

Systemic risk in the insurance sector: A semi-parametric approach based on Spearman's rho

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Abstract

We propose a new method to measure systemic risk in the global insurance sector by analyzing interconnect-edness among firms under different market conditions. Using a semi-parametric approach that relies on the Spearman correlation and copula-based partial dependence, we assess relationships in relatively stable, extremely bullish, and extremely bearish markets. Our approach provides a more flexible and robust framework than traditional methods that rely on linear correlation and the multivariate normal distribution. We show that geographic proximity and shared stock exchanges drive interconnectedness, while the Russo–Ukrainian war had a notable impact on the sector's network under relatively stable market conditions.

1 | INTRODUCTION

Systemic risk refers to the threat of financial instability spreading so widely that it disrupts the functioning of the entire financial system, leading to significant economic consequences. The 2007–2008 global financial crisis is a key example of how financial instability can propagate globally through the complex network of connections among financial institutions. Since the onset of the 2007–2008 crisis, supervisors and regulators have developed tools and supervision regimes to control systemic and moral hazard risks in both the banking and insurance sectors.

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Examples of policies related to the banking sector are those introduced by the Financial Stability Board (FSB). The FSB developed a policy framework to address the “too-big-to-fail” risk, that is, the problem posed by systemically important financial institutions (SIFIs).¹ In 2011, with the help of the Basel Committee on Banking Supervision (BCBS), the FSB identified an initial group of global systemically important banks on which to apply the policy measures drawn up (see FSB, 2011, 2023).² While much attention has been devoted to banking sector risk, insurance companies have increasingly come under scrutiny for their potential role in propagating systemic instability. For example, Eling and Pankoke (2016) review systemic risk in this sector, highlighting new methodological approaches and identifying future research priorities in light of evolving insurance-specific activities and regulatory changes. Indeed, since the 2008 Federal Reserve bailout of AIG, the industry’s largest player, the efforts to monitor and mitigate systemic risk have intensified substantially (see, among others, Jobst, 2016, Denkowska & Wanat, 2020, Clemente & Cornaro, 2022, and Jourde, 2022).³ For example, in 2013, the International Association of Insurance Supervisors (IAIS) developed an assessment methodology to identify global systemically important insurers (G-SIIs), which the FSB then used in consultation with IAIS to designate an initial list of nine G-SIIs (see FSB, 2023 and IAIS, 2013a, 2013b).⁴ This study investigates systemic risk within the global insurance industry, introducing an innovative approach to quantifying the interconnectedness among insurance companies worldwide.

Over the last several years, academic research in insurance and risk management has broadened substantially, reflecting the increasing complexity and interconnectedness of modern financial systems. Recent work has particularly emphasized cross-sector linkages and the rapidly evolving dimensions of environmental and climate-related risks within the sector. This focus is evident in studies such as Kraus (2024), which uses a text-mining analysis to shed light on environmental risk management and strategic disclosure practices in European banks and insurers. Similarly, Kousky and Netusil (2023) empirically investigate the determinants of flood insurance literacy and risk knowledge, offering critical insights into climate risk perception and insurance demand, particularly concerning catastrophic weather events. A second important direction in contemporary insurance research concerns the organizational and enterprise risk management (ERM) response to crisis events. For instance, Dahmen (2023) explores the mechanisms of organizational resilience, underlining the crucial role of robust ERM frameworks for navigating severe and novel crisis situations.

Academic research on systemic risk has also flourished. Benoit et al. (2016) provide a survey on systemic risk and identify two distinct approaches. The first one, labeled “source specific,” is

¹SIFIs are financial institutions that, in case of distress or disorderly failure, would significantly affect the wider financial system and economic activity because of their size, complexity, and systemic interconnectedness.

²The FSB conducts an annual review of this list in November, working closely with BCBS and national regulatory authorities.

³The European Insurance and Occupational Pensions Authority (EIOPA) contributed by publishing a number of discussion papers on systemic risk and macroprudential policy in insurance, and one target was the promotion of some macroprudential tools in addition to the ones already existing in the Solvency II framework (see EIOPA, 2017, 2018a, 2018b).

⁴This G-SII group was updated annually based on new data until 2019. After that, the FSB suspended the updating process in 2020 and applied a holistic framework for the assessment and mitigation of systemic risk in the insurance sector developed by the IAIS in November 2019 (see FSB, 2023 and IAIS, 2019). The FSB announced in November 2022 that it would continue to base its considerations on systemic risk in the insurance sector through the IAIS holistic framework (see FSB, 2022, 2023).

based on confidential data. It considers different sources of systemic risk in isolation and proposes targeted but complex regulatory tools. In contrast, the second approach—central to our analysis—utilizes publicly available market data to generate global measures of systemic risk. Grounded in the efficient market hypothesis, this global measure approach posits that current market prices can serve as indicators of financial stability (or lack thereof). Broadly speaking, two classes of measures are derived from observed prices.

The first class of measures employs the joint distribution of prices to derive tail or probability-based risk indicators, with several notable methodological approaches emerging, starting with measures based on the expected shortfall. Acharya et al. (2016) propose the marginal expected shortfall (MES) and the systemic expected shortfall (SES). MES is defined as the marginal contribution of an institution to systemic risk, where the latter is measured as the expected shortfall of the system. Building on MES, SES estimates the expected capital shortfall of a bank during a broader financial system collapse.⁵ An alternative approach is represented by measures derived from Value at Risk (VaR). An example is the ΔCoVaR of Adrian and Brunnermeier (2016), which, for a given firm, is defined as the difference between the VaR of the financial system conditional on the firm being in financial distress and the VaR of the financial system conditional on the firm being in its median state. A third approach consists of indicators based on estimates of implied joint default probabilities for financial institutions. For instance, Segoviano and Goodhart (2009) view the bank system as a portfolio of banks and determine empirical measurements of distress probabilities for each bank included in the portfolio. Then, they compute the banking system's multivariate density and estimate some banking stability measures. Alternatively, Giglio (2016) combines credit default swaps (CDS) and bond price data to infer the probability of joint default of several banks and, without any assumption about the shape of the joint distribution function, estimates bounds on the probability that several banks default together.⁶

The second class of global measures focuses on interconnectedness. Billio et al. (2012) study systemic risk from a network perspective and develop several measures of interconnectedness. Using Granger-causality networks and principal component analysis applied to monthly returns from hedge funds, banks, broker-dealers, and insurance companies, they find an increase in sectoral interdependence and that banks play a greater role in transmitting shocks than other financial institutions. In the same vein, Diebold and Yilmaz (2014) use a vector autoregressive framework to model stock returns and empirically estimate directional volatility connectedness measures among major US financial institutions. In particular, they show the usefulness of 'connectedness thinking' for systemic risk measurement. Recently, Shahzad et al. (2023) use partial correlation analysis to construct influence quantities among firms in the global energy sector, and

⁵The SRISK measure proposed by Acharya et al. (2012) and Brownlees and Engle (2017) extends the MES by including the liabilities and the size of the financial institution.

⁶Other works belonging to this latter category are those of Huang et al. (2009) and Oh and Patton (2018). Huang et al. (2009) compute a systemic risk indicator based on a hypothetical portfolio consisting of debt instruments issued by banks and with weights equal to the liabilities size of each bank. The systemic risk measure is defined as the expected portfolio credit loss that exceeds a certain share of the banking sector's total liabilities. This expected loss is derived from default probabilities extracted by CDS and forecasts of default correlations, and it takes the name of distress insurance premium because it represents the actuarial premium of an insurance policy against the distress of the hypothetical portfolio. Oh and Patton (2018) propose a new class of copula-based dynamic models for high-dimensional conditional distributions they apply to a collection of daily CDS spreads on 100 US firms over the period 2006 to 2012. Their analysis shows that systemic risk, measured as the joint probability of distress, has increased after the financial crisis.

they compute connectedness measures as defined by Diebold and Yilmaz (2014). Partial correlation analysis is a tool to determine the correlation between two variables when conditioning on one or several other variables, and it can be used to define the average influence that a firm exerts on another one in a given financial system (see, among others, Kenett et al., 2010 and Kenett et al., 2015). In addition to the Pearson correlation, Shahzad et al. (2023) apply partial correlation analysis with the extreme downside correlation (EDC) and extreme upside correlation (EUC) measures proposed by Harris et al. (2019). They use the Pearson coefficient to analyze the connectedness in the energy sector under relatively stable market conditions, and the EDC and EUC to analyze the connectedness under extremely bearish and bullish market conditions, respectively.

Building on Shahzad et al. (2023), we propose systemic risk measures under different market conditions and apply them to the insurance sector. Specifically, our study does not investigate how the insurance sector generates systemic risk for the entire economic system but aims to explore how insurance companies are interconnected and hence systemically linked. Insurance companies form a strongly connected network, not only because they engage in similar economic activities, but also through their business, contractual, and financial relationships. Measuring systemic risk conditional on market conditions is crucial, as systemic vulnerabilities often amplify during periods of market turbulence. Our method is based on three association measures. We employ the Spearman correlation to assess connectedness under relatively stable market conditions, and apply the extreme downside and upside correlations, reformulated in terms of Spearman correlation, to examine connectedness under extremely bearish and bullish market conditions, respectively. In addition to the global versions of these association measures, we also need their partial versions, which can be defined with the help of copula functions. These partial versions quantify the relationship between two variables while excluding the influence of a third variable. Then, we quantify the influence of company k on the relationship between companies i and j by computing the difference between the global association measure between i and j and their partial association measure accounting for k 's influence. Connectedness measures are then computed from these influence indexes.

Our approach has two significant advantages over those based on the partial Pearson correlation. First, using the Spearman correlation, we can detect any monotonic relationship between variables, not just linear ones, as with the Pearson correlation. Hence, our approach gains flexibility by capturing a broader range of correlations. Second, our copula-based method of partial dependence can be used in any stochastic environment and is not limited to any specific dependence structure between three variables. Indeed, the partial Pearson correlation completely characterizes the dependence structure between two variables taking a third one into account only in a Gaussian environment.

Clemente and Cornaro (2022) and Denkowska and Wanat (2020) also study systemic risk in the insurance sector. We differ from their approaches at least in the way we measure systemic risk. The systemic risk measure of Clemente and Cornaro (2022) is based on the difference between the ES of a given insurance company and its marginal ES (i.e., its expected return conditional on the return of another insurer being below its VaR). Denkowska and Wanat (2020) capture systemic risk via tail-dependence coefficients derived from a copula-DCC-GARCH model. Our method instead quantifies systemic risk by measuring how each company influences the pairwise relationships between all other companies in the system, using an association measure to evaluate these relationships.⁷ An advantage of our approach is that it

⁷This approach is equivalent to that of Kenett et al. (2010) and applied by others, such as Kenett et al. (2015) and Shahzad et al. (2023).

allows capturing systemic risk in insurance companies in the case of relatively stable market conditions, while both the approaches of Clemente and Cornaro (2022) and Denkowska and Wanat (2020) are useful only to capture systemic risk during extreme market conditions. We also make an incremental contribution with respect to Jourde (2022), since the measure of connectedness developed by the author is based on a multifactor model of equity returns. In our study, instead, we use a similar factor model only to derive the residuals and employ a method that captures how each insurance company contributes to the interconnectedness among the other companies. Similar to Shahzad et al. (2023), we use the triangulated maximally filtered graph (TMFG) algorithm of Massara et al. (2016) to obtain graphical representations of the interconnectedness among the insurance firms under the three market conditions. The resulting plots help us assess the level of systemic risk in the insurance sector and identify clusters of companies or single companies that play a prominent role in transmitting risk under different market conditions.

Our results confirm that the country of belonging, or more broadly, the geographical proximity, and the sharing of the stock exchange market are leading factors in establishing the strongest connections among the 82 insurance companies used for the empirical analysis. In addition, we find that, for the observation period from 30 November 2016 to 31 October 2023, the transmission and receiving of influence in the insurance sector do not increase during extremely bearish and extremely bullish market conditions compared to relatively stable market conditions. We also conduct a dynamic analysis to determine how systemic risk, measured through a total connectedness index, evolves throughout the sample period. This time interval encompasses both the COVID-19 pandemic and the Russo–Ukrainian war. Our results indicate that the pandemic's impact on the insurance sector was limited to extremely bullish market conditions and emerged only after 3 months from the initial outbreak. In contrast, the combined effects of the war and the concurrent inflation surge influenced the insurance sector's dependency network under relatively stable market conditions.

The rest of the paper is organized as follows. Section 2 presents the methodology devised to measure the degree of interconnectedness at the firm level in a financial system. Section 3 provides information about the considered data set and shows two types of analysis: a static analysis in Section 3.1 and a dynamic analysis in Section 3.2. Finally, Section 4 concludes the paper.

2 | METHODOLOGY

We consider the returns of N insurance companies and denote by $p_{i,t}$ the adjusted closing price⁸ at the end of day t for company i . The return over $[t - 1, t]$ for the i th company is defined as

$$r_{i,t} = \log \left(\frac{p_{i,t}}{p_{i,t-1}} \right).$$

To control for the overall market conditions we use, for each company, the residuals of the Fama-French 3-factor model, which has been modified to reflect the increased volatility in asset

⁸The adjusted closing price is the value of a single share at the close of a trading day modified to account for dividends, stock splits, and new stock offerings.

returns caused by the COVID-19 pandemic. Indeed, since our dataset includes observations over the pandemic period, the direct application of the Fama-French model would not consider the changes in shock volatility occurring in March 2020 and the following months. Specifically, we apply the solution proposed by Lenza and Primiceri (2022) in the context of VAR models and thus multiply the daily shocks in March, April, and May 2020 by the unknown parameters $\bar{s}_0$, $\bar{s}_1$, and $\bar{s}_2$, respectively, and those in the j th month after May 2020 by $1 + (\bar{s}_2 - 1)\phi^j$. Then, the modified Fama-French 3-factor model for the i th firm is given by

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{i,1}(r_{m,t} - r_{f,t}) + \beta_{i,2}SMB_t + \beta_{i,3}HML_t + s_t\epsilon_{i,t}, \quad (1)$$

where $r_{f,t}$ is the risk-free return rate at time t , $r_{m,t}$ is the return of the market portfolio at time t , SMB_t is the difference in the returns at time t of portfolios of small company stocks and big company stocks, HML_t is the difference in the returns at time t of portfolios with high Book-to-Market ratios and low Book-to-Market ratios, $\epsilon_{i,t}$ is the shock at time t , and s_t is the residual volatility re-scaling factor at time t and equals 1 up to 29/02/2020, $\bar{s}_0$ in March 2020, $\bar{s}_1$ in April 2020, $\bar{s}_2$ in May 2020, and $1 + (\bar{s}_2 - 1)\phi^j$ in the j th month after May 2020. We assume that all companies within the same geographical area have the same re-scaling factor s_t .⁹ The parameters of the model can be estimated by a quasi-maximum likelihood procedure as explained in Appendix B. We denote by $e_{i,t}$ the estimated time t residual for company i .

To study the connectedness links in the system formed by the N insurance companies, we need to define an association measure between two variables and a partial version of it, excluding the influence of a third variable. We consider three measures of association: Spearman's rho and two extreme correlation measures, all defined in terms of two-dimensional copula functions. Appendix C provides a brief discussion of two-dimensional copula functions.

Given a two-dimensional random vector (E_i, E_j) with marginal distribution functions F_{E_i} and F_{E_j} and copula function $C_{i,j}$, Spearman's rho is defined as

$$\begin{aligned} \rho_S(i, j) &= \frac{\text{cov}(U_i, U_j)}{\sqrt{\text{var}(U_i)}\sqrt{\text{var}(U_j)}} = \frac{\int_0^1 \int_0^1 (u - 0.5)(v - 0.5) dC_{i,j}(u, v)}{\int_0^1 (u - 0.5)^2 du} \\ &= 12 \int_0^1 \int_0^1 (u - 0.5)(v - 0.5) dC_{i,j}(u, v) = 12 \left(\int_0^1 \int_0^1 uv dC_{i,j}(u, v) - \frac{1}{4} \right) \\ &= 12 \int_0^1 \int_0^1 C_{i,j}(u, v) dudv - 3, \end{aligned}$$

where the transformation $(U_i, U_j) = (F_{E_i}(E_i), F_{E_j}(E_j))$ has $C_{i,j}$ as the joint distribution function. To assess the Spearman correlation in the left tail of (E_i, E_j) , we use a Spearman-based analog of the extreme downside correlation of Harris et al. (2019):

⁹We apply our methodology to companies from different geographical areas. Since the values of the three Fama-French factors vary with the geographical region, the same holds for the estimates of the parameters $\bar{s}_0$, $\bar{s}_1$, and ϕ .

$$\begin{aligned}\rho_L(i, j; p) &= \frac{\int_0^p \int_0^p (u - 0.5)(v - 0.5) dC_{i,j}(u, v)}{\int_0^p (u - 0.5)^2 du} \\ &= \frac{12}{4p^3 - 6p^2 + 3p} \left[C_{i,j}(p, p) \left(p^2 - p + \frac{1}{4} \right) + \left(\frac{1}{2} - p \right) \int_0^p C_{i,j}(u, p) du + \right. \\ &\quad \left. + \left(\frac{1}{2} - p \right) \int_0^p C_{i,j}(p, v) dv + \int_0^p \int_0^p C(u, v) dudv \right],\end{aligned}$$

where p is a small probability level, typically less than or equal to 10%. The correlation ρ_L takes values in $[0, 1]$ and measures the degree of dependence between E_i and E_j in the left tail. It can be interpreted as a localized version of Spearman's rho, as it restricts the double integral in Spearman's numerator to the square $[0, p]^2$, and applies a normalization that yields the value 1 when the variables are perfectly positively dependent in that region. Therefore, ρ_L takes values close to 1 when E_i and E_j exhibit strong positive dependence in the left tail, and values close to 0 when such dependence is weak.

As observed by Shahzad et al. (2023), the extreme downside correlation can be modified to compute the correlation at other quantile levels. Thus, we can quantify the Spearman correlation in the right tail through the extreme upside correlation:

$$\begin{aligned}\rho_U(i, j; p) &= \frac{\int_{1-p}^1 \int_{1-p}^1 (u - 0.5)(v - 0.5) dC_{i,j}(u, v)}{\int_{1-p}^1 (u - 0.5)^2 du} \\ &= \frac{12}{4p^3 - 6p^2 + 4p} \int_0^p \int_0^p (u - 0.5)(v - 0.5) dC_{i,j}^S(u, v) \\ &= \frac{12}{4p^3 - 6p^2 + 3p} \left[C_{i,j}^S(p, p) \left(p^2 - p + \frac{1}{4} \right) + \left(\frac{1}{2} - p \right) \int_0^p C_{i,j}^S(u, p) du + \right. \\ &\quad \left. + \left(\frac{1}{2} - p \right) \int_0^p C_{i,j}^S(p, v) dv + \int_0^p \int_0^p C^S(u, v) dudv \right],\end{aligned}$$

where p is again less than or equal to 10%, and $C_{i,j}^S$ is the survival copula associated to $C_{i,j}$, i.e.,

$$C_{i,j}^S(u, v) = \mathbb{P}(1 - U_i \leq u, 1 - U_j \leq v) = \mathbb{P}(U_i \geq 1 - u, U_j \geq 1 - v).$$

Like the correlation ρ_L , the measure ρ_U also takes values in $[0, 1]$, but unlike ρ_L , it evaluates the degree of dependence between E_i and E_j in the right tail.

To assess how the extreme downside and upside correlations, ρ_L and ρ_U , capture tail dependence, we compute their values for some standard copula functions by numerically evaluating the integrals in their definitions. For a fixed probability $p = 5\%$, Table 1 presents the values of the dependence measures ρ_L and ρ_U for two tail-symmetric copulas, the Gaussian and the Student's t , and for two tail-asymmetric copulas, the Gumbel and the Clayton. The table also includes the corresponding ρ_S values. For the tail-symmetric copulas, ρ_L and ρ_U coincide and increase as the dependence parameter ρ increases. It is worth noting that, for ρ fixed, the Student's t copula exhibits higher values of ρ_L and ρ_U than the Gaussian copula, due to its heavier tails. For the tail-asymmetric copulas, ρ_L and ρ_U

TABLE 1 Values of the correlation measures ρ_S , ρ_L , and ρ_U for different copula functions. The probability level p for ρ_L and ρ_U is 5%.

Copula	ρ_S	ρ_L	ρ_U	Copula	ρ_S	ρ_L	ρ_U
Gaussian ($\rho = 0.25$)	0.2394	0.1239	0.1239	Gumbel ($\theta = 2$)	0.6822	0.2931	0.6126
Gaussian ($\rho = 0.50$)	0.4826	0.2474	0.2474	Gumbel ($\theta = 5$)	0.9432	0.6510	0.8650
Gaussian ($\rho = 0.75$)	0.7341	0.4485	0.4485	Gumbel ($\theta = 10$)	0.9855	0.8167	0.9359
Student's t ($\nu = 4, \rho = 0.25$)	0.2319	0.2204	0.2204	Clayton ($\theta = 2$)	0.6822	0.7201	0.1365
Student's t ($\nu = 4, \rho = 0.50$)	0.4690	0.3458	0.3458	Clayton ($\theta = 5$)	0.8846	0.8794	0.2413
Student's t ($\nu = 4, \rho = 0.75$)	0.7196	0.5293	0.5293	Clayton ($\theta = 10$)	0.9582	0.9386	0.3715

differ. In particular, the Gumbel copula, characterized by strong upper-tail dependence, exhibits ρ_U values that are higher than the corresponding ρ_L values. Conversely, the Clayton copula, which displays strong lower-tail dependence, shows ρ_L values greater than ρ_U . In both cases, ρ_L and ρ_U increase as the dependence parameter θ increases.

To define partial association measures for the dependence between E_i and E_j after removing the effect of E_k , we refer to the concept of partial copula (see Gijbels et al., 2015). The partial copula $\bar{C}_{i,j|k}$ is a copula between two transformations that are independent of E_k and preserve the dependence structure of E_i and E_j after the removal of E_k . Specifically, we consider the copulas $C_{i,k}$ and $C_{j,k}$ and compute the two new variables

$$U_{h|k} = F_{U_h|U_k}(U_h|U_k) = \frac{\partial C_{h,k}(U_h, U_k)}{\partial U_k}, h = i, j, \tag{2}$$

which are both uniformly distributed on $[0, 1]$ and independent of U_k , and thus of E_k . Their copula, the partial copula $\bar{C}_{i,j|k}$, can be seen as the expectation of the conditional copula $C_{i,j|k}(\cdot, \cdot|U_k)$ with respect to U_k (i.e., it coincides with the so-called average conditional copula). We then define the partial versions of the previous association measures as

$$\begin{aligned} \rho_S(i, j|k) &= 12 \int_0^1 \int_0^1 \bar{C}_{i,j|k}(u, v) du dv - 3 \\ \rho_L(i, j; p|k) &= \frac{12}{4p^3 - 6p^2 + 3p} \left[\bar{C}_{i,j|k}(p, p) \left(p^2 - p + \frac{1}{4} \right) + \left(\frac{1}{2} - p \right) \int_0^p \bar{C}_{i,j|k}(u, p) du \right. \\ &\quad \left. + \left(\frac{1}{2} - p \right) \int_0^p \bar{C}_{i,j|k}(p, v) dv + \int_0^p \int_0^p \bar{C}_{i,j|k}(u, v) du dv \right] \\ \rho_U(i, j; p|k) &= \frac{12}{4p^3 - 6p^2 + 3p} \left[\bar{C}_{i,j|k}^S(p, p) \left(p^2 - p + \frac{1}{4} \right) + \left(\frac{1}{2} - p \right) \int_0^p \bar{C}_{i,j|k}^S(u, p) du \right. \\ &\quad \left. + \left(\frac{1}{2} - p \right) \int_0^p \bar{C}_{i,j|k}^S(p, v) dv + \int_0^p \int_0^p \bar{C}_{i,j|k}^S(u, v) du dv \right], \end{aligned}$$

where $\bar{C}_{i,j|k}^S$ is the survival copula associated to $\bar{C}_{i,j|k}$.

We can now recall some connectedness indexes to analyze the system composed of the N insurance companies. Let $\rho(i, j)$ be any of the three association measures defined above between companies i and j , and $\rho(i, j|k)$ the corresponding partial association measure adjusted for the third company k . Then, the influence of variable k on the association measure between i and j can be measured by

$$d(i, j|k) = \rho(i, j) - \rho(i, j|k).$$

The average influence of variable k on variable i is given by

$$d(i, k) = \frac{1}{N-2} \sum_{j \neq i, k}^N d(i, j|k). \quad (3)$$

Note that, in general, $d(i, k) \neq d(k, i)$ and hence the dependency matrix D with generic element $d(i, k)$ is not symmetric. We can compute the total connectedness index as the sum, divided by N , of all the off-diagonal elements of the matrix D :

$$C = \frac{1}{N} \sum_{i=1}^N \sum_{k \neq i}^N d(i, k). \quad (4)$$

The contribution of variable i to the system can be measured by

$$C(i \rightarrow) = \sum_{j \neq i}^N d(j, i), \quad (5)$$

while the influence of the system to variable i by

$$C(i \leftarrow) = \sum_{k \neq i}^N d(i, k). \quad (6)$$

Finally, the net contribution of variable i to the system is obtained as

$$C(i) = C(i \rightarrow) - C(i \leftarrow). \quad (7)$$

When using Spearman's rho as the association measure, we assess systemic risk in the insurance sector during relatively stable market conditions. In contrast, extreme downside and upside correlations allow us to examine systemic risk under extreme bearish and bullish market conditions, respectively.

2.1 | Estimation of ρ_S , ρ_L , and ρ_U

Computing the previous connectedness indexes requires estimating the non-partial and partial versions of the three association measures ρ_S , ρ_L , and ρ_U .

Given the time series $\{(e_{i,t}, e_{j,t}), t = 1, \dots, T\}$, we first compute the values

$$u_{i,t} = \widehat{F}_{E_i, T}(e_{i,t}) \quad \text{and} \quad u_{j,t} = \widehat{F}_{E_j, T}(e_{j,t}),$$

for $t = 1, \dots, T$, where $\widehat{F}_{E_i, T}$ and $\widehat{F}_{E_j, T}$ denote the empirical distribution functions:

$$\widehat{F}_{E_h, T}(u) = \frac{1}{T+1} \sum_{t=1}^T \mathbf{1}(e_{h,t} \leq u), \quad h = i, j,$$

and $\mathbf{1}(\cdot)$ denotes the indicator function, which equals 1 if the condition inside is satisfied and 0 otherwise. Then, the three association measures $\rho_S(i, j)$, $\rho_L(i, j; p)$, and $\rho_U(i, j; p)$ can respectively be estimated as

$$\begin{aligned} \widehat{\rho}_S(i, j) &= \frac{\sum_{t=1}^T (u_{i,t} - 0.5)(u_{j,t} - 0.5)}{\sqrt{\sum_{t=1}^T (u_{i,t} - 0.5)^2} \sqrt{\sum_{t=1}^T (u_{j,t} - 0.5)^2}} \\ \widehat{\rho}_L(i, j; p) &= \frac{\sum_{t=1}^T (u_{i,t} - 0.5)(u_{j,t} - 0.5) \mathbf{1}(u_{i,t} \leq p, u_{j,t} \leq p)}{\sqrt{\sum_{t=1}^T (u_{i,t} - 0.5)^2 \mathbf{1}(u_{i,t} \leq p)} \sqrt{\sum_{t=1}^T (u_{j,t} - 0.5)^2 \mathbf{1}(u_{j,t} \leq p)}} \\ \widehat{\rho}_U(i, j; p) &= \frac{\sum_{t=1}^T (u_{i,t} - 0.5)(u_{j,t} - 0.5) \mathbf{1}(u_{i,t} \geq 1 - p, u_{j,t} \geq 1 - p)}{\sqrt{\sum_{t=1}^T (u_{i,t} - 0.5)^2 \mathbf{1}(u_{i,t} \geq 1 - p)} \sqrt{\sum_{t=1}^T (u_{j,t} - 0.5)^2 \mathbf{1}(u_{j,t} \geq 1 - p)}}. \end{aligned}$$

For the partial versions of the three association measures, we need realizations of the variables U_{ilk} and U_{jlk} , whose computation relies on the copulas $C_{i,k}$ and $C_{j,k}$, respectively. Given the two samples $\{(u_{i,t}, u_{k,t}), t = 1, \dots, T\}$ and $\{(u_{j,t}, u_{k,t}), t = 1, \dots, T\}$, we select the best-fitting theoretical copulas from a predefined set according to specific criteria. This set of theoretical copula functions includes the independence, Gaussian, Student's t , Clayton, Gumbel, Frank, and Joe copulas along with 90° , 180° , and 270° rotations of the Clayton, Gumbel, and Joe copulas. We use the inversion of Kendall's tau as an estimation method for each copula inside the set and adopt the Akaike Information Criterion to select the best copula. The partial derivatives in (2), called h -functions in the copula jargon, have closed-form expressions for all copulas considered in this study (see Schepsmeier & Stöber, 2014). The components of the bivariate random vector (U_{ilk}, U_{jlk}) are obtained as

$$u_{h|k,t} = \frac{\partial \widehat{C}_{h,k}(u_h, u_k)}{\partial u_k} \bigg|_{(u_{h,t}, u_{k,t})}, \quad h = i, j, t = 1, \dots, T,$$

where the two copulas $\widehat{C}_{i,k}$ and $\widehat{C}_{j,k}$ are estimates of $C_{i,k}$ and $C_{j,k}$, respectively. Finally, the estimates of the partial association measures are given by

$$\begin{aligned} \widehat{\rho}_S(i, j|k) &= \frac{\sum_{t=1}^T (u_{i|k,t} - 0.5)(u_{j|k,t} - 0.5)}{\sqrt{\sum_{t=1}^T (u_{i|k,t} - 0.5)^2} \sqrt{\sum_{t=1}^T (u_{j|k,t} - 0.5)^2}} \widehat{\rho}_L(i, j; p|k) \\ &= \frac{\sum_{t=1}^T (u_{i|k,t} - 0.5)(u_{j|k,t} - 0.5) \mathbf{1}(u_{i|k,t} \leq p, u_{j|k,t} \leq p)}{\sqrt{\sum_{t=1}^T (u_{i|k,t} - 0.5)^2 \mathbf{1}(u_{i|k,t} \leq p)} \sqrt{\sum_{t=1}^T (u_{j|k,t} - 0.5)^2 \mathbf{1}(u_{j|k,t} \leq p)}} \widehat{\rho}_U(i, j; p|k) \\ &= \frac{\sum_{t=1}^T (u_{i|k,t} - 0.5)(u_{j|k,t} - 0.5) \mathbf{1}(u_{i|k,t} \geq 1 - p, u_{j|k,t} \geq 1 - p)}{\sqrt{\sum_{t=1}^T (u_{i|k,t} - 0.5)^2 \mathbf{1}(u_{i|k,t} \geq 1 - p)} \sqrt{\sum_{t=1}^T (u_{j|k,t} - 0.5)^2 \mathbf{1}(u_{j|k,t} \geq 1 - p)}}. \end{aligned}$$

3 | EMPIRICAL RESULTS

Our empirical analysis focuses on daily adjusted closing prices of 82 insurance companies across 23 countries¹⁰: Australia (4), Austria (2), Belgium (1), Bermuda (3), Canada (5), China (4), Denmark (1), Finland (1), France (3), Germany (4), Hong Kong (3), Italy (3), Japan (5), Netherlands (3), Norway (1), Poland (1), Singapore (1), South Korea (1), Spain (2), Switzerland (6), Taiwan (3), United Kingdom (5), United States (20). Daily adjusted closing prices were obtained from Refinitiv Eikon for the period spanning November 30, 2016, to October 31, 2023. All closing prices in foreign currencies were converted to U.S. dollars using exchange rates from Refinitiv Eikon before calculating daily returns. For each insurance company, Table A1 reports the company name (Name), Refinitiv Eikon acronym (Symbol), company headquarters country (Country), stock exchange as reported in Refinitiv Eikon (Exchange), the main statistics about returns over the entire sample period, the Jarque-Bera statistic to test the normality assumption, and, in the last column, the Augmented Dickey-Fuller (ADF) statistic to test for a unit root. The table is organized so that the top 33 companies are based in Europe, the next 28 in North America, and the bottom 21 in Asia Pacific. We observe, as expected, daily returns with means very close to zero for each insurance company. The reported standard deviations range from 0.9% to 2.5% averaging 1.8%. We also notice that the daily returns of most insurance firms exhibit negative skewness, indicating that the left tail of the return distribution is longer or fatter than the right tail, hence implying that large negative returns occur more frequently than large positive returns. All return series exhibit kurtosis values exceeding three, suggesting leptokurtic distributions with heavier tails than the normal distribution. Indeed, the reported values of skewness and kurtosis entail non-normal distributions, as evidenced by the Jarque-Bera test statistics. Finally, the last column with the ADF statistics ensures that all the return series are stationary at the 1% level. The sample period is characterized by the COVID-19 pandemic, which was detected in China in December 2019 and spread globally in early 2020. It remained a global health emergency until 5 May 2023, even though some developed countries considered it an endemic disease as early as 2022. The sample period also includes the Russian invasion of Ukraine, which began in February 2022 and was still ongoing at the end of the sample period. Since the insurance companies in the sample belong to three broad geographical regions, to compute the residuals from our modified Fama-French 3-factor model (see Section 2 for the adjustment accounting for the increased residual variance due to COVID-19), we use regional Fama-French factors for North America, Europe, Asia Pacific (excluding Japan), and Japan, obtained from Kenneth French's website.¹¹ Table 2 reports the estimates of the parameters $\bar{s}_0$, $\bar{s}_1$, $\bar{s}_2$, and ϕ of the modified Fama-French 3-factor model with standard errors reported in brackets. These estimates confirm that March 2020, the initial month of significant global economic impact from COVID-19, witnessed an increased shock volatility across all four geographical areas. The growth is sharper in Europe and North America than in Asia (Japan excluded) and Japan. High volatility persisted in April and May 2020, albeit with diminished intensity compared to March 2020. We also observe that shock volatility in Asia (Japan excluded) is higher in May 2020 than in April 2020 because $\bar{s}_2$ is greater than $\bar{s}_1$. Estimated values of the parameter ϕ , which controls the rate at which shock volatility reverts to its pre-pandemic level, are 0.96257, 0.96142, and 0.97826 for the geographical areas of North America, Asia (Japan excluded), and Japan, respectively. For Europe, the

¹⁰The number in parentheses indicates the number of companies from that country.

¹¹The Fama-French factors data can be downloaded from Kenneth French's data library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

estimate is 0.73307, indicating a more rapid return to pre-pandemic volatility levels compared to the other regions.

To show that controlling for the Fama-French factors is essential for removing common effects, Figure 1 presents a scatter plot of Spearman's correlation coefficients computed with the returns (y-axis) and those computed with the residuals from the modified Fama-French 3-factor model (x-axis). Since almost all points lay below the diagonal line, a significant portion of the correlations among returns is explained by common factors. Therefore, an analysis based on pure pairwise correlations requires first filtering the data with the Fama-French factors.

The residuals from the modified Fama-French 3-factor model are expected to contain information on the business, contractual, and financial interdependencies among the companies and can therefore be used to assess systemic risk in the insurance sector. To test this conjecture, we conduct a small empirical analysis on a subgroup of 18 European insurance companies.¹² We focus on European insurers because, for only 18 of them, it was possible to retrieve the following balance sheet information for the year 2022, one of the years included in our sample period, from Moody's Analytics' *InsuranceFocus* database: premiums received (Life and Non-Life), reinsurance held expenses (Life and Non-Life), cash and deposits with credit institutions, bonds and other fixed-interest securities, shares and other variable-interest instruments, mortgages and loans, and real estate. For each pair of companies, we compute three measures of similarity: (i) a business similarity based on premiums received (Life and Non-Life); (ii) a contractual similarity based on reinsurance held expenses (Life and Non-Life); and (iii) a financial similarity based on cash and deposits with credit institutions, bonds and other fixed-interest securities, shares and other variable-interest instruments, mortgages and loans, and real estate. These measures are computed using cosine similarity. For instance, considering the business dimension, we first normalize the two variables, premiums received (Life) and premiums received (Non-Life), so that, for each company, the values lie between 0 and 1. Then, if x_i denotes the two-dimensional vector containing the normalized values of premiums received (Life) and premiums received (Non-Life) for company i , and x_j denotes the corresponding vector for company j , the business similarity for the pair (i, j) is given by

$$\text{sim}(i, j) = \frac{x_{i,1}x_{j,1} + x_{i,2}x_{j,2}}{\sqrt{x_{i,1}^2 + x_{i,2}^2} \sqrt{x_{j,1}^2 + x_{j,2}^2}}.$$

We use cosine similarity because it captures the angle between the corresponding vectors of variables, and is therefore sensitive to the relative composition of the variables rather than their absolute magnitude. Specifically, cosine similarity compares companies in terms of the structure of their activities or investments, and is thus suitable for identifying similarities in business mix, reinsurance structure, and asset allocation. Our empirical analysis to test the presence of information on business, contractual, and financial interdependencies then uses the Spearman correlations computed from the residuals for the year 2022 and estimates the model

$$y(i, j) = \beta_0 + \beta_1 \text{sim}_b(i, j) + \beta_2 \text{sim}_c(i, j) + \beta_3 \text{sim}_f(i, j) + \epsilon, \quad (8)$$

where $y(i, j) = \tanh(\hat{\rho}_S(i, j))$, i.e., $y(i, j)$ equals the hyperbolic tangent of $\hat{\rho}_S(i, j)$, and $\text{sim}_b(i, j)$, $\text{sim}_c(i, j)$, and $\text{sim}_f(i, j)$ denote the business, contractual, and financial similarities,

¹²In Table A1, these 18 European insurance companies are marked with an asterisk beside their name.

TABLE 2 Estimates of the parameters $\bar{s}_0$, $\bar{s}_1$, $\bar{s}_2$, and ϕ in the modified Fama-French 3-factor model for each geographical area. Standard errors are reported in brackets.

	$\bar{s}_0$	$\bar{s}_1$	$\bar{s}_2$	ϕ
Europe	3.22024 (0.0916)	2.19115 (0.0647)	1.69884 (0.0472)	0.73307 (0.0194)
North America	4.37315 (0.1239)	2.35695 (0.0673)	1.53380 (0.0193)	0.96257 (0.0024)
Asia (ex Japan)	2.15869 (0.0856)	1.21321 (0.0565)	1.42981 (0.0265)	0.96142 (0.0036)
Japan	2.62289 (0.1846)	1.36370 (0.0961)	1.31597 (0.0380)	0.97826 (0.0061)

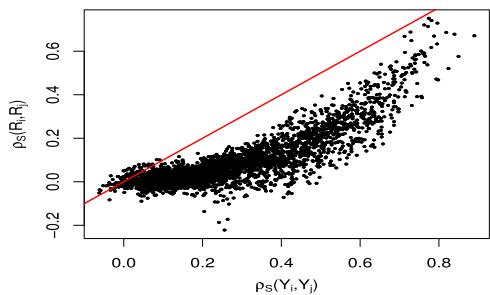


FIGURE 1 Scatter plot between Spearman's correlation coefficients computed with the returns (y-axis) and those computed with the residuals from the modified Fama-French 3-factor model (x-axis). The correlation coefficients have been estimated using the observations over the entire sample period (30/11/2016– 31/10/2023).

respectively, for the pair (i, j) . Table 3 reports the estimate of Model (8), showing that the coefficients β_1 and β_2 are significant at the 5% level and β_3 at the 10% level. These results confirm that the 2022 residuals contain information about the business, contractual, and financial interdependencies within the small subgroup of European companies considered in the analysis. Regarding the negative estimate of β_1 , this result can be interpreted as evidence that insurance companies with similar business structures tend to diversify more on the asset side or to manage risks differently, thereby reducing the degree of co-movement captured by the model.

We recall that, to estimate the partial association measures $\rho_S(i, j|k)$, $\rho_L(i, j|k)$, and $\rho_U(i, j|k)$ between companies i and j after removing the influence of company k , our method first estimates the copula functions $C_{i,k}$ and $C_{j,k}$. The estimated copulas, $\hat{C}_{i,k}$ and $\hat{C}_{j,k}$, are then used to determine the realizations $\{(u_{i|k,t}, u_{j|k,t}), t = 1, \dots, T\}$ of i and j not influenced by k , which in turn are used to compute the estimates $\hat{\rho}_S(i, j|k)$, $\hat{\rho}_L(i, j|k)$, and $\hat{\rho}_U(i, j|k)$. A critical step of the method, therefore, lies in estimating the copula functions $C_{i,k}$ and $C_{j,k}$, which are obtained by selecting the best-fitting functions from a set of theoretical copulas according to the Akaike Information Criterion. Table 4 reports the distribution of the 3321 copula functions estimated across the 82 insurance companies under study, based on the residuals from our modified

TABLE 3 Estimates of Model (8), assessing whether residuals from the modified Fama-French 3-factor model contain information on the business, contractual, and financial interdependencies among the companies. Standard errors are reported inside round brackets. *** and ** denote significance at the 5% and 10% level, respectively.

β_0	β_1	β_2	β_3
0.20159	-0.27482**	0.14643**	0.26878*
(0.16081)	(0.10997)	(0.06597)	(0.16193)

Fama-French 3-factor model applied to asset returns over the entire sample period, that is, from November 30, 2016 to October 31, 2023. The table is organized so that upper-tail-dependence copulas appear at the top, tail-symmetric copulas in the middle, and left-tail-dependence copulas at the bottom. Notably, a significant proportion, 25.59%, of the copulas are identified as independence copulas, suggesting that some companies remain only weakly connected to each other after removing the effect of the Fama-French factors from the asset returns. The remaining proportion of the tail-symmetric copulas amounts to 48.05%, with the Student's t and Frank copulas having proportions of 25.53% and 15.84%, respectively, and being those that exhibit heavier tail dependence. The proportions of upper- and lower-tail-dependence copulas are 8.04% and 18.30%, respectively. This indicates that a significant number of companies are characterized by stronger dependence in only one tail, with lower-tail dependence being more common than upper-tail dependence.

This copula distribution across the 82 globally dispersed insurance companies suggests that companies sharing business markets within the same world regions and/or having contractual and financial ties tend to exhibit dependence structures, identified through the Student's t and Frank copulas, that are tail-symmetric and characterized by heavy tails. Moreover, a meaningful share of lower-tail-dependence copulas is observed, confirming that some companies become more interconnected during periods of market turmoil. However, the sizable proportion of independence copulas also supports the view that certain companies remain only weakly connected once the effect of market-wide factors is removed.

Given a system of N insurance companies and an association measure ρ , the number of influence measures $d(i, j|k)$ is $N(N-1)(N-2)/2$. To identify the non-trivial influences, we apply the empirical statistical significance test proposed by Kenett et al. (2015), which we briefly outline below. We fix $M = 100$ and proceed as follows:

1. For $m = 1, \dots, M$, we independently shuffle the time series $\{e_{i,t}, t = 1, \dots, T\}$ of each company i , thereby destroying the dependence structure across firms while preserving the marginal distribution of each series;
2. We compute the influence measures $\hat{d}_m(i, j|k)$ resulting from the reshuffled system at the m th iteration;
3. The collection $\{\hat{d}_m(i, j|k), m = 1, \dots, M\}$ provides realizations of the influence measure under the null hypothesis of cross-company independence;
4. We use the empirical distribution $\{\hat{d}_m(i, j|k), m = 1, \dots, M\}$ to determine the significance thresholds at the desired level.

For instance, given the residuals from the modified Fama-French 3-factor model applied to the entire sample period and using Spearman's rho as the association measure, Figure 2 shows the

TABLE 4 Distribution of the 3321 copula functions estimated across the 82 insurance companies under study, based on the residuals from the modified Fama-French 3-factor model applied to asset returns over the entire sample period. The copulas are grouped by tail-dependence type and tail symmetry, sorted in descending order within each group. Values are expressed as percentages.

Copula	Value	Copula	Value
Upper-tail-dependence copulas			
Gumbel	4.43%	Joe	2.50%
Rotated Clayton 270 degrees	0.66%	Rotated Joe 270 degrees	0.45%
Tail-symmetric copulas			
Independence	25.59%	Student's <i>t</i>	25.53%
Frank	15.84%	Gaussian	5.45%
Rotated Clayton 90 degrees	0.51%	Rotated Gumbel 90 degrees	0.42%
Rotated Gumbel 270 degrees	0.30%		
Lower-tail-dependence copulas			
Rotated Gumbel 180 degrees	7.20%	Rotated Joe 180 degrees	3.79%
Rotated Clayton 180 degrees	3.49%	Clayton	2.56%
Rotated Joe 90 degrees	1.26%		

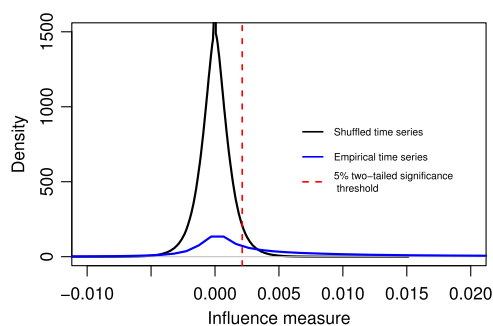


FIGURE 2 Distributions of $\hat{d}(i, j|k)$ from the shuffled time series (black curve) and of $d(i, j|k)$ from the empirical time series (blue curve) when using Spearman's rho as the association measure. The curves are computed from the residuals of the modified Fama-French 3-factor model applied to the entire sample period (30/11/2016–31/10/2023). The dashed red vertical line corresponds to the two-tailed 5% significance threshold.

distribution of $\hat{d}_m(i, j|k)$ from the reshuffled data (the black curve) compared with $d(i, j|k)$ from the empirical time series (the blue curve). The dashed red vertical line corresponds to the 5% two-tailed significance threshold, that is, the 97.5% quantile of the distribution of $\hat{d}_m(i, j|k)$. Only influences exceeding this threshold in absolute value are considered non-trivial. Table 5 reports the 5% two-tailed significance thresholds for the three association measures ρ_S , ρ_L , and ρ_U , which we use in the static analysis of Section 3.1 to identify non-trivial influences. For ρ_L and ρ_U , the thresholds are obtained by setting $p = 5\%$ in the formulas defining the measures. Here, p specifies the extent of the left and right tails considered in the integrals, so that ρ_L and ρ_U focus on the lower and upper tails of the joint distribution, respectively.

TABLE 5 Two-tailed 5% significance thresholds for the three association measures, ρ_S , ρ_L , and ρ_U , obtained from the shuffling of residuals from the modified Fama-French 3-factor model over the entire sample period (30/11/2016–31/10/2023). These thresholds indicate the values of $d(i, j|k)$ that can be considered statistically significant. For ρ_L and ρ_U , the thresholds are calculated by setting $p = 5\%$ in the formulas defining the left- and right-tail contributions.

	ρ_S	ρ_L	ρ_U
Threshold	0.002127	0.014873	0.014875

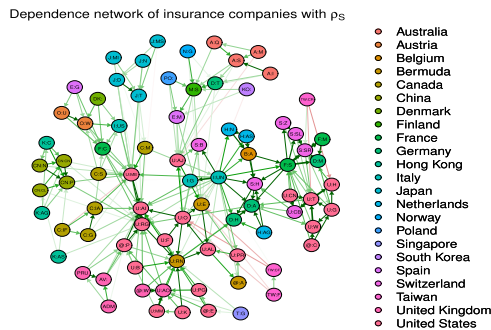


FIGURE 3 Dependence network of stock returns of insurance companies over the entire sample period (December 2016 to October 2023) under relatively stable market conditions. There are 82 companies from 23 countries across three geographical regions (North America, Asia Pacific, and Europe). Spearman's rho ρ_S is used to build the dependence network under relatively stable market conditions, and the triangulated maximally filtered graph (TMFG) algorithm is applied to determine the significant links across the insurance companies. The companies of a country are shown with the same color. The thickness of the edges is proportional to the strength of the connection between each pair of companies. The green arrows mean a positive link, while the red ones a negative link.

3.1 | Static analysis

We use the TMFG algorithm of Massara et al. (2016) to study dependence networks in the insurance sector under relatively stable, extremely bearish, and extremely bullish market conditions. The TMFG algorithm is a network-filtering method that provides an approximate solution to the *weighted maximal planar graph* problem. Specifically, it can be used to visualize the dependence structure among companies, represented as nodes or vertices, and the dependencies between pairs of stock returns, represented as edges. Figures 3, 4, and 5 display the dependence networks of the insurance company stock returns over the entire sample period using Spearman's rho, the extreme downside correlation, and the extreme upside correlation, respectively. For the latter two extreme correlations, the parameter p controlling the extent in the left and right tails equals 5%. The edges connecting the companies are determined through the asymmetric matrix D with generic element $d(i, j)$ of Equation (3). Following Kenett et al. (2010), to keep information about the main direction of influence and avoid multiple links, we set $d(j, i) = 0$ if $|d(i, j)| > |d(j, i)|$ and $d(i, j) = 0$ otherwise. The thickness of the edges is proportional to the strength of the connection between each pair of companies.

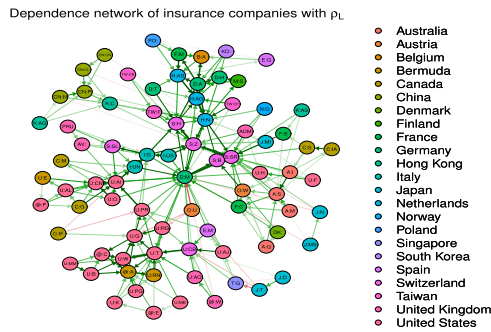


FIGURE 4 Dependence network of stock returns of insurance companies over the entire sample period (December 2016 to October 2023) under extremely bearish market conditions. There are 82 companies from 23 countries across three geographical regions (North America, Asia Pacific, and Europe). The extreme downside correlation ρ_L is used to build the dependence network under extremely bearish market conditions, and the triangulated maximally filtered graph (TMFG) algorithm is applied to determine the significant links across the insurance companies. The companies of a country are shown with the same color. The thickness of the edges is proportional to the strength of the connection between each pair of companies. The green arrows mean a positive link, while the red ones a negative link.

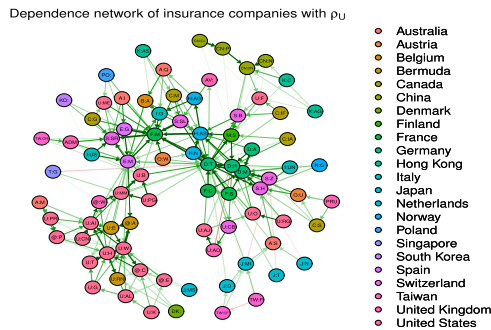


FIGURE 5 Dependence network of stock returns of insurance companies over the entire sample period (December 2016 to October 2023) under extremely bullish market conditions. There are 82 companies from 23 countries across three geographical regions (North America, Asia Pacific, and Europe). The extreme upside correlation ρ_U is used to build the dependence network under extremely bullish market conditions, and the triangulated maximally filtered graph (TMFG) algorithm is applied to determine the significant links across the insurance companies. The companies of a country are shown with the same color. The thickness of the edges is proportional to the strength of the connection between each pair of companies. The green arrows mean a positive link, while the red ones a negative link.

Looking at Figure 3, we notice that the geographical area, or the stock exchange market, explains the strongest connections among insurance firms. For instance, we can see thick edges connecting U.S. and Bermudian companies at the middle bottom of the graph. These companies are all listed on the New York Stock Exchange (NYSE) or the Nasdaq Stock Market (NASDAQ). Another small group of North American companies with thick edges is located at the right of the graph, and it also includes the Swiss company *Chubb* listed on the NYSE. Other clusters of companies with thick edges can always be explained through the geographical area, such as the group of European companies at the right-middle of the graph. Under extremely bearish and bullish market conditions, we have similar results, that is, the geographical area or

the stock market justifies the strongest connections among insurance firms. This similarity in the dependence networks under the three market conditions can also be confirmed quantitatively: Spearman correlations between the asymmetric matrices D before the adjustment, which preserves information about the main direction of influence, range from 0.41 to 0.62, while after the adjustment, they range from 0.13 to 0.19. Thus, the connections among insurance companies remain quite stable regardless of the market conditions, although the direction of the main dependence is sensitive to the condition.

Figure 6 shows the relative importance of individual companies within the entire insurance sector under three market conditions: stable (Panel a), extremely bearish (Panel b), and extremely bullish (Panel c). Each panel displays the *to*, *from* and *net* contribution measures defined in Equations (5), (6), and (7), respectively. The *to* measure gives a size of the influence

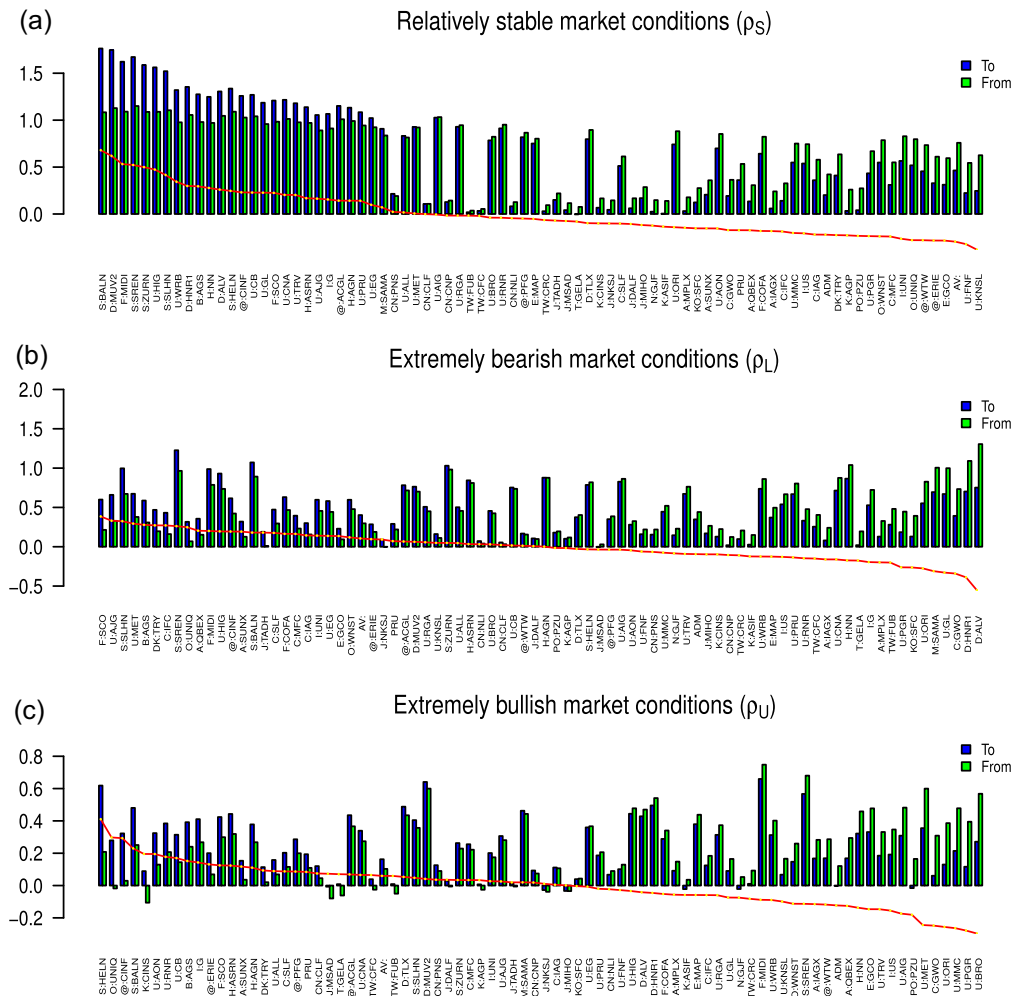


FIGURE 6 *To*, *from* and *net* contribution measures between each insurance company and the system represented by all the other companies under three market conditions over the whole sample period: relatively stable conditions in (a), extremely bearish conditions in (b), and extremely bullish conditions in (c). The red line with yellow dots in each panel represents the net contribution of each company to the remaining companies. The insurance companies are ordered from the highest net transmitter of influence to the lowest net transmitter.

that a company exercises on the system represented by all the other insurance companies, the *from* one quantifies the influence that the system exerts on a company, and the *net* one is simply the difference between the influence transmitted and received by an insurance company. For each bar plot, the companies are ordered according to the *net* measure. We observe that North American and European companies display *to* and *from* bars higher than those of the Asia-Pacific companies under relatively stable market conditions. This remark agrees with Figure 3, where we have groups of highly interconnected firms mainly composed of North American and European companies. Under extremely bearish market circumstances, that is, in Panel b, the levels of the *to* and *from* measures are lower than those under relatively stable market conditions. Thus, adverse market circumstances do not exacerbate the interactions among insurance companies. As in Panel b, Panel c shows a general decrease in influence transmission and reception compared to stable market conditions. Moreover, we also observe that some insurance companies, mainly from the Asia Pacific region, show one or both of the *to* and *from* measures with slightly negative values. A negative *to* measure means that the company exerts an influence that makes all the other firms less interconnected among them, while a negative *from* measure means that the market's influence makes the company less interconnected to the other firms. From these bar plots, the relative importance of the individual companies does not change much across market conditions, both in terms of influence transmitted (*to* measure) and received (*from* measure). However, some shifts are observed in the role of net contributors, that is, companies that transmit more influence than they receive. We confirm these visual impressions by computing the Spearman correlations between the influence measures across the three market conditions. For the transmitted and received influences, the correlations range from 0.61 to 0.91, indicating a fairly stable ranking of companies. By contrast, the Spearman correlations for the net measures are much lower, ranging from -0.02 to 0.23 , which reflects the higher variability of companies' net roles.

3.2 | Dynamic analysis

In this section, we examine the evolution of the dependence networks among insurance companies over the period under study. This period was marked by the health emergency triggered by the COVID-19 pandemic and Russia's invasion of Ukraine, which were among the main causes of the inflationary surge that began in mid-2021 and was still ongoing at the end of the sample period. Hence, for the period of study, examining changes in the insurance sector's interconnectedness over time is crucial. Specifically, we apply a rolling window approach similar to those of Diebold and Yilmaz (2012), Diebold and Yilmaz (2014), and Shahzad et al. (2023). Figure 7 shows three plots of the time-varying total connectedness index defined in Equation (4): Panel a displays the dynamics under relatively stable market conditions and uses Spearman's rho to quantify the connectedness in the insurance sector; Panel b shows the time evolution under extremely bearish market conditions and uses the extreme downside correlation ρ_L with $p = 5\%$; Panel c exhibits the time-varying connectedness index under extremely bullish market conditions and uses the extreme upside correlation ρ_U with $p = 5\%$. We apply a rolling window of 500 trading days to compute all the total time-varying connectedness indexes. In Appendix D, we provide a robustness analysis to motivate the choice of 500 trading days as the window size.

Figure 7 reveals that the COVID-19 pandemic did not significantly affect the dependence network of the insurance sector under relatively stable market conditions. Indeed, in Panel a,

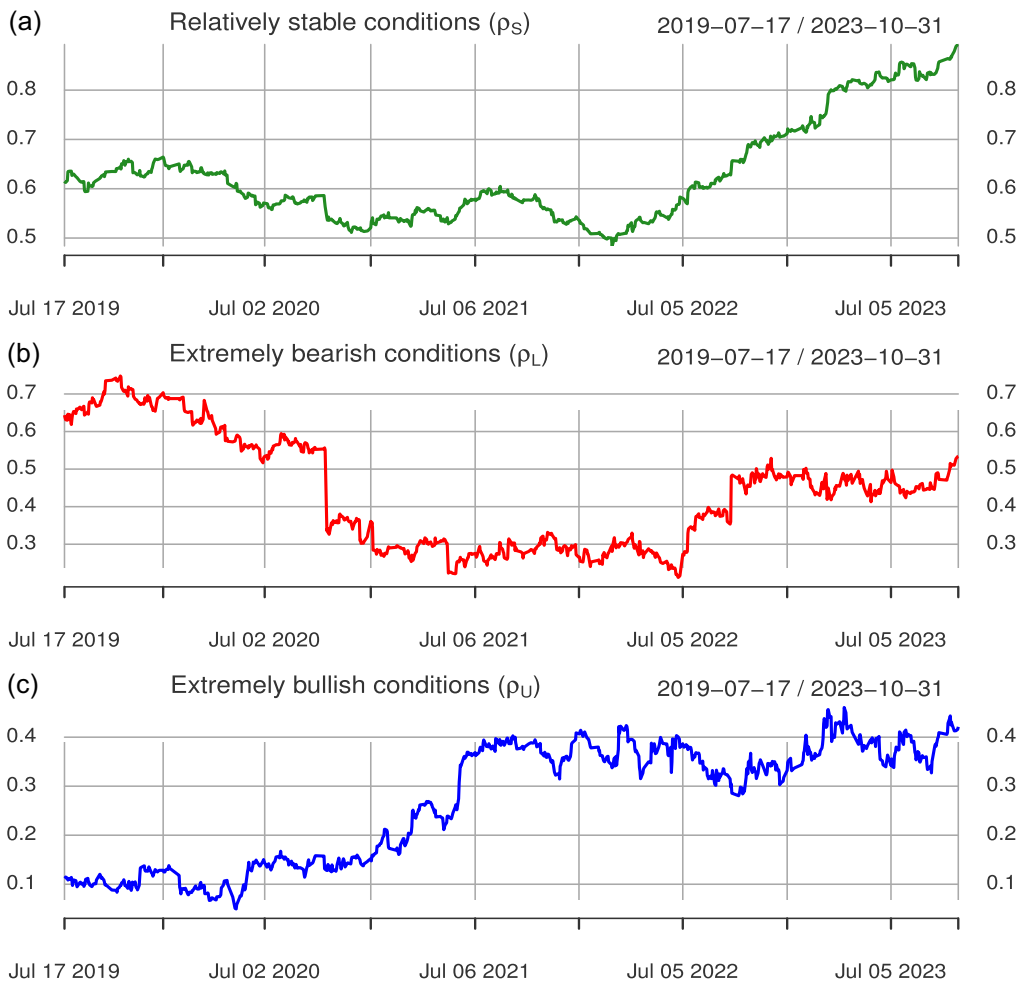


FIGURE 7 Time-varying total connectedness index under three market conditions over the whole sample period: relatively stable conditions in (a), extremely bearish conditions in (b), and extremely bullish conditions in (c). A rolling window of 500 trading days is applied for the computation of the three total connectedness indexes.

the curve of the total connectedness index does not show any abrupt change when COVID-19 started to develop into a pandemic, that is, around February 2020, and emergency measures were taken to prevent its spread. To explain this result, we argue that since the COVID-19 outbreak disrupted virtually all economic sectors, controlling for the three Fama-French factors effectively removes its systematic impact on the insurance sector's network of dependencies. We also note that the curve of the total connectedness index exhibits low values from February 2020 to February 2022, the period heavily affected by the COVID-19 pandemic and characterized by lockdowns in many developed countries. We justify this result as previously discussed: during this period, many sectors of the economy were similarly affected, and the regression on the three Fama-French factors removes the COVID-19 influence on the dependence network in the insurance sector. Even under extremely bearish market conditions, the total connectedness index does not seem to be particularly influenced by the COVID-19 pandemic. A different result emerges from Panel c, where the curve follows an upward trend during the pandemic but only after 3 months from the coronavirus outbreak.

Russia's invasion of Ukraine, which began in late February 2022, affects the total connectedness index under relatively stable conditions. Indeed, the curve in Panel a starts to increase around February 2022 and follows this trend until the end of the period under study, October 2023, when the Russian invasion was still ongoing. The upward trend of the curve in this period can also be ascribed to the high inflation triggered by the fiscal stimuli previously introduced to address the outbreak of COVID-19 and by the reduction in the supply of gas and oil caused by the Russian invasion of Ukraine. Under extremely bearish market conditions, the influence of the Ukrainian war is relatively weak and emerges only after some time. Finally, under extremely bullish conditions, the effect of the war appears to be absent.

The period from the start of the war in Ukraine to the end of the sample was marked by rising interest rates, which affected insurance companies' market prices. Although our systemic risk measures are based on the residuals from the Fama-French 3-factor model, these residuals may still be influenced by changes in interest rates. This is because the Fama-French model removes only broad market effects and does not explicitly account for discounting, investment income, or capital structure channels that are particularly relevant for the insurance sector. As a result, our dynamic analysis might mistakenly interpret the observed increase in interconnectedness as a rise in systemic risk, when in fact it is a consequence of the interest rate hikes. To assess whether interest rate changes have driven the increase in interconnectedness, we report in Table 6, for all three market conditions, the results obtained with the following model:

$$\Delta \rho_t = \beta_0 + \beta_1 \Delta R_t + \beta_2 W_t + \beta_3 (\Delta R_t \cdot W_t) + \epsilon_t, \quad (9)$$

where $\Delta \rho_t$ is the first difference of the systemic risk measure, ΔR_t is the first difference of the U.S. 10-Year Treasury yield, and W_t is a dummy variable equal to 1 from the date 24 February 2022 onward, marking the start of the war. The results indicate that, under relatively stable conditions, changes in interest rates did not have a statistically significant effect on systemic risk, whereas the war had a clearly significant impact. For the extremely bearish scenario, we observe a negative effect of interest rates on systemic risk during the war, although this effect is only marginally

TABLE 6 Estimates of Model (9) under three market conditions (relatively stable, extremely bearish, and extremely bullish), assessing whether changes in interest rates contributed to the increase in interconnectedness among insurance companies from the start of the Ukrainian war until the end of the sample period. Standard errors are reported inside round brackets. “***” and “*” denote significance at the 1% and 10% level, respectively.

	Stable	Bearish	Bullish
β_0	−0.0002 (0.0002)	−0.0008 (0.0006)	0.0005 (0.0005)
β_1	0.0011 (0.0037)	−0.0006 (0.0108)	0.0020 (0.0076)
β_2	0.0015*** (0.0004)	0.0018* (0.0010)	−0.0003 (0.0007)
β_3	−0.0048 (0.0048)	−0.0254* (0.0141)	0.0036 (0.0100)

significant. Hence, the analysis suggests that the Ukrainian war had a weak influence on the increase in systemic risk, and that interest rate hikes may have contributed to it. Finally, under extremely bullish market conditions, the results suggest that neither interest rates nor the war had a statistically significant effect on the interconnectedness of insurance companies.

To investigate the dynamics of the connectedness indexes, we explore whether their behavior can be captured within a jump-diffusion framework. We fit the Merton jump diffusion (JD) model to the log-returns of the total connectedness indexes. In continuous time, the model specifies that the asset or index of interest, S , evolves according to the following stochastic differential equation:

$$dS_t = S_t(\mu dt + \sigma dB_t + dZ_t), \quad (10)$$

where B_t is a Brownian motion, $Z_t = \sum_{i=1}^{N_t} (Y_i - 1)$, where N_t is a Poisson process with intensity λ and the Y_i 's are i.i.d lognormally distributed random variables, that is, $\log(Y_i) \sim N(m, b^2)$. We estimate model (10) using the maximum likelihood method. The results of the estimation are reported in Table 7. In the table, a comparison is made with respect to the lognormal (LN) model, which does not feature the jump component dZ_t . Using the Akaike (AIC) and Bayesian (BIC) information criteria, we find evidence that the JD models have a better fit compared to the LN models. The Merton jump diffusion model better captures the behavior of the connectedness indexes, which often exhibit sudden, extreme changes (jumps) not well represented by simple lognormal processes. This finding is consistent with the fact that financial connectedness often spikes during crises, reflecting abrupt contagion or systemic shocks. The JD model quantifies both the frequency (λ) and size (b) of these jumps, allowing for more realistic assessment of the likelihood and impact of rare, extreme events.

TABLE 7 Estimation of Model (10) for the total connectedness index under three market conditions (relatively stable, extremely bearish, and extremely bullish). ‘***’ denotes significance at the 1% level.

	Stable		Bearish		Bullish	
	JD	LN	JD	LN	JD	LN
μ	0.0002 (0.0003)	0.0005 (0.0003)	0.0003 (0.0009)	−0.0002 (0.0013)	0.0018 (0.0013)	0.0016 (0.0017)
σ	0.0028*** (0.0004)	0.0081*** (0.0002)	0.0219*** (0.0010)	0.0378*** (0.0009)	0.0165*** (0.0025)	0.0485*** (0.0012)
λ	0.9147*** (0.1716)		0.0778*** (0.0257)		0.8186*** (0.1702)	
m	0.0003 (0.0004)		−0.0065 (0.0140)		−0.0002 (0.0023)	
b	0.0078*** (0.0007)		0.1024*** (0.0191)		0.0471*** (0.0046)	
LogLik	2858.2682	2775.9347	1765.4155	1515.9092	1435.1854	1312.2831
AIC	−5706.5363	−5547.8695	−3520.8310	−3027.8184	−2860.3707	−2620.5663
BIC	−5683.0142	−5538.4606	−3497.3090	−3018.4096	−2836.8486	−2611.1574

4 | CONCLUSIONS

The method presented in this paper allows measuring systemic risk under relatively stable, extremely bearish, and extremely bullish market conditions. Extending Shahzad et al. (2023) Pearson correlation-based approach, we employ Spearman's correlation to better capture monotonic relationships between variables. The method resorts to copula theory to measure the association between two variables after removing the influence of a third variable.

To study systemic risk in the worldwide insurance sector, the empirical analysis focuses on the stock returns of 82 insurance companies spread over three geographical areas: North America, Europe, and Asia-Pacific. The observation period spans from November 30, 2016, to October 31, 2023, encompassing significant global events including the COVID-19 pandemic and the Russo-Ukrainian war. The first empirical analysis is static and uses the entire sample. The TMFG algorithm is employed to build planar graphical representations of the insurance sector's dependence structure under three market conditions. The resulting plots highlight how the geographical area and the stock exchange listing play an important role in explaining the connection between insurance companies. In particular, strong links exist among North American companies, European companies, or companies that, even though not located in the same geographical area, are listed on the same exchange. Based on bar plots representing the transmitted and received influence of each company, the North American and European companies transmit and receive influence more than the Asia-Pacific firms. The result is consistent with the planar graphical representations. Moreover, under extremely bearish and extremely bullish conditions, the transmitted and received influence in general does not increase, that is, extreme market conditions do not exacerbate the interactions among insurance firms. Using a dynamic analysis based on rolling window, we find that COVID-19 pandemic affects systemic risk in the insurance sector only under extremely bullish market conditions and some time after the outbreak. It does not impact the dependence network under the other two market conditions. We explain these results by noting that the pandemic disrupted all the economic sectors, and thus the regression on the Fama-French factors removes much of its influence from the stock returns. Instead, we detect the influences of the Russo-Ukrainian war and the inflation surge on the dependence network under relatively stable market conditions.

The methodology presented in this paper can be extended in two directions. The first is to make it fully parametric by computing the three association measures, Spearman's rho, extreme downside correlation, and extreme upside correlation, with formulae based on copula functions. The second direction concerns the possibility of defining association measures that are time-varying, which would eliminate the subjectivity of window size selection in the dynamic analysis.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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APPENDIX A: LIST OF INSURANCE COMPANIES

TABLE A1 For each insurance company, this table reports the company name (Name), Refinitiv Eikon acronym (Symbol), company headquarters country (Country), stock exchange as reported in Refinitiv Eikon (Exchange), the main statistics about returns over the entire sample period, the Jarque-Bera statistic to test the normality assumption, and, in the last column, the Augmented Dickey-Fuller (ADF) statistic to test the unit-root presence. The table is also organized so that the top 33 companies are based in Europe, the next 28 in North America, and the bottom 21 in Asia Pacific. Companies marked with an asterisk (*) are those included in the subgroup of 18 European insurers used in the residual-based analysis in Section 3.

Name	Symbol	Country	Exchange	Mean	SD	Skewness	Kurtosis	JB	ADF
ALLIANZ*	D:ALV	Germany	Deutsche Boerse AG	0.00031	0.016	-1.112	19.902	15,992.366***	-12.809***
MUENCHENER RUCK*	D:MUV2	Germany	Deutsche Boerse AG	0.00078	0.017	-0.097	23.851	23,923.645***	-15.040***
HANNOVER RUECK*	D:HNRI	Germany	Deutsche Boerse AG	0.00053	0.017	-0.958	24.071	24,633.011***	-14.819***
TALANX AKTGSF*	D:TLX	Germany	Deutsche Boerse AG	0.00032	0.018	-0.910	19.060	14,375.720***	-13.536***
AXA	F:MIDI	France	Euronext. liffe Paris	0.00006	0.018	-0.793	22.901	21,931.303***	-12.203***
COFACE	F:COFA	France	Euronext.liffe Paris	0.00012	0.024	-1.203	16.000	9619.156***	-12.285***
SCOR SE*	F:SCO	France	Euronext. liffe Paris	0.00009	0.024	-0.796	22.171	20,363.371***	-12.765***
ASSICURAZIONI GENERALI*	I:G	Italy	Milan	0.00062	0.016	-0.850	15.839	9230.842***	-12.299***
UNIPOL GRUPPO FINANZIARIO*	I:UNI	Italy	Milan	0.00059	0.020	-0.930	15.749	9136.136***	-12.799***
UNIPOLSAI	I:US	Italy	Milan	0.00048	0.014	-0.364	6.439	681.367***	-12.979***
MAPFRE	E:MAP	Spain	Mercado Continuo Espanol	-0.00017	0.018	0.258	14.196	6914.982***	-12.952***
GRUPO CATALANA OCCIDENTE*	E:GCO	Spain	Mercado Continuo Espanol	0.00009	0.017	-1.280	16.056	9742.688***	-11.111***
AEGON	H:AGN	Netherlands	Euronext.liffe Amsterdam	-0.00035	0.024	-1.520	20.104	16,606.427***	-12.367***

TABLE A1 (Continued)

Name	Symbol	Country	Exchange	Mean	SD	Skewness	Kurtosis	JB	ADF
NN GROUP	H:NN	Netherlands	Euronext.liffe Amsterdam	0.00000	0.019	-2.558	31.919	47,448.920***	-12.656***
ASR NEDERLAND*	H:ASRN	Netherlands	Euronext.liffe Amsterdam	0.00032	0.019	-1.202	18.549	13,622.617***	-12.129***
AGEAS (EX-FORTIS)*	B:AGS	Belgium	Euronext.liffe Brussels	0.00031	0.019	-1.145	17.854	12,431.808***	-14.030***
SAMPO 'A'	M:SAMA	Finland	Helsinki	-0.00026	0.016	-1.158	24.581	25,921.871***	-15.451***
UNIQA INSU GR AG*	O:UNIQ	Austria	Vienna Stock Exchange	0.00006	0.015	-0.601	8.951	2030.272***	-12.671***
VIENNA INSURANCE GROUP A*	O:WNST	Austria	Vienna Stock Exchange	0.00001	0.016	-0.807	10.865	3548.883***	-12.285***
CHUBB	U:CB	Switzerland	NYSE	0.00045	0.017	-1.247	18.992	14,415.297***	-12.630***
ZURICH INSURANCE GROUP*	S:ZURN	Switzerland	Six Swiss	0.00053	0.014	-1.110	27.819	34,163.360***	-14.386***
SWISS RE	S:SREN	Switzerland	Six Swiss	0.00019	0.017	-1.271	25.937	29,302.892***	-13.779***
SWISS LIFE HOLDING*	S:SLHN	Switzerland	Six Swiss	0.00051	0.016	-1.123	26.019	29,432.355***	-13.852***
HELVETIA HOLDING N*	S:HELN	Switzerland	Six Swiss	0.00030	0.016	-1.552	24.043	24,894.300***	-13.130***
BALOISE HOLDING*	S:BALN	Switzerland	Six Swiss	0.00033	0.014	-0.596	18.860	13,920.603***	-13.150***
TRYG	DK:TRY	Denmark	OMX Nordic Exchange Copenhagen	0.00036	0.014	-0.631	9.333	2296.580***	-13.061***
GJENSIDIGE FORSIKRING	N:GJF	Norway	Oslo Bors	0.00008	0.017	-1.029	12.585	5290.777***	-13.749***
PZU GROUP*	PO:PZU	Poland	Warsaw	0.00006	0.020	-0.400	7.020	925.938***	-12.727***

(Continues)

TABLE A1 (Continued)

Name	Symbol	Country	Exchange	Mean	SD	Skewness	Kurtosis	JB	ADF
AON CLASS A	U:AON	United Kingdom	NYSE	0.00038	0.015	−1.063	25.804	28,860.298***	−12.452***
WILLIS TOWERS WATSON	@WTW	United Kingdom	NASDAQ	0.00008	0.016	−0.583	14.403	7232.289***	−13.165***
PRUDENTIAL	PRU	United Kingdom	London	−0.00032	0.024	−0.326	13.523	6118.625***	−14.539***
AVIVA*	AV.	United Kingdom	London	−0.00016	0.020	−0.027	14.105	6788.611***	−12.894***
ADMIRAL GROUP	ADM	United Kingdom	London	0.00034	0.018	−1.644	25.915	29,486.422***	−13.729***
ARCH CAP.GP.	@ACGL	Bermuda	NASDAQ	0.00075	0.019	−0.892	19.864	15,824.655***	−11.368***
EVEREST GROUP	U:EG	Bermuda	NYSE	0.00042	0.019	−0.499	12.665	5197.374***	−12.769***
RENAISSANCERE HDG.	U:RNR	Bermuda	NYSE	0.00038	0.018	−0.958	14.873	7960.853***	−12.297***
MARSH & MCLENNAN	U:MMC	United States	NYSE	0.00049	0.014	−0.621	19.341	14,780.296***	−12.506***
PROGRESSIVE OHIO	U:PGR	United States	NYSE	0.00088	0.017	−0.434	12.784	5311.268***	−12.893***
ARTHUR J GALLAGHER	U:AIG	United States	NYSE	0.00060	0.015	−1.363	23.837	24,297.927***	−12.373***
METLIFE	U:MET	United States	NYSE	−0.00000	0.021	−0.883	18.721	13,772.567***	−11.889***
AMERICAN INTL.GP.	U:AIG	United States	NYSE	−0.00019	0.024	−1.283	21.235	18,660.311***	−12.240***
PRUDENTIAL FINL.	U:PRU	United States	NYSE	−0.00012	0.023	−1.029	24.423	25,486.205***	−12.355***
TRAVELERS COS.	U:TRV	United States	NYSE	0.00036	0.017	−2.481	40.006	76,689.501***	−13.616***
ALLSTATE ORD SHS	U:ALL	United States	NYSE	0.00022	0.017	−1.365	16.402	10,295.676***	−12.134***
BROWN & BROWN	U:BRO	United States	NYSE	0.00058	0.015	−0.836	14.548	7493.767***	−13.326***

TABLE A1 (Continued)

Name	Symbol	Country	Exchange	Mean	SD	Skewness	Kurtosis	JB	ADF
CNA FINANCIAL	U:CNA	United States	NYSE	0.00002	0.017	-0.886	15.800	9189.956***	-13.389***
HARTFORD FINL. SVS. GP.	U:HIG	United States	NYSE	0.00044	0.021	-0.448	44.205	93,447.329***	-13.429***
CININNATI FINL.	@CINF	United States	NASDAQ	0.00009	0.020	-0.305	17.228	11,162.335***	-13.583***
PRINCIPAL FINL.GP.	@PFG	United States	NASDAQ	-0.00006	0.023	-0.361	18.793	13,755.130***	-12.928***
W R BERKLEY	U:WRB	United States	NYSE	0.00046	0.017	-0.889	19.205	14,624.191***	-12.825***
GLOBE LIFE	U:GL	United States	NYSE	0.00017	0.018	-0.995	18.018	12,629.366***	-12.216***
KINSALE CAPITAL GROUP	U:KNSL	United States	NYSE	0.00139	0.025	-0.678	17.205	11,205.689***	-12.957***
REINSURANCE GROUP OF AM.	U:RGA	United States	NYSE	0.00022	0.023	-0.145	18.097	12,548.315***	-11.730***
FIDELITY NAT.FINANCIAL	U:FNF	United States	NYSE	0.00041	0.019	-1.698	26.525	31,084.879***	-12.658***
ERIE INDEMNITY 'A'	@ERIE	United States	NADAQ	0.00044	0.019	0.075	22.994	21,998.981***	-12.425***
OLD REPUBLIC INTL.	U:ORI	United States	NYSE	0.00018	0.019	-1.770	32.640	49,024.587***	-12.933***
MANULIFE FINANCIAL	C:MFC	Canada	Toronto	-0.00001	0.020	-0.854	27.750	33,862.929***	-12.859***
GREAT WEST LIFE	C:GWO	Canada	Toronto	0.00019	0.016	-1.764	38.184	68,789.034***	-11.787***
INTACT FINANCIAL	C:IFC	Canada	Toronto	0.00052	0.013	-0.369	15.190	8208.747***	-13.198***
SUN LIFE FINL.	C:SLF	Canada	Toronto	0.00010	0.015	-1.109	24.646	26,052.549***	-11.276***
IA FINANCIAL	C:IAG	Canada	Toronto	0.00035	0.020	-1.215	21.076	18,304.336***	-11.433***
AIA GROUP	K:AGP	Hong Kong	Hong Kong	-0.00006	0.019	-0.063	5.143	254.485***	-12.851***
CHINA TAIPING INSURANCE HLDGS	K:CINS	Hong Kong	Hong Kong	-0.00101	0.025	0.488	5.774	476.896***	-12.124***
ASIA FINANCIAL HDG.	K:ASIF	Hong Kong	Hong Kong	-0.00039	0.014	-0.220	8.260	1534.965***	-11.742***
CHINA LIFE INSURANCE 'A'	CN:CLF	China	Shanghai	0.00007	0.022	0.490	6.706	810.101***	-12.801***

(Continues)

TABLE A1 (Continued)

Name	Symbol	Country	Exchange	Mean	SD	Skewness	Kurtosis	JB	ADF
PING AN INSURANCE (GP.) CO. OF CHINA 'A'	CN:PNS	China	Shanghai	−0.00011	0.018	0.484	5.309	345.853***	−12.468***
CHINA PAC.IN.(GROUP) 'A'	CN:CNP	China	Shanghai	−0.00042	0.022	0.308	5.117	268.262***	−13.658***
NEW CHINA LIFE IN.'A'	CN:NLI	China	Shanghai	−0.00060	0.023	0.422	6.040	548.950***	−12.745***
QBE INSURANCE GROUP	A:QBEX	Australia	ASX tradematch	−0.00014	0.020	−1.149	14.741	7878.285***	−11.982***
SUNCORP GROUP	A:SUNX	Australia	ASX tradematch	−0.00001	0.018	−0.811	13.762	6520.708***	−11.766***
INSURANCE AUS.GROUP	A:IAGX	Australia	ASX tradematch	0.00000	0.017	−0.105	8.307	1554.143***	−13.966***
MEDIBANK PRIVATE	A:MPLX	Australia	ASX tradematch	0.00020	0.016	−0.331	7.323	1054.249***	−13.372***
CATHAY FINL.HLDG.	TW:CFC	Taiwan	Taiwan	−0.00005	0.013	0.148	9.035	2010.841***	−12.872***
FUBON FINL.HLDG.	TW:FUB	Taiwan	Taiwan	0.00009	0.014	0.074	8.620	1741.288***	−12.382***
CENTRAL REIN.	TW:CRC	Taiwan	Taiwan	0.00004	0.014	0.345	17.500	11,596.659***	−13.253***
GREAT EASTERN HDG.	T:GELA	Singapore	Singapore	−0.00030	0.009	0.187	11.198	3707.807***	−12.389***
SAMSUNG LIFE INSURANCE	KO:SFC	South Korea	Korea	−0.00029	0.020	0.578	16.184	9640.396***	−12.651***
TOKIO MARINE HOLDINGS	J:MIHO	Japan	Tokyo	0.00026	0.016	−0.107	5.271	287,384***	−13.981***
DAI-ICHI LIFE HOLDINGS	J:DALF	Japan	Tokyo	0.00018	0.020	0.212	6.440	662.495***	−13.461***
MS&AD INSURANCE GP.HDG.	J:MSAD	Japan	Tokyo	0.00008	0.014	−0.177	6.010	506.650***	−13.707***
SOMPO HOLDINGS	J:NKSJ	Japan	Tokyo	−0.00006	0.017	0.086	6.821	806.604***	−14.190***
T & D HOLDINGS	J:TADH	Japan	Tokyo	0.00021	0.022	0.028	5.742	414,930***	−12.535***

APPENDIX B: THE MODIFIED FAMA-FRENCH 3-FACTOR MODEL

We first rewrite Equation (1) in matrix form for the n companies belonging to the same geographical region:

$$\mathbf{y}_t = \boldsymbol{\gamma}' \mathbf{x}_t + s_t \epsilon_t \quad (\text{B1})$$

$$\text{where } \mathbf{y}_t = (r_{1,t} - r_{f,t}, \dots, r_{n,t} - r_{f,t})', \mathbf{x}_t = (1, r_{m,t} - r_{f,t}, \text{SMB}_t, \text{HML}_t)', \boldsymbol{\gamma} = \begin{pmatrix} \alpha_1 & \dots & \alpha_n \\ \beta_{1,1} & \dots & \beta_{n,1} \\ \beta_{1,2} & \dots & \beta_{n,2} \\ \beta_{1,3} & \dots & \beta_{n,3} \end{pmatrix}, \text{ and}$$

$\epsilon_t = (\epsilon_{1,t}, \dots, \epsilon_{n,t})' \sim N(0, \boldsymbol{\Sigma})$. Setting $\tilde{\mathbf{y}}_t = \mathbf{y}_t/s_t$, $\tilde{\mathbf{x}}_t = \mathbf{x}_t/s_t$, and dividing both sides of (B1) by s_t gives

$$\tilde{\mathbf{y}}_t = \boldsymbol{\gamma}' \tilde{\mathbf{x}}_t + \epsilon_t. \quad (\text{B2})$$

Denoting by $\boldsymbol{\nu} = (\bar{s}_0, \bar{s}_1, \bar{s}_2, \boldsymbol{\phi})'$ the vector of parameters in the re-scaling coefficients s_t , the likelihood function of model (B1) is given by

$$L(\mathbf{y}|\boldsymbol{\gamma}, \boldsymbol{\Sigma}, \boldsymbol{\nu}) = \prod_{t=1}^T (2\pi)^{-\frac{n}{2}} |\mathbf{s}_t^2 \boldsymbol{\Sigma}|^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2} \sum_{t=1}^T (\mathbf{y}_t - \boldsymbol{\gamma}' \mathbf{x}_t)' (\mathbf{s}_t^2 \boldsymbol{\Sigma})^{-1} (\mathbf{y}_t - \boldsymbol{\gamma}' \mathbf{x}_t) \right\}.$$

Using (B2) and ignoring the constant terms

$$L(\mathbf{y}|\boldsymbol{\gamma}, \boldsymbol{\Sigma}, \boldsymbol{\nu}) \propto \left(\prod_{t=1}^T s_t^{-n} \right) |\boldsymbol{\Sigma}|^{-\frac{T}{2}} \exp \left\{ -\frac{1}{2} \sum_{t=1}^T (\tilde{\mathbf{y}}_t - \boldsymbol{\gamma}' \tilde{\mathbf{x}}_t)' \boldsymbol{\Sigma}^{-1} (\tilde{\mathbf{y}}_t - \boldsymbol{\gamma}' \tilde{\mathbf{x}}_t) \right\}. \quad (\text{B3})$$

Based on the last equation, and upon defining $\tilde{\mathbf{Y}}$ and $\tilde{\mathbf{X}}$ as the matrices obtained by stacking $\tilde{\mathbf{y}}_1', \dots, \tilde{\mathbf{y}}_T'$ and $\tilde{\mathbf{x}}_1', \dots, \tilde{\mathbf{x}}_T'$, respectively, we immediately see that

$$\begin{aligned} \hat{\boldsymbol{\gamma}}(\boldsymbol{\nu}) &= (\tilde{\mathbf{X}}' \tilde{\mathbf{X}})^{-1} \tilde{\mathbf{X}}' \tilde{\mathbf{Y}} \\ \hat{\boldsymbol{\Sigma}}(\boldsymbol{\nu}) &= \frac{1}{T} (\tilde{\mathbf{Y}} - \tilde{\mathbf{X}} \hat{\boldsymbol{\gamma}}(\boldsymbol{\nu}))' (\tilde{\mathbf{Y}} - \tilde{\mathbf{X}} \hat{\boldsymbol{\gamma}}(\boldsymbol{\nu})) \end{aligned}$$

give the maximum likelihood estimators of $\boldsymbol{\gamma}$ and $\boldsymbol{\Sigma}$, as functions of $\boldsymbol{\nu}$. Substituting the above estimates into (B3) yields the concentrated likelihood

$$L(\mathbf{y}|\hat{\boldsymbol{\gamma}}(\boldsymbol{\nu}), \hat{\boldsymbol{\Sigma}}(\boldsymbol{\nu}), \boldsymbol{\nu}) \propto \left(\prod_{t=1}^T s_t^{-n} \right) \left| \frac{1}{T} (\tilde{\mathbf{Y}} - \tilde{\mathbf{X}} \hat{\boldsymbol{\gamma}}(\boldsymbol{\nu}))' (\tilde{\mathbf{Y}} - \tilde{\mathbf{X}} \hat{\boldsymbol{\gamma}}(\boldsymbol{\nu})) \right|^{-\frac{T}{2}}$$

which can be numerically maximized with respect to $\boldsymbol{\nu}$.

APPENDIX C: TWO-DIMENSIONAL COPULA FUNCTIONS

In this appendix, we provide a brief introduction to two-dimensional copula functions and refer the reader to the textbooks by Nelsen (2006) and McNeil et al. (2015) for a comprehensive treatment, including extensions to the multivariate case.

A two-dimensional copula function C is a distribution function on $[0, 1]^2$ with standard uniform marginal distributions. Hence, C is a mapping from the unit square into the unit interval that satisfies the following three properties:

1. $C(u, 0) = C(0, v) = 0$;
2. $C(u, 1) = u$ and $C(1, v) = v$;
3. for all $(u_1, v_1), (u_2, v_2) \in [0, 1]^2$ such that $u_1 \leq u_2$ and $v_1 \leq v_2$, it holds that

$$C(u_2, v_2) - C(u_1, v_2) - C(u_2, v_1) + C(u_1, v_1) \geq 0.$$

Observe that the second property ensures that the marginals are uniformly distributed, while the third one ensures that, if (U, V) is a random vector with distribution function C , then the probability $\mathbb{P}(u_1 \leq U \leq u_2, v_1 \leq V \leq v_2)$ is non-negative.

The importance of copula functions lies in Sklar's Theorem, which states, first, that any multivariate distribution function can be expressed in terms of its marginals and a copula function, and second, that copula functions can be used in conjunction with univariate distributions to construct multivariate distribution functions. In the two-dimensional case, the first part of the theorem states that if F is a distribution function with marginals F_1 and F_2 , then there exists a copula function $C : [0, 1]^2 \rightarrow [0, 1]$ such that

$$F(x, y) = C(F_1(x), F_2(y)), x, y \in [-\infty, \infty]. \quad (C1)$$

If the marginals are continuous, then C is unique; otherwise, C is uniquely determined on $\text{Ran}F_1 \times \text{Ran}F_2$, where $\text{Ran}F_1$ and $\text{Ran}F_2$ denote the ranges of the two marginals F_1 and F_2 , respectively. The second part of the theorem states that if $C : [0, 1]^2 \rightarrow [0, 1]$ is a copula function and F_1 and F_2 are univariate distribution functions, then the function defined in (C1) is a two-dimensional distribution function with marginals F_1 and F_2 .

For any two-dimensional copula function C , it can be shown that the following bounds hold:

$$\max\{u + v - 1, 0\} \leq C(u, v) \leq \min\{u, v\},$$

where the two bounding functions, $\max\{u + v - 1, 0\}$ and $\min\{u, v\}$, are themselves copula functions, known as the countermonotonicity copula and the comonotonicity copula, respectively. The countermonotonicity copula is the copula function of two random variables that are perfectly negatively dependent, while the comonotonicity copula is the copula function of two random variables that are perfectly positively dependent. Another fundamental copula function is the independence copula, defined as $\Pi(u, v) = uv$.

We now present four examples of copula functions:

1. The two-dimensional Gaussian copula is the copula function associated with a random vector following a bivariate normal distribution. Denoting by ρ the correlation coefficient between the two components of the random vector, it can be shown that the Gaussian copula is given by

$$C^{\text{Ga}}(u, v) = \int_{-\infty}^{\Phi^{-1}(u)} \int_{-\infty}^{\Phi^{-1}(v)} \frac{1}{2\pi\sqrt{1-\rho^2}} \exp\left(-\frac{s^2 - 2\rho st + t^2}{2(1-\rho^2)}\right) ds dt,$$

where Φ^{-1} denotes the inverse of the standard normal distribution function Φ . The Gaussian copula coincides with the independence copula when $\rho = 0$. In the limiting cases $\rho \rightarrow 1$ and $\rho \rightarrow -1$, it converges to the comonotonicity and countermonotonicity copulas, respectively. Hence, the Gaussian copula provides a flexible dependence structure ranging from perfect positive to perfect negative dependence, with the parameter ρ controlling the strength and direction of dependence.

2. The two-dimensional Student's t copula is given by

$$C_{\nu, \rho}^t(u, v) = \int_{-\infty}^{t_{\nu}^{-1}(u)} \int_{-\infty}^{t_{\nu}^{-1}(v)} \frac{\Gamma\left(\frac{\nu+2}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right) \nu \pi \sqrt{1-\rho^2}} \left[1 + \frac{s^2 - 2\rho st + t^2}{\nu(1-\rho^2)} \right]^{-\frac{\nu+2}{2}} ds dt,$$

where $\nu > 0, \rho \in (-1, 1)$, Γ denotes the gamma function, and t_{ν}^{-1} is the inverse of the distribution function of a standard univariate t -distribution with ν degrees of freedom. For fixed ν , the Student's t copula converges to the comonotonicity copula as $\rho \rightarrow 1$, and to the countermonotonicity copula as $\rho \rightarrow -1$, similar to the Gaussian copula. However, unlike the Gaussian copula, the Student's t copula does not reduce to the independence copula when $\rho = 0$ and $\nu < \infty$.

3. The two-dimensional Gumbel copula is given by

$$C^{\text{Gu}}(u, v) = \exp\left(-[(-\ln u)^{\theta} + (-\ln v)^{\theta}]^{1/\theta}\right), 1 \leq \theta < \infty,$$

where the parameter θ controls the strength of dependence: $\theta = 1$ yields the independence copula, and the limit of $C^{\text{Gu}}(u, v)$ as $\theta \rightarrow \infty$ is the comonotonicity copula.

4. Finally, the two-dimensional Clayton copula is given by

$$C^{\text{Cl}}(u, v) = (u^{-\theta} + v^{-\theta} - 1)^{-1/\theta}, 0 \leq \theta < \infty,$$

where the parameter θ again controls the strength of dependence: $\theta = 0$ should be interpreted as the limit of $C^{\text{Cl}}(u, v)$ as $\theta \rightarrow 0$, which yields the independence copula, and the limit of $C^{\text{Cl}}(u, v)$ as $\theta \rightarrow \infty$ is the comonotonicity copula.

Figure C1 shows scatterplots for the four copula functions described above. Each two-dimensional distribution assumes standard normal marginals to highlight tail behaviors, with the following parameters: the Gaussian copula uses $\rho = 0.7$; the Student's t copula uses $\rho = 0.7$ and $\nu = 4$; the Gumbel copula uses $\theta = 2$; and the Clayton copula also uses $\theta = 2$. The Gaussian and Student's t copulas are characterized by tail symmetry, as reflected in the figure by similarly shaped lower and upper tails. It is also worth recalling that the Student's t copula exhibits heavier tails than the Gaussian copula for $\nu < \infty$ and approaches the Gaussian copula as $\nu \rightarrow \infty$. In contrast, the Gumbel copula is tail-asymmetric, with a heavier upper tail than lower tail. This is clearly visible in the figure, where the scatterplot for the Gumbel copula shows a higher concentration of points in the upper tail than in the lower tail. Similarly, the Clayton copula is also tail-asymmetric but, unlike the Gumbel copula, features a heavier lower tail than upper tail. This is confirmed by the figure, in which the scatterplot for the Clayton copula displays a higher concentration of points in the lower tail than in the upper tail.

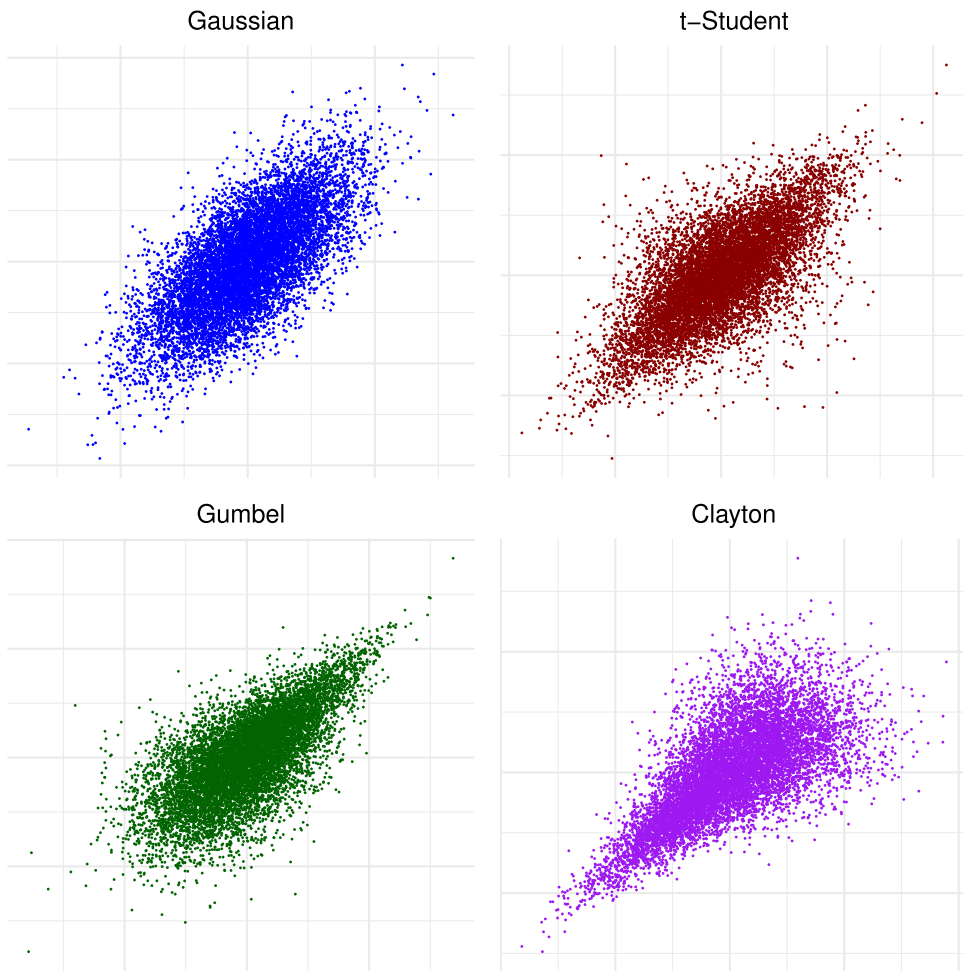


FIGURE C1 Examples of dependence structures for four copula families with standard normal margins. Gaussian and Student's t copulas exhibit symmetric tail dependence, while Gumbel and Clayton copulas display asymmetric tail dependence, with heavier upper and lower tails, respectively.

APPENDIX D: ROBUSTNESS ANALYSIS

This appendix assesses the robustness of the choice of rolling window for the dynamic analysis of Section 3.2. Figure D1 shows three panels: Panel a refers to relatively stable market conditions, Panel b extremely bearish market conditions, and Panel c extremely bullish market conditions. In each Panel, the green curve corresponds to our baseline setting with 500 trading days, the red one to the setting with 375 days, and the blue one to the setting with 250 days. The curves in Panels a and c are very close implying a high robustness of the results for any size of the rolling window. Instead, Panel b reveals a slightly more pronounced divergence between the curves, with the largest gap occurring between the blue and green curves. Thus, a small window size might produce little reliable results for the dynamic analysis under extremely bearish market conditions. The choice of 500 trading days as window size should guarantee robust results for all three market conditions. Table D1 reports Pearson correlations for the time series plotted in Figure D1. The correlations confirm that the curves

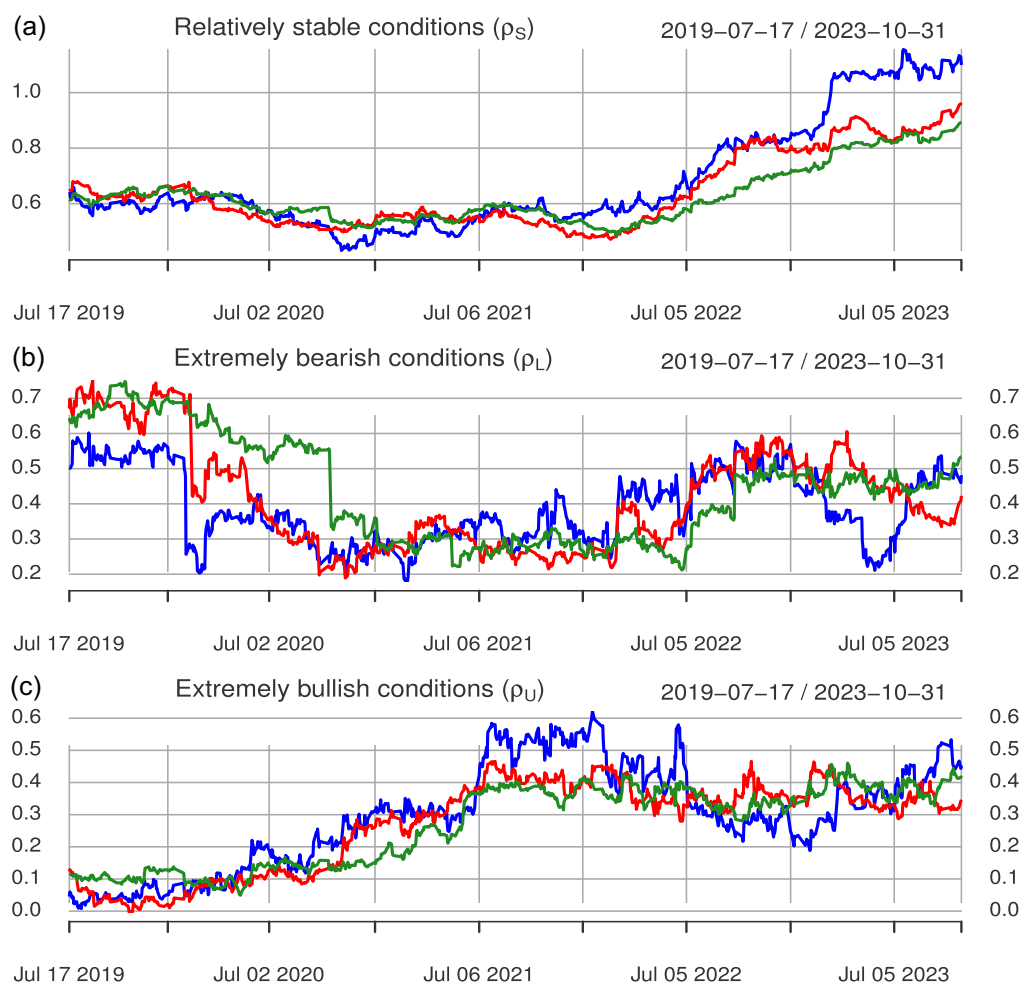


FIGURE D1 Robustness of the choice of rolling window. In each Panel, the green curve corresponds to our baseline setting with 500 trading days, the red one to the setting with 375 days, and the blue one to the setting with 250 days.

TABLE D1 Pearson correlations for the time series plotted in Figure D1.

	Stable conditions			Bearish conditions			Bullish conditions		
	500 days	375 days	250 days	500 days	375 days	250 days	500 days	375 days	250 days
500 days	1	0.938	0.941	1	0.757	0.464	1	0.905	0.833
375 days		1	0.938		1	0.698		1	0.851
250 days			1			1			1

are sufficiently close when the sizes are 500 and 375 days for each market conditions scenario. Indeed, for these two window sizes, the smallest correlation is 0.757.