j,t-1}, 0)$, and $(r_{j,t-1})^- = -\min(r_{j,t-1}, 0)$.

We use the asymmetric slope specification to take into account potential asymmetric effects of past returns on VaR. By doing so, we differentiate between the effects of positive and negative lagged returns on the estimated

⁷We set $\tau = 0.05$ in our empirical analysis.

quantile. This specification is particularly useful in financial frameworks where extreme negative returns might influence risk estimates more strongly than positive returns (Engle and Manganelli, 2004). After obtaining the CAViaR time series from Equation (A.5) for $j = 1, \dots, n$, we then estimate the GFEVD model by setting $\mathbf{x}_t = [x_{1,t} = f_t(\gamma_1) \cdots x_{n,t} = f_t(\gamma_n)]'$.

Furthermore, we consider the expected shortfall (ES) as fourth measure of performance and risk. In contrast to VaR, that does not necessarily satisfy the subadditivity property, ES is a coherent measure of risk (Artzner et al., 1999). Moreover, VaR only gives the threshold loss level at a specific confidence level, but ignores what happens beyond this point, while ES captures the expected loss at a given confidence level. The better properties of ES are reflected in the recent changes in financial regulation. In fact, Basel III guidelines recommend ES over VaR for calculating market risk in financial institutions.

In general, ES is defined as the expected return of a given asset conditional on the fact that such return is less than its VaR at a given confidence level τ . We obtain a time-varying ES by adopting the approach proposed by Taylor (2007), that builds on expectiles. In particular, the population expectile of the random variable R_j at level ψ is defined as the quantity $\delta(R_j, \psi)$ that minimizes the following expected loss:

$$\mathbb{E} \left[\left| \psi - \mathbb{I}_{\{R_j < \delta(R_j, \psi)\}} \right| (R_j - \delta(R_j, \psi))^2 \right], \quad (\text{A.6})$$

where $\psi \in (0, 1)$, and $\mathbb{I}_{\{\cdot\}}$ is an indicator function which takes the value of one if the condition into braces is true, and the value of zero otherwise.

Taylor (2007) showed that the ES of R_j at the confidence level τ , denoted as $\text{ES}(R_j, \tau)$, is a function of $\delta(R_j, \psi)$ through the following relationship:

$$\text{ES}(R_j, \tau) = \left(1 + \frac{\psi}{(1 - 2\psi)\tau} \right) \delta(R_j, \psi) - \frac{\psi}{(1 - 2\psi)\tau} \mathbb{E}[R_j], \quad (\text{A.7})$$

where $\mathbb{E}[R_j]$ is the expected value of R_j .

The relationship given in Equation (A.7) is defined for scalar expectile and ES. However, Taylor (2007) showed that such relationship holds even if expectiles are conditional on a set of explanatory variables, for instance, through the following Conditional AutoRegressive Expectile (CARE) model:

$$\delta(r_{j,t}, \psi) = \eta_{0,j,\psi} + \eta_{1,j,\psi} \delta(r_{j,t-1}, \psi) + \eta_{2,j,\psi} |r_{j,t-1}|. \quad (\text{A.8})$$

Therefore, similar to CAViaR, the CARE model captures the persistence and dynamics of expectiles over time. In empirical applications, Taylor

(2007) showed that the time-varying ES at the probability level τ coincides with the ψ_j^* -th expectile, denoted as $\delta(r_{j,t}, \psi_j^*)$, where ψ_j^* is the value of the expectile level ψ given in Equation (A.8) that makes the percentage of in-sample violations equal to τ :

$$(T - 1)^{-1} \sum_{t=2}^T \mathbb{I}_{\{r_{j,t} < \delta(r_{j,t}, \psi_j^*)\}} = \tau. \quad (\text{A.9})$$

This rule leads to the Conditional AutoRegressive Expected Shortfall (CARES) model of Taylor (2007).⁸ We stress the fact that ψ_j^* and ψ_i^* do not necessarily take the same values, for $j, i = 1, \dots, n$ and $j \neq i$. However, $\delta(r_{j,t}, \psi_j^*)$ and $\delta(r_{i,t}, \psi_i^*)$ are both ESs at the probability level τ . Therefore, we finally estimate the GFEVD model on the time-varying ESs, by setting $\mathbf{x}_t = [x_{1,t} = \delta(r_{1,t}, \psi_1^*) \cdots x_{n,t} = \delta(r_{n,t}, \psi_n^*)]'$.

B. Additional tables and figures

Table (A.1) List of insurance companies

Label	Company	Country	Subsector	Network
ADM	Admiral	GB	Pro.Cas.	1
ADRS	Adris Grupa	HR	Mul.Lin.	1
AGESA	Agesa Hayat Ve Emeklilik	TU	Lif.Hea.	1
AGN	Aegon	NE	Mul.Lin.	1
AGS	Ageas	BE	Mul.Lin.	1
AKGRT	Aksigorta	TU	Pro.Cas.	1
ALMB	Alm Brand	DE	Mul.Lin.	1
ALPTR	Patris Investimentos SGPS	PO	Lif.Hea.	0
ALV	Allianz	GE	Mul.Lin.	1
AMSO	AMS Osiguranje	RR	Others	0
ANHYT	Anadolu Hayat Emeklilik	TU	Lif.Hea.	1
ANSGR	Anadolu Anonim Turk Sigorta	TU	Pro.Cas.	1
ARMBRK2	UNIQA Osiguranje	BY	Mul.Lin.	0
ASRNL	ASR Nederland	NE	Mul.Lin.	1

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⁸Following Bonaccolto et al. (2022), in the empirical analysis we iteratively estimate the CARE model in Equation (A.8) using a dense sequence of ψ values with starting point $10,000^{-1}$. We then select the ψ value that produces the minimum distance between the percentage of in-sample violations and τ , setting it as ψ_j^* .

Label	Company	Country	Subsector	Network
ASSI	Assiteca Assicurativo	IT	Ins.Bro.	0
ATL	Atlantic Insurance	CC	Mul.Lin.	1
AV.	Aviva	GB	Lif.Hea.	1
BALN	Baloise Holding	SZ	Lif.Hea.	1
BEZ	Beazley	GB	Pro.Cas.	1
BSOSRK1	BSO	BY	Mul.Lin.	0
BSRSRK2	Bosna Reosiguranje	BY	Reins.	0
CASS	Genertel	IT	Mul.Lin.	1
CB	Chubb	SZ	Mul.Lin.	1
CBP	Curtis Banks	GB	Others	0
CNP	CNP Assurances Saca	FR	Mul.Lin.	1
COFA	Coface	FR	Pro.Cas.	1
CONT	Contract Ins. and Fin. Services	GR	Lif.Hea.	0
COS	Cosmos	CC	Pro.Cas.	0
CRHVP	Credimo Holding	BE	Lif.Hea.	0
CROS	Croatia Osiguranje	HR	Mul.Lin.	1
CS	AXA	FR	Pro.Cas.	1
CSN	Chesnara	GB	Lif.Hea.	1
DEOS	Generali Osiguranje Monten.	YV	Pro.Cas.	0
DFV	DFV Deutsche Familienvers.	GE	Pro.Cas.	0
DLG	Direct Line	GB	Mul.Lin.	1
DLLLF	Delta Lloyd	NE	Mul.Lin.	0
DNOS	Dunav Osiguranje	RR	Mul.Lin.	1
DNREM	Dunav	RR	Reins.	0
DROSRA	Drina Osiguranje	BY	Mul.Lin.	0
DZHS	Source Insurance	UK	Pro.Cas.	0
ENGR	Energogarant OJSC	RU	Mul.Lin.	0
EUC	Europejskie Centrum Odszk.	PD	Pro.Cas.	1
EUMK	Euromak Broker	MC	Lif.Hea.	0
EUPIC	European Reliance General	GR	Pro.Cas.	1
FBD	FBD	IR	Pro.Cas.	1
G	Generali	IT	Lif.Hea.	1
GCL	Lifestar Holding	MB	Others	0
GCO	Grupo Catalana Occidente	SP	Mul.Lin.	1
GJF	Gjensidige Forsikring	NO	Pro.Cas.	1
GRAW	Grawe Osiguranje	YV	Ins.Bro.	0
HELN	Helvetia Holding	SZ	Mul.Lin.	1
HNR1	Hannover Rueck	GE	Reins.	1
HSD	Hansard Global	IO	Lif.Hea.	1
HUW	Helios Underwriting	GB	Reins.	0
INGS	Ingosstrakh	RU	Mul.Lin.	0
INLI	Interlife General Insurance	GR	Mul.Lin.	0
JDOS	Adriatic Osiguranje	HR	Mul.Lin.	0

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Label	Company	Country	Subsector	Network
JOSVP	Groupe Josi	BE	Reins.	0
JUST	Just Group	GB	Lif.Hea.	1
KDVORA	Dunav Osiguranje	BY	Mul.Lin.	0
KJUBI	Makedonija Osiguruvane	MC	Ins.Bro.	0
KKOSRA	Triglav Osiguranje	BY	Mul.Lin.	0
KMKS	K Mk Broker Skopje	MC	Mul.Lin.	0
KROSRA	Krajina Osiguranje	BY	Mul.Lin.	0
LDA	Linea Directa Aseguradora	SP	Ins.Bro.	0
LGEN	Legal & General	GB	Lif.Hea.	1
LRE	Lancashire	GB	Pro.Cas.	1
LSI	Lifestar	MB	Lif.Hea.	0
MAOS	Magnat Osiguranje	YV	Ins.Bro.	0
MAP	Mapfre	SP	Mul.Lin.	1
MINE	Minerva Insurance	CC	Lif.Hea.	1
MKOSRA	Mikrofin Osiguranje	BY	Ins.Bro.	0
MMS	Mapfre Middlesea	MB	Mul.Lin.	0
MNG	M&G	GB	Lif.Hea.	0
MNOS	Sava Osiguranje	YV	Pro.Cas.	0
MSOS	Evroins Osiguruvane Skopje	MC	Lif.Hea.	0
MUV2	Muench. Rueckvers.-Gesell.	GE	Reins.	1
NBG6	Nuernberger Beteiligungs	GE	Mul.Lin.	1
NET	Net Insurance	IT	Pro.Cas.	0
NN	NN Group	NE	Lif.Hea.	1
ONDO	Ondo Insur Tech	GB	Pro.Cas.	0
OPTIM	Optimco	BE	Mul.Lin.	0
OSPO	Osiguritelna Polisa Skopje	MC	Others	0
OTIS	Cia Internacionala De Asig. As.	MK	Mul.Lin.	0
PANNONIA	CIG Pannonia Life	HU	Lif.Hea.	1
PGH	Personal	GB	Pro.Cas.	1
PHNX	Phoenix	GB	Lif.Hea.	1
POSR	Pozavarovalnica Sava	SV	Reins.	1
PPDT	Prva	SV	Others	0
PROT	Protector Forsikring	NO	Pro.Cas.	1
PRU	Prudential	HK	Lif.Hea.	1
PYDR	Paydrive	SW	Ins.Bro.	0
PZU	Powszechny Zaklad Ubezpiec.	PD	Pro.Cas.	1
RAYSG	Ray Sigorta	TU	Lif.Hea.	1
RENI	Renaissance Insurance Group	RU	Mul.Lin.	0
RLV	Rheinland Holding	GE	Mul.Lin.	1
SAMPO	Sampo Oyj	FI	Mul.Lin.	1
SBRE	Sabre	GB	Pro.Cas.	0
SCR	SCOR	FR	Reins.	1
SFAB	Solid Forsakring	SW	Pro.Cas.	0

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Label	Company	Country	Subsector	Network
SGS	Cash Life	GE	Ins.Bro.	1
SJOVA	Sjova-Almennar Tryggingar	IC	Mul.Lin.	1
SKUN	Universalna	UK	Mul.Lin.	0
SLHN	Swiss Life Holding	SZ	Lif.Hea.	1
SLP401E	Allianz-Slovenska Poistovna	SO	Mul.Lin.	0
SODJRA	Wiener Osiguranje Vienna	BY	Pro.Cas.	0
SORN	Oranta	UK	Mul.Lin.	0
SOSOR	Sarajevo Osiguranje	BY	Mul.Lin.	0
SREN	Swiss Re	SZ	Reins.	1
STB	Storebrand	NO	Mul.Lin.	1
SWIO	Grawe Nezivotno Osiguranje	YV	Pro.Cas.	0
TBK	Transilvania Broker de Asig.	RO	Ins.Bro.	0
TBKO	Sava Osiguruvanje	MC	Pro.Cas.	0
TLX	Talanx	GE	Reins.	1
TM	Tm Hf	IC	Pro.Cas.	0
TOP	Topdanmark	DE	Pro.Cas.	1
TRYG	Tryg	DE	Pro.Cas.	1
TURSG	Turkiye Sigorta	TU	Pro.Cas.	1
UNI	Unipol Gruppo	IT	Mul.Lin.	1
UQA	UNIQA	AS	Mul.Lin.	1
US	Unipolsai Assicurazioni	IT	Mul.Lin.	1
VAHN	Vaudoise Assurances Holding	SZ	Pro.Cas.	1
VIG	Vienna Insurance Group	AS	Mul.Lin.	1
VROS	Vardar Osiguruvane	MC	Pro.Cas.	0
WTW	Willis Towers Watson	GB	Ins.Bro.	1
WUW	Wuestenrot & Wuerttemberg.	GE	Lif.Hea.	1
ZEOS	Uniqa Zivotno Osiguranje	YV	Lif.Hea.	0
ZURN	Zurich	SZ	Mul.Lin.	1
ZVTG	Zavarovalnica Triglav	SV	Lif.Hea.	1

Notes: From left to right, the table reports the following information on the insurance companies included in our sample: (i) the company’s abbreviated name (Label); (ii) the full company name (Company); (iii) the country of origin (Country); (iv) the insurance subsector to which the company belongs (Subsector), considering insurance brokers (Ins.Bro.), life health (Lif.Hea.), multiline (Mul.Lin.), property and casualty (Pro.Cas.), and reinsurance (Reins.); and (v) a dummy variable (Network) which takes the value of one if the company meets the data availability and liquidity requirements to be included in the network analysis described in Figures 6—9, and the value of zero otherwise.

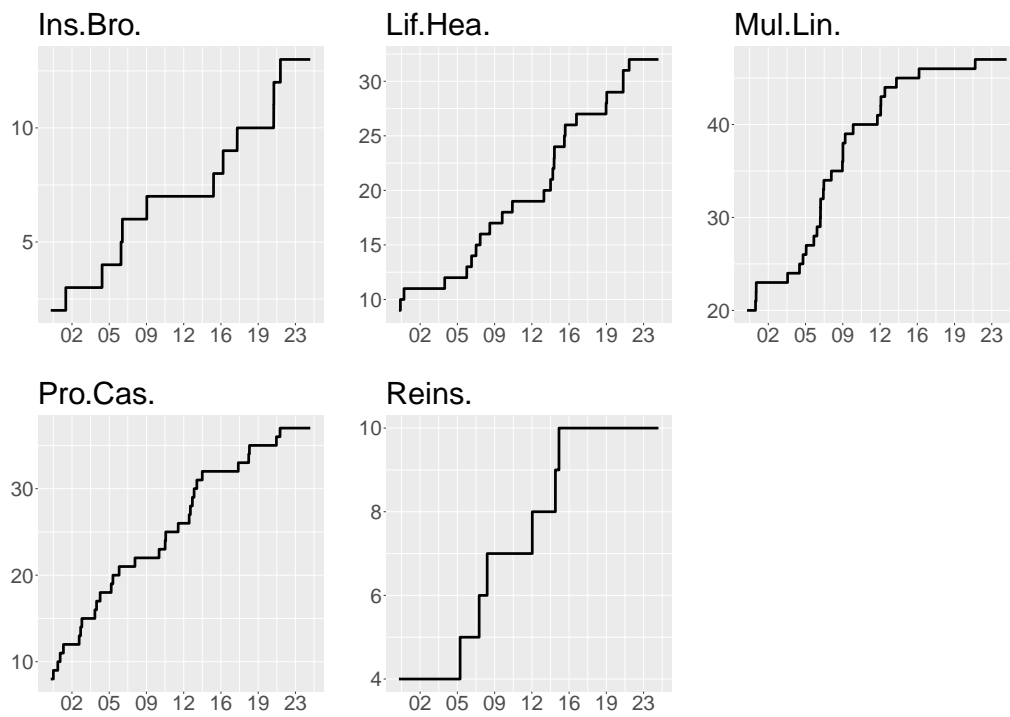


Figure (A.1) This figure plots the evolution of the number of individual European insurance companies in our sample by subsector. The subsectors are: insurance brokers (Ins.Bro.), life health (Lif.Hea.), multiline (Mul.Lin.), property and casualty (Pro.Cas.), and reinsurance (Reins.). The sample goes from January 3, 2000 to October 22, 2024. Data are from Bloomberg.

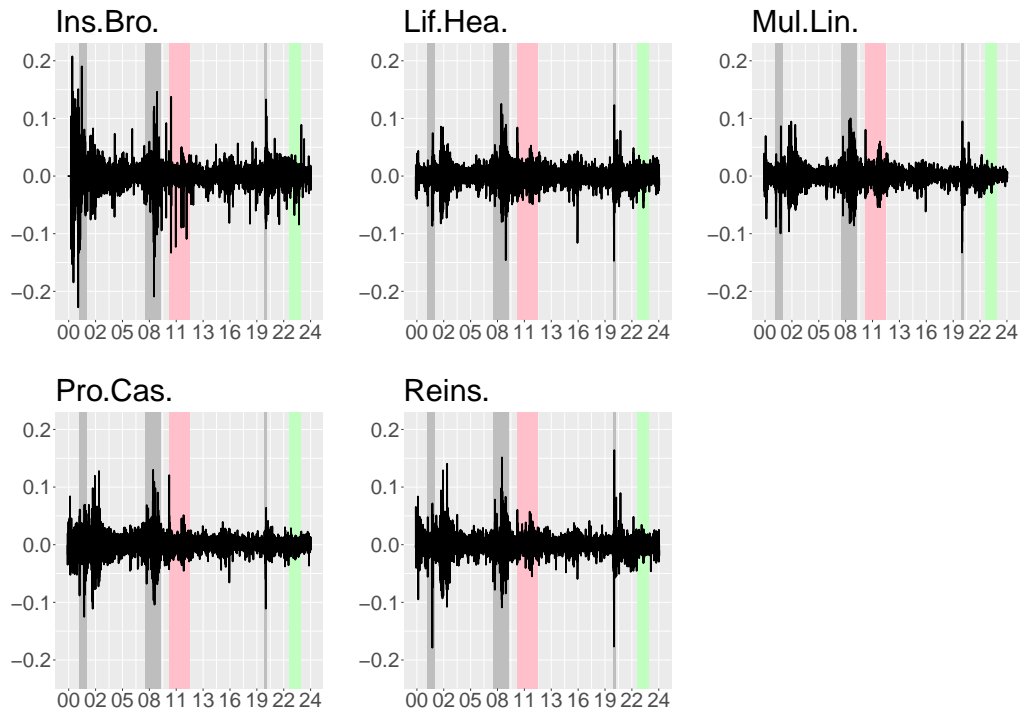


Figure (A.2) This figure plots the logged daily returns the following subsectors of the insurance market: insurance brokers (Ins.Bro.), life health (Lif.Hea.), multiline (Mul.Lin.), property and casualty (Pro.Cas.), and reinsurance (Reins.). The sample goes from January 3, 2000 to October 22, 2024. Data are from Bloomberg.

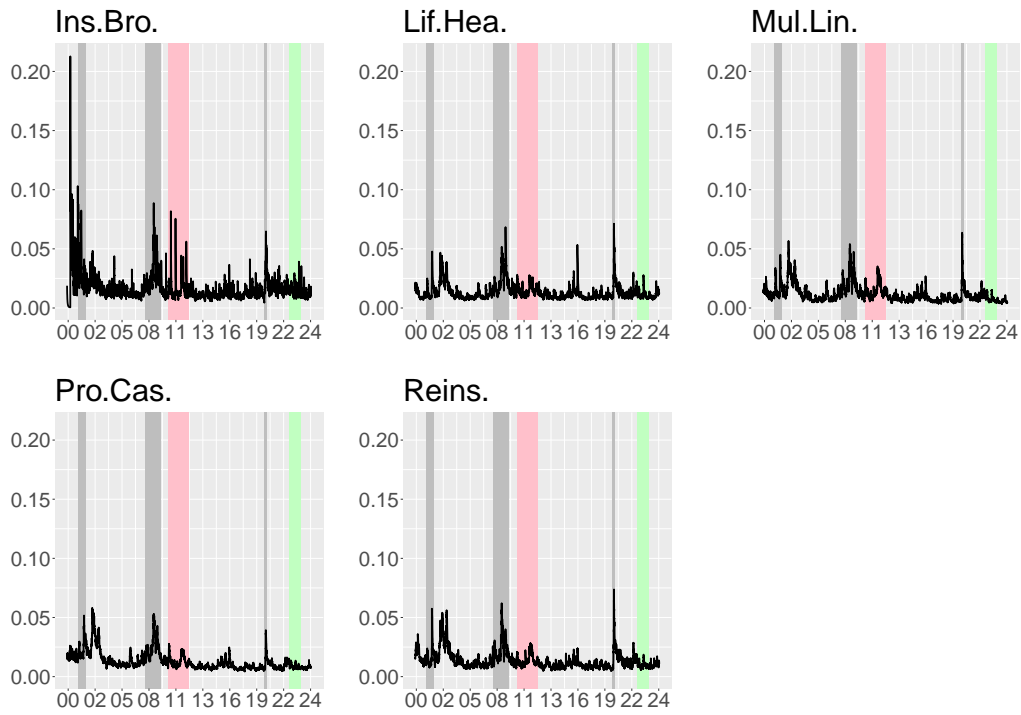


Figure (A.3) This figure plots the daily conditional volatility of the following subsectors of the insurance market: insurance brokers (Ins.Bro.), life health (Lif.Hea.), multiline (Mul.Lin.), property and casualty (Pro.Cas.), and reinsurance (Reins.). The sample goes from January 3, 2000 to October 22, 2024.

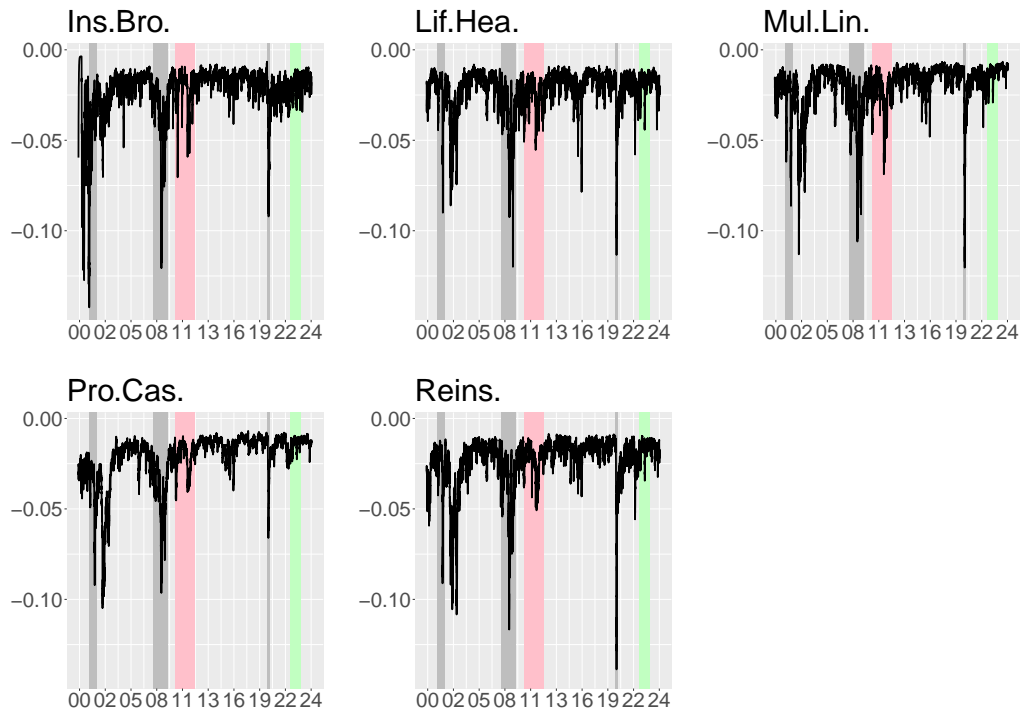


Figure (A.4) This figure plots the daily conditional value-at-risk estimated by the CAViaR model of the following subsectors of the insurance market: insurance brokers (Ins.Bro.), life health (Lif.Hea.), multiline (Mul.Lin.), property and casualty (Pro.Cas.), and reinsurance (Reins.). The sample goes from January 3, 2000 to October 22, 2024.

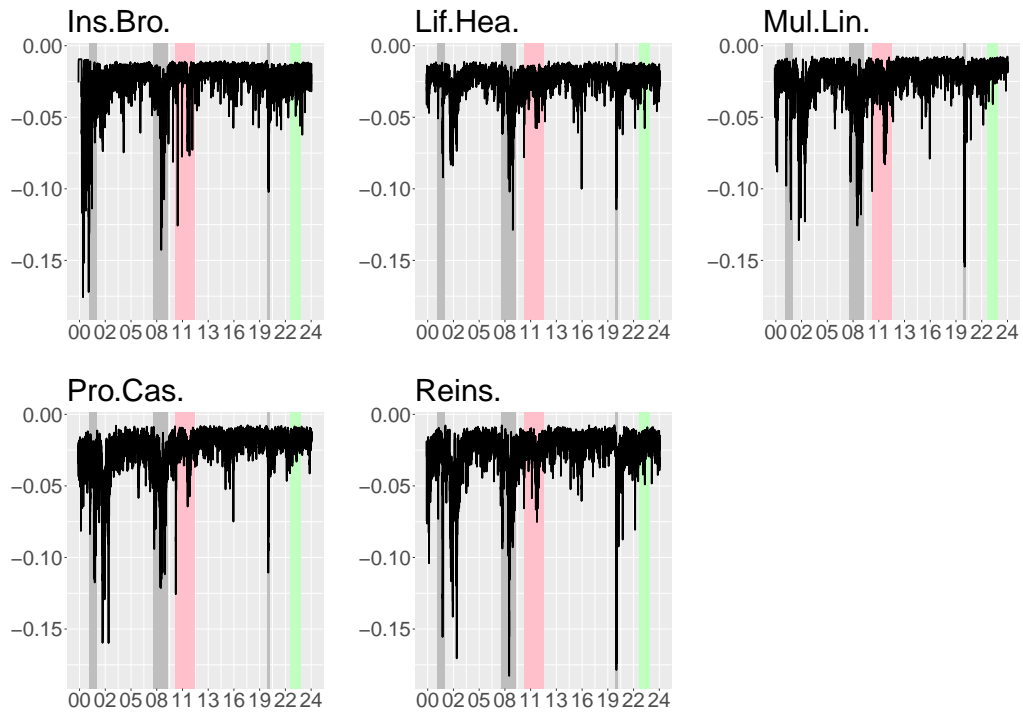


Figure (A.5) This figure plots the daily conditional expected shortfall estimated by the CARES model of the following subsectors of the insurance market: insurance brokers (Ins.Bro.), life health (Lif.Hea.), multiline (Mul.Lin.), property and casualty (Pro.Cas.), and reinsurance (Reins.). The sample goes from January 3, 2000 to October 22, 2024.