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Systemic Risk in the Global Reinsurance Ecosystem

A DCC-GARCH, ΔCoVaR and Network Analysis of Listed Reinsurers and Reinsurance-Related Insurance Groups

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Audentes fortuna iuvat

ABSTRACT

This thesis studies systemic risk in the global reinsurance ecosystem, focusing on listed global reinsurers and large integrated insurance groups with relevant reinsurance activities. Although reinsurance is designed to spread and diversify risk, retrocession chains, common underwriting exposures, correlated investment portfolios, and stress-period co-movements may create channels of systemic interdependence. Using daily equity returns for 20 listed insurance and reinsurance groups over the period 2010–2024, the thesis combines a DCC-GARCH model with a ΔCoVaR framework to measure time-varying interconnectedness, Systemic Contribution, and Systemic Vulnerability. A complementary correlation-based network analysis is then used to examine the structural position of each institution through centrality measures, community detection, and the Minimum Spanning Tree. The results are interpreted as market-based indicators of statistical interdependence rather than as evidence of direct contractual exposures or causal contagion.

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INTRODUCTION

Context

Reinsurance plays a central role in the functioning of modern insurance markets. By allowing primary insurers to transfer part of their underwriting risk to specialised reinsurers, reinsurance increases the risk-bearing capacity of the insurance sector and supports the provision of coverage for large, complex and low-frequency risks that would otherwise be difficult for individual insurers to absorb (Froot, 2001; Cummins and Weiss, 2014). Through this mechanism, risks that would remain concentrated within the balance sheets of individual insurers can be redistributed across institutions, business lines and geographical areas.

This risk-sharing function has become increasingly important in recent years. The insurance sector has faced a growing exposure to natural catastrophes, climate-related events, cyber risk, pandemics, geopolitical shocks and financial-market volatility. At the same time, the macro-financial environment has changed substantially. These developments have placed renewed attention on the resilience of reinsurers, which act as global absorbers of extreme losses and as providers of capacity to primary insurance markets (Swiss Re Institute, 2025; AM Best, 2025).

The global reinsurance market is also characterised by a relatively high degree of concentration. A significant share of global reinsurance capacity is provided by a limited number of large, internationally active groups, including both specialised reinsurers and diversified insurance groups with relevant reinsurance activities. This concentration does not necessarily imply systemic fragility, since large reinsurance-related groups are often geographically diversified and well capitalised. However, it does imply that their risk profile may be relevant beyond the boundaries of the individual firm. If the distress of a major reinsurance-related group were associated with a reduction in reinsurance capacity, a deterioration in counterparty confidence, or stronger co-movement with other financial institutions, the consequences could extend beyond its own balance sheet and affect the wider insurance system (Swiss Re Institute, 2025; AM Best, 2025).

Problem statement

The systemic relevance of reinsurance arises from the tension between risk diversification and risk interdependence. Reinsurance is designed to spread risk, but the process of spreading risk can also create layers of financial dependence across insurers, reinsurers, and capital markets. When a primary insurer transfers risk to a reinsurer, and that reinsurer transfers part of the same exposure to another reinsurer through retrocession, the original risk may move through several layers of the market. If these transfers are transparent, well diversified and supported by sufficient capital, they can strengthen the resilience of the system. If they are opaque, circular or concentrated among a limited number of global firms, the same mechanism may create hidden vulnerabilities.

Several channels may therefore make reinsurance relevant from a systemic-risk perspective. First, retrocession can create multi-layered risk-transfer chains, making the final allocation of losses difficult to observe. Second, primary insurance companies may rely on reinsurers for capacity and coverage of large or difficult risks. Third, the reinsurers themselves may have exposure to the same risk factors, such as natural catastrophe risk, cyber risk, pandemic risk or liability risk. Fourth, as large institutional investors, reinsurers can also have exposure to interest rate risk, credit risk, stock market risk and other financial risks. Fifth, the reliance between institutions can become even higher during times of stress. These mechanisms suggest that the systemic relevance of reinsurance does not arise primarily from bank-like liquidity runs, but from the interaction between risk transfer, common exposures, market-based interdependence and stress-period co-movement (Cummins and Weiss, 2014; Park and Xie, 2014; Weiß and Mühlnickel, 2014; Bierth, Irresberger, and Weiß, 2015).

For these reasons, the systemic importance of reinsurance cannot be assessed only through the solvency position of individual firms. A microprudential perspective is necessary to evaluate the soundness of each institution, but it is not sufficient to understand how vulnerabilities may be distributed across the sector or how institutions may become jointly exposed to common shocks. A macroprudential perspective is therefore required, focusing not only on individual solvency, but also on the distribution, concentration and possible transmission of vulnerabilities across the system (De Bandt and Hartmann, 2000; Borio, 2003; Brunnermeier et al., 2009). This view is consistent with the evolution of international insurance supervision: the IAIS Holistic Framework recognises that systemic risk in insurance may arise not only from the distress of an individual insurer, but also from collective exposures and activities at the sector-wide level (IAIS, 2019).

The objective of this thesis is therefore not to assess whether reinsurance is risky in isolation, but to examine how market-based interconnectedness among listed global reinsurers and reinsurance-related insurance groups evolves over time, which institutions appear more systemically relevant in terms of contribution and vulnerability, and whether this systemic relevance is reflected in the structure of the correlation-based network. Since the empirical analysis is based on equity returns, ΔCoVaR estimates and correlation networks, the thesis does not identify direct contractual exposures or causal contagion channels. Instead, it provides market-based evidence on statistical interdependence, stress-period co-movement and structural centrality within the global reinsurance ecosystem.

Research questions

Building on this objective, the analysis is organised around three specific research questions, each addressing a different dimension of the systemic relevance discussed above: the dynamic evolution of market-based interconnectedness, the cross-sectional ranking of Systemic Contribution and Vulnerability, and the relationship between these rankings and the structural position of institutions within the correlation-based network.

Specifically, the thesis addresses the following three research questions:

RQ1. How does market-based interconnectedness among listed global reinsurers and reinsurance-related insurance groups evolve over time and across regions?

This question focuses on the dynamic dimension of systemic risk. It is addressed through the DCC-GARCH model and the analysis of time-varying conditional correlations, with particular attention to stress episodes such as the European sovereign debt crisis, the COVID-19 pandemic, the 2022 monetary tightening cycle, and regional shocks. The objective is to assess whether interconnectedness increases during periods of market stress and whether this pattern differs across Europe, North America and Bermuda, and APAC.

RQ2. Which institutions display the highest Systemic Contribution and Systemic Vulnerability according to the DCC-GARCH ΔCoVaR framework?

This question focuses on the cross-sectional dimension of systemic risk. It is addressed through the two directional ΔCoVaR measures used in the thesis: Systemic Contribution, which captures how an institution's distress is associated with system-wide risk, and Systemic Vulnerability, which captures how an institution's own risk changes when the broader insurance market is under distress. The aim is to identify whether the same institutions are relevant in both directions, or whether some firms appear mainly as contributors, while others appear mainly as vulnerable receivers of market-wide distress.

RQ3. To what extent are institutions with higher Systemic Contribution or Vulnerability also more central within the correlation-based network?

This question links the Systemic Contribution and Systemic Vulnerability results with the network analysis. The comparison is not intended as an independent validation of the systemic-risk measures, since both approaches are constructed from equity-return dependence and therefore share part of the same underlying information. Rather, the objective is to examine the degree of concordance between institution-level systemic-risk rankings and network position, and, more importantly, to identify the additional structural information provided by the network. Strength centrality captures broad embeddedness in the correlation structure, while betweenness centrality and community membership identify bridging positions and clustering patterns that are not contained in the institution-to-market systemic-risk measures. Particular attention is therefore given both to ranking overlap and to institutions for which the two perspectives diverge.

Contribution

This thesis contributes to the literature in three main ways. First, it focuses on listed global reinsurers and reinsurance-related insurance groups as a specific segment of the broader insurance sector. This wording is used deliberately, since the empirical sample includes both specialised reinsurers and large integrated insurance groups for which reinsurance is one relevant activity within a broader corporate structure. While the systemic-risk literature has extensively studied banks and, more recently, large insurance groups, the reinsurance sector remains less widely examined as a distinct object of empirical analysis, especially from a market-based and network-oriented perspective (Park and Xie, 2014; Weiß and Mühlnickel, 2014; Bierth, Irresberger, and Weiß, 2015). This is important because reinsurers occupy a specific position in the financial system: they absorb and redistribute extreme underwriting risks, provide capacity to primary insurers, participate in retrocession markets, and may share common asset-side exposures with other financial institutions.

Second, the thesis combines a dynamic DCC-GARCH framework with ΔCoVaR in order to analyse both the time and cross-sectional dimensions of systemic risk. The DCC-GARCH methodology helps understand the dynamics of conditional volatility and correlation throughout time, and thus allows for an analysis of how market interconnectedness increases in stressful times. In turn, the ΔCoVaR framework converts this dynamic dependence structure into institution-specific metrics of Systemic Contribution and Systemic Vulnerability. This will allow for the thesis to differentiate between institutions where distress results in an increase in aggregate risk, and institutions that are more vulnerable when there is distress within the overall insurance industry.

Finally, the thesis enhances the ΔCoVaR analysis with a correlation-based network approach. By generating networks based on co-movement of equity returns, the analysis will look at whether institutions considered systemically relevant in terms of ΔCoVaR also hold a central or bridging position in the dependence structure of the sector. This contribution links market-based systemic-risk measurement with network topology, following the broader literature that emphasises the multidimensional nature of systemic risk and the usefulness of combining institution-level risk measures with information on financial interconnectedness (Billio et al., 2012; Diebold and Yilmaz, 2014; Hautsch, Schaumburg, and Schienle, 2015; Denkowska and Wanat, 2020). At the same time, the interpretation remains deliberately cautious: the network does not represent direct contractual reinsurance exposures or observed retrocession links, but rather a market-based representation of statistical interdependence among listed firms.

Overall, the contribution of the thesis is to provide an integrated empirical framework for assessing systemic risk in the global reinsurance ecosystem. The analysis does not aim to produce direct regulatory prescriptions or firm-specific capital-buffer recommendations. Instead, it provides complementary market-based indicators that may help identify institutions, regions, and stress periods that deserve closer attention from a macroprudential monitoring perspective.

Thesis structure

The thesis is organised as follows. Chapter 1 introduces the global reinsurance ecosystem and motivates the analysis of reinsurance from a systemic-risk perspective. It discusses the economic function of reinsurance, the composition of the global reinsurance market, the inclusion of both specialised reinsurers and reinsurance-related insurance groups, and the main channels through which reinsurance may become systemically relevant.

Chapter 2 reviews the academic literature that underpins the empirical analysis. It first discusses the definition of systemic risk and its main transmission channels, then introduces the distinction between the cross-sectional and time dimensions of systemic risk. The chapter subsequently reviews market-based measures of systemic risk, the literature on systemic risk in insurance and reinsurance, and network-based approaches to financial interconnectedness. It concludes by identifying the literature gap addressed by the thesis.

Chapter 3 presents the data and methodology. It describes the sample selection, the data sources, the construction of daily equity returns and the choice of the market factor. It then

introduces the DCC-GARCH model used to estimate time-varying volatilities and correlations, the DCC-GARCH-based ΔCoVaR framework used to measure Systemic Contribution and Vulnerability, and the network methodology used to analyse correlation-based interconnectedness, centrality, the Minimum Spanning Tree and community structure.

Chapter 4 presents the empirical results on dynamic interconnectedness and ΔCoVaR. It first analyses regional patterns in Europe, North America and Bermuda, and APAC, focusing on how conditional correlations evolve during stress episodes. It then presents the global DCC-GARCH results and the ΔCoVaR rankings, distinguishing between Systemic Contribution and Systemic Vulnerability. The chapter also reports robustness checks based on alternative distress thresholds, an alternative market index and an alternative distributional assumption.

Chapter 5 examines the network structure of the global reinsurance ecosystem through a correlation-based analysis of the sampled listed insurance and reinsurance groups. It analyses the correlation-based network, the Minimum Spanning Tree and the structural evolution of the network across different sub-periods. It also links the network results to the ΔCoVaR analysis by comparing Systemic Contribution and Vulnerability rankings with network centrality measures and community membership.

Chapter 6 analyses the implications of the findings for risk management and macroprudential considerations. The chapter considers the empirical findings as complementary measures for macroprudential surveillance, highlighting at the same time the shortcomings of market-based measures. Specifically, it makes it clear that the findings should not be considered as providing enough evidence for firm-specific capital buffer suggestions, but rather as providing signals which can support supervisory surveillance when combined with balance sheet and contractual information.

The thesis concludes by returning explicitly to the three research questions, summarising the main empirical findings, discussing the contribution of the analysis, and outlining the main limitations and directions for future research.

CHAPTER 1

The Global Reinsurance Ecosystem and the Motivation for a Systemic-Risk Perspective

1.1 The Reinsurance Mechanism: Risk Transfer and Risk Sharing

Reinsurance plays a central role in the functioning of modern insurance markets. Primary insurers are able to enhance their risk tolerance capacity by sharing some of the underwriting risk to specialized reinsurers, which allows them to even out their loss experience and continue offering coverage to risks that would be outside their capital base individually (Froot, 2001; Cummins & Weiss, 2014). This function becomes especially important in the case of low-frequency and high-severity risks, including natural disasters, extreme liability events, pandemics, cyber-attacks, and other extreme losses. In such situations, the loss may be too severe or too concentrated to be handled efficiently by one insurer. Thus, reinsurance becomes an instrument through which risks are spread among various companies and even across different business segments and regions.

As far as the implementation of the reinsurance contract is concerned, there are a number of different types that can be used in practice, and such variation is important to understand the way risk propagates through the process. The first type of the contract considered by Cummins and Outreville (1987) is proportional reinsurance (quota-share, surplus treaties) in which the reinsurer is paid a predetermined proportion of premiums and pays the same proportion of losses, sharing the risks according to the size of the original insurance contract. Non-proportional (excess-of-loss) reinsurance, on the contrary, implies the situation when the reinsurer gets involved in the contract only if losses exceed the level of retention up to the predetermined limit. For the primary insurer, it is an opportunity to cover risks in the tail of the loss distribution and to transfer not all layers of the portfolio. (Klages-Mundt and Minca, 2020). Reinsurance contracts can further be arranged on a treaty basis, covering an entire portfolio of risks automatically, or on a facultative basis, negotiated individually for a single risk; large reinsurers and integrated groups typically combine both approaches depending on the line of business and the size of the exposure.

As discussed later in this chapter (Section 1.4), this contractual variety matters for the systemic-risk analysis because non-proportional reinsurance, and its extension through retrocession, is one of the mechanisms that can transform a well-diversified risk-transfer process into a source of concentration and opacity, as illustrated historically by the London Market Excess of Loss spiral (Bell, 2014).

1.2 The Global Reinsurance Market

The global reinsurance market has become a large and economically significant component of the broader insurance sector. According to the International Association of Insurance Supervisors (IAIS, 2025a), reported gross reinsurance premiums reached almost USD 1.75 trillion at year-end 2024, while net reinsurance premiums exceeded USD 1.2 trillion. On the basis of the IAIS reporting sample, gross reinsurance premiums represented approximately 23% of total global gross insurance premiums written. The long-run series reported by the IAIS also shows a substantial expansion in reported reinsurance volumes over time, although changes in reporting scope, particularly in 2019 and 2024, mean that individual jumps in the series should not be interpreted entirely as organic market growth.

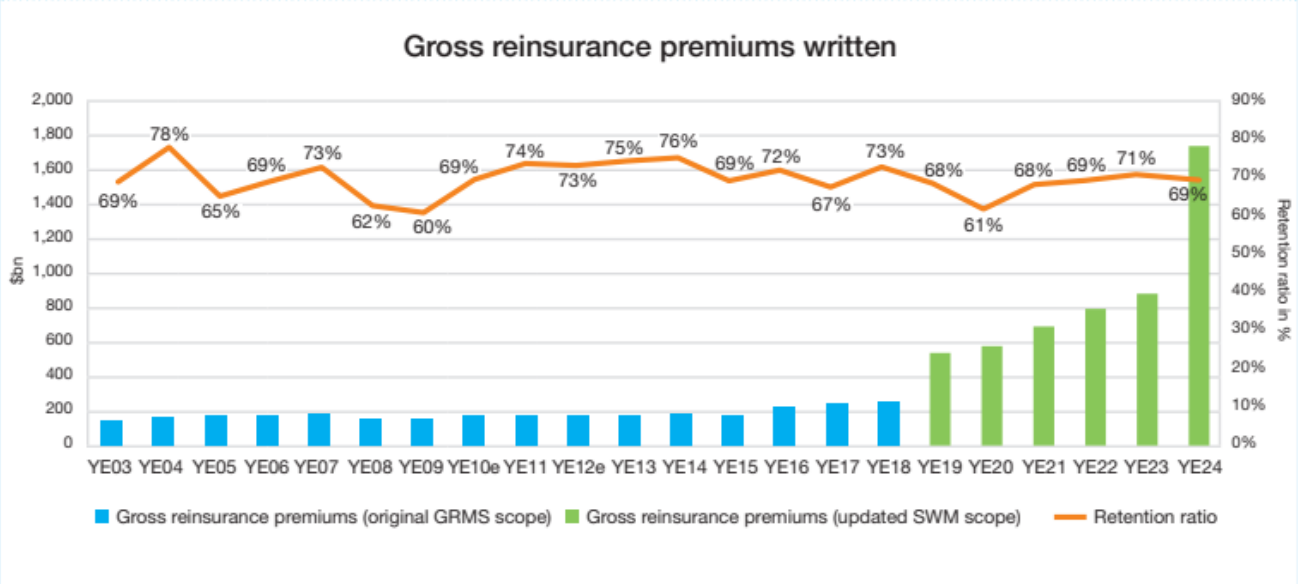

Figure 1: Evolution of Global Gross Reinsurance Premiums, 2003-2024.

The bars report gross reinsurance premiums written, while the line reports the retention ratio. Changes in reporting scope affect year-to-year comparability, particularly in 2019 and 2024. Source: IAIS (2025a), Global Insurance Market Report 2025, Figure 38

The market is also heterogeneous across business lines. At year-end 2024, approximately 25% of reported gross reinsurance premiums related to life business, while around 75% consisted of non-life and catastrophe reinsurance. Within non-life reinsurance, property represents the largest component, followed by liability business and financial lines. The composition also varies geographically, reflecting differences in underlying insurance markets and risk structures across regions (IAIS, 2025a).

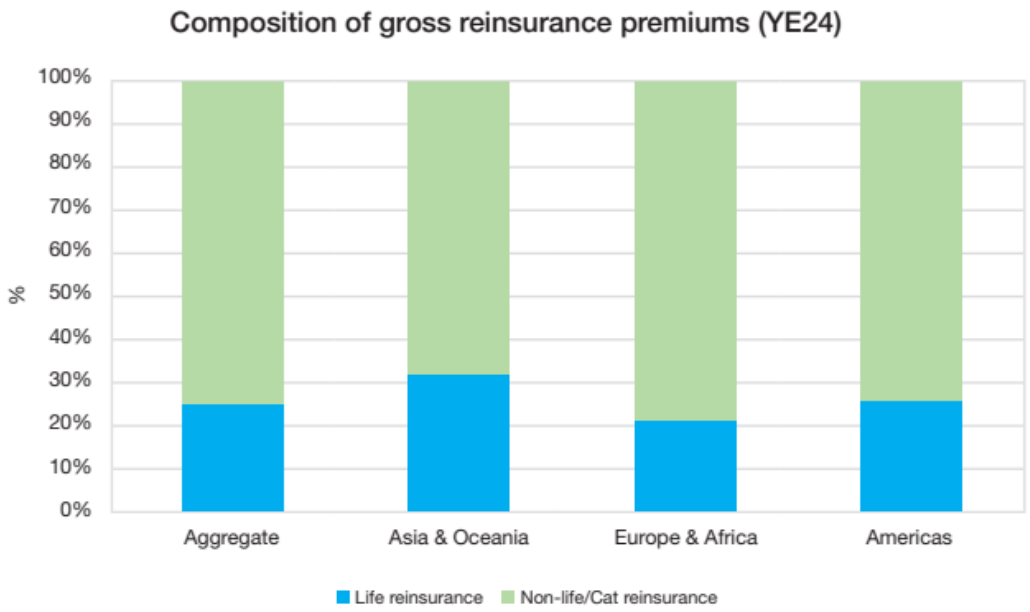

Figure 2: Composition of Global Gross Reinsurance Premiums by Business Type and Region, 2024.

The figure reports the share of life and non-life/Cat reinsurance premiums for the aggregate market and across the main geographical regions. Source: IAIS (2025a), Global Insurance Market Report 2025, Figure 39

Reinsurance activity is geographically concentrated. Based on the IAIS data reported for 2024, the United States and Bermuda together account for almost three quarters of reported global reinsurance premiums, while Germany, Switzerland and the United Kingdom are also among the largest reinsurance jurisdictions. These figures should be interpreted with some caution because reporting scopes differ across jurisdictions, but they nevertheless illustrate the importance of a relatively small number of global reinsurance centres.

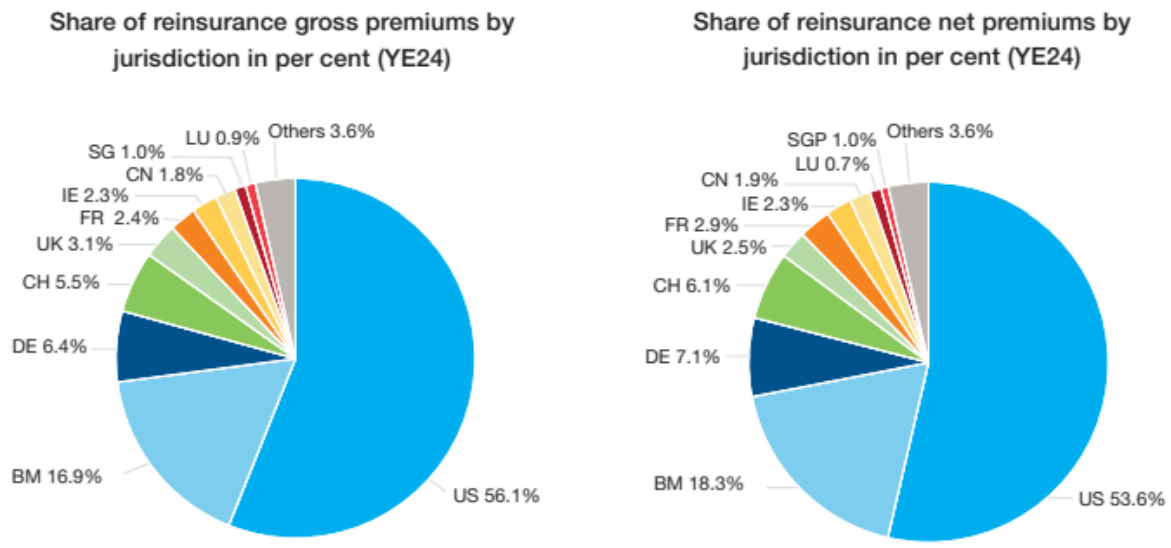

Figure 3: Geographical Distribution of Global Reinsurance Premiums by Jurisdiction, 2024.

The figure reports the shares of gross and net reinsurance premiums by jurisdiction. The United States and Bermuda account for the largest reported shares; cross-jurisdictional comparisons should be interpreted with caution because reporting scopes differ. Source: IAIS (2025a), Global Insurance Market Report 2025, Figure 45

The composition of reinsurance capacity has also evolved. Aon (2025) estimates that global reinsurer capital increased from USD 565 billion in 2015 to USD 715 billion in 2024 and USD 720 billion in the first quarter of 2025. Over the same period, alternative capital increased from USD 72 billion to USD 115 billion, alongside the continued expansion of traditional reinsurer capital. This development illustrates the growing role of capital-market-based capacity, including catastrophe bonds and sidecar structures, alongside conventional balance-sheet reinsurance. On the demand side, primary insurers remain the principal purchasers of reinsurance, while reinsurers themselves also purchase protection through retrocession. More recently, the life insurance sector has also seen increasing use of cross-border asset-intensive reinsurance for capital-intensive liabilities such as annuities and long-term savings products (IAIS, 2025b).

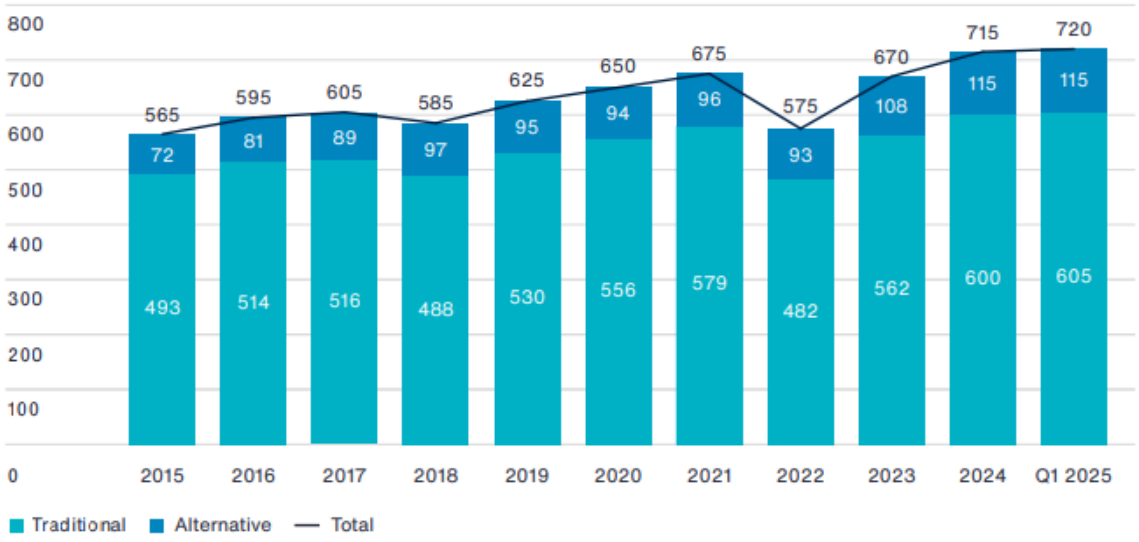

Figure 4: Evolution and Composition of Global Reinsurer Capital, 2015-Q1 2025.

The figure distinguishes between traditional reinsurer capital and alternative capital, illustrating the increasing role of capital-market-based capacity alongside traditional reinsurance balance sheets. Source: Aon (2025), Reinsurance Market Dynamics: Midyear 2025 Renewal, Exhibit 1

Market participation is also heterogeneous. Primary insurers purchase reinsurance to transfer part of their underwriting risk, while reinsurers may themselves become buyers of protection through retrocession (IAIS, 2025a). On the supply side, traditional reinsurance capacity is increasingly complemented by alternative capital, including catastrophe bonds and sidecar structures (Aon, 2025). In the life segment, the growing use of cross-border asset-intensive reinsurance has also increased the involvement of reinsurers affiliated or partnered with asset managers (IAIS, 2025b). Taken together, these developments show that reinsurance is not only a sizeable and internationally concentrated market, but also an increasingly heterogeneous one in terms of products, jurisdictions and sources of risk-bearing capacity.

The global reinsurance market is not composed exclusively of stand-alone reinsurers. Reinsurance capacity is provided by different types of institutions, including specialised reinsurers, multiline reinsurance groups, and large integrated insurance groups that combine primary insurance, reinsurance, asset management and other financial activities within the same corporate structure (Cummins and Weiss, 2014; AM Best, 2025). This distinction is important because the economic function of reinsurance is not limited to firms whose only activity is reinsurance. Large integrated insurance groups may also provide significant reinsurance capacity, participate in retrocession markets, absorb large underwriting risks, and transmit or receive market-based shocks through their investment portfolios and broader financial activities (Park and Xie, 2014; Bierth, Irresberger, and Weiß, 2015; IAIS, 2019).

This is accentuated by the concentration characteristic of the worldwide reinsurance market. Reinsurance capacity is not spread out evenly over many small firms, but rather a substantial proportion comes from a few large companies that operate on an international level. This concentration does not necessarily mean that the system is fragile, since large reinsurers tend to be diversified in their business and geographical presence. However, it does make their market-based behaviour relevant for the rest of the sector. If a small number of groups

provide a substantial share of global reinsurance capacity, their distress, repricing decisions or reduction in underwriting appetite may affect the availability and cost of reinsurance for primary insurers. For this reason, the systemic relevance of reinsurance should be analysed not only through contractual exposures, but also through the market-based interdependence of the listed groups that provide or support global reinsurance capacity (Cummins and Weiss, 2014; AM Best, 2025; IAIS, 2019).

For this reason, the empirical sample used in this thesis should not be interpreted as a homogeneous set of pure reinsurers. Rather, it represents a group of listed global reinsurers and reinsurance-related insurance groups selected to capture the main publicly traded institutions that provide relevant capacity within the global reinsurance ecosystem. The sample therefore includes both specialised reinsurers, whose business model is primarily centred on reinsurance, and larger integrated insurance groups for which reinsurance is one important activity within a broader insurance or financial conglomerate (AM Best, 2025; Cummins and Weiss, 2014).

This choice is consistent with the objective of the thesis. The aim is not to analyse reinsurance contracts at the legal-entity level, nor to reconstruct the exact contractual network of retrocession exposures. Instead, the thesis adopts a market-based perspective and studies whether the listed groups that provide or are closely connected to global reinsurance capacity display patterns of systemic relevance in equity markets. Since the empirical analysis relies on daily stock returns, ΔCoVaR estimates and correlation-based networks, the relevant unit of observation is the listed corporate group rather than the individual reinsurance subsidiary. This implies that the results should be interpreted as market-based evidence on the systemic relevance of reinsurance-related groups, not as direct evidence on the contractual exposures of pure reinsurance entities alone (Bierth, Irresberger, and Weiß, 2015; Denkowska and Wanat, 2020).

The inclusion of integrated insurance groups is also justified from a macroprudential perspective. Systemic risk in insurance may arise not only from the distress of an individual insurer, but also from collective exposures and activities at the sector-wide level (IAIS, 2019). Large diversified groups might create systemic interdependencies due to the similarity of their asset allocations, the presence of correlated investment strategies, their use of the global capital markets, and their position as users or suppliers of reinsurance capacity (Cummins and Weiss, 2014; Park and Xie, 2014; Weiß and Mühlnickel, 2014; Bierth, Irresberger, and Weiß, 2015). Hence, leaving those companies aside would provide a limited picture of the global reinsurance network and possibly miss some institutions that are important for shock propagation.

Throughout the thesis, this distinction will be clearly made. In case of mentioning the empirical sample of the research, the expressions “listed global reinsurers and insurance groups that operate in reinsurance business” or “insurance and reinsurance groups” will be employed. The expression “pure reinsurers” will be used in case the business model of an institution is primarily related to reinsurance. The importance of such terminological distinctions lies in the interpretation of the findings: a high level of Systemic Contribution or centrality in the network based on correlation means not necessarily that the reinsurance subsidiary itself is systemically important but that the listed group operating in the field of reinsurance is.

1.3 From Risk Transfer to Systemic Interdependence

From this perspective, reinsurance is usually interpreted as a stabilising mechanism. It allows primary insurers to smooth the impact of large losses, reduces the concentration of underwriting risk, and increases the overall capacity of the insurance sector (Cummins and Outreville, 1987; Froot, 2001). In addition, major institutions within the global reinsurance ecosystem operate across multiple markets and lines of business, which allows them to diversify exposures internationally. This diversification capability becomes even more significant in an age when the most extreme risks are increasingly becoming global, interconnected, and correlated. Climate events, cyber threats, market disruptions, and geopolitical risks are all becoming potentially capable of affecting many companies at once, thereby increasing the importance of being global risk absorbers.

However, reinsurance does not eliminate risk from the financial system. It redistributes it. The same mechanism that allows risks to be spread across a broader set of institutions may also create channels of interdependence between insurers, reinsurers, financial markets and policyholders. Under normal conditions, this process can improve diversification and financial resilience. Under stress conditions, however, it may contribute to the transmission or amplification of losses if the institutions involved are highly interconnected, exposed to similar shocks, or dependent on the same sources of reinsurance capacity. (Cummins and Weiss, 2014; Weiß and Mühlnickel, 2014; Bierth, Irresberger, and Weiß, 2015).

The systemic relevance of reinsurance therefore depends on the conditions under which risk redistribution takes place. However, when such risks are adequately diversified among independent parties, reinsurance can help decrease the vulnerability of the insurance industry. However, when such risks become concentrated among a few reinsurers, repeatedly retroceded through various layers, or related to similar assets exposures, the diversification effect becomes less effective. In this situation, reinsurance can play its role in transferring risks individually, but increase the interdependence from the system point of view. This distinction is central for the empirical analysis of this thesis, which does not assume that reinsurance is destabilising per se, but investigates whether listed reinsurance-related groups display market-based patterns of co-movement and systemic relevance during stress periods (Cummins and Weiss, 2014; Weiß and Mühlnickel, 2014; Bierth, Irresberger, and Weiß, 2015).

This dual role makes reinsurance particularly relevant from a systemic-risk perspective. Contrary to banks, reinsurers have a lower potential for suffering from conventional liquidity runs due to the limited withdrawability of liabilities and a different business model that does not rely on deposits or maturity transformation (Cummins and Weiss, 2014). However, lack of liquidity runs does not mean that the reinsurers cannot be systemically important entities. It can happen via other ways: either through taking up a large amount of catastrophe and liability risks, or by being important for primary insurance companies, or even through participating in a retrocession chain, correlated investments, and similar exposures. The relevant question is therefore not whether reinsurance creates systemic risk in the same way as banking, but whether the structure of the global reinsurance market may allow shocks to become more correlated, more concentrated, or more difficult to monitor.

1.4 Main Channels of Systemic Relevance in Reinsurance

A distinctive feature of reinsurance is that risk transfer does not necessarily stop at the first reinsurer. Primary insurers cede part of their underwriting risk to reinsurers, but reinsurers may then transfer part of the same risk to other reinsurers through retrocession. Retrocession can therefore be regarded as reinsurance for the reinsurers, enabling them to deal with heavy exposures, stabilizing their balance sheets, and increasing their underwriting capacity. Thus, in this respect, retrocession takes the idea of reinsurance one step further, creating in addition a very intricate web of interdependencies in the sector.

The rationale behind such a procedure is that while reinsurance transfers risk to another party, it does not necessarily reduce it. By retroceding the risk, the initial exposure of the institution is thus dispersed among other companies. When such dispersion of the exposure is wide enough, the retrocession procedure will thus enhance the robustness of the sector. Yet, in the situation when a single risk is retroceded by several levels of reinsurance and retrocession, determining who suffers what loss becomes a much more complicated matter. The problem here lies in the fact that several institutions could be indirectly linked to the same claim via different insurance/reinsurance agreements. More generally, network models of systemic risk show that financial linkages may be stabilising in normal conditions but can become channels for loss propagation during stress periods (Caccioli, Barucca, and Kobayashi, 2018).

A historical illustration of this mechanism is the London Market Excess of Loss spiral, commonly referred to as the LMX spiral. Bell (2014) describes the LMX spiral as a structure based on overlapping layers of excess-of-loss reinsurance within the London market, where reinsurers repeatedly reinsured other reinsurers and, in some cases, effectively reinsured risks that had already circulated through previous layers. In this context, the same fundamental risks would have passed through a number of layers of reinsurance and retrocession, ultimately becoming hard to track. What makes the systemically relevant LMX spiral not only the magnitude of the original catastrophic loss, but also the manner in which that loss was repeatedly layered through the complex system of reinsurance contracts. According to Bell (2014), the LMX spiral created opacity, circularity and concentration of risks in such a way that a tool aimed at distributing risk contributed to systemic instability of the London reinsurance market. This example is therefore useful for the present thesis because it illustrates how repeated risk transfer may transform diversification into structural interdependence when the final distribution of risk becomes difficult to identify.

Recent modelling work on reinsurance networks provides a more formal support for this intuition. Klages-Mundt and Minca (2020) analyse cascading losses in reinsurance networks and show that the contractual structure of reinsurance matters for systemic risk. For instance, excess-of-loss arrangements might include nonlinear features that complicate loss propagation, and simplified approaches relying on only proportional reinsurance may underestimate contagion effects. It is especially significant when considering retrocession, where the same shock may trigger multiple levels of contractual arrangements and produce loss effects that cannot be traced back to the initial risk exposure directly.

Systemic significance of retrocession is also linked to the reliance of primary insurers on prominent reinsurers. Park and Xie (2014) demonstrate that downgrading of a reinsurer may have a negative impact on property-casualty insurers who use that reinsurer for risk transfer. Such a finding is important because it demonstrates that distress of reinsurers may have an impact outside the reinsurer. Specifically, if a reinsurer becomes distressed, primary insurers

may suffer from counterparty risk, limited reinsurance capacity, or increasing cost of future reinsurance coverage. In other words, the systemic significance of a reinsurer is determined not by its solvency, but also by its role in the risk transfer chain.

In addition to retrocession, reinsurance is also exposed to common underwriting and investment risks. Large global reinsurers and reinsurance-related insurance groups may insure similar types of extreme risks, including natural catastrophes, climate-related events, cyber losses, pandemics, and liability shocks. At the same time, reinsurers are also large institutional investors, and their asset portfolios may be exposed to similar interest-rate, credit, equity-market, and macro-financial risks. EIOPA (2012) underlines the significance of market and investment risks for financial stability in the insurance industry. Therefore, even when the risk profile of underwriting business is diversified through geographic diversification, reinsurers can still suffer correlated losses as a result of exposures on the asset side.

The asset side mechanism plays a crucial role in a market-based approach. Two reinsurance-related firms which are not connected in any way from a reinsurance perspective may still be expected to exhibit comovement of their stock price returns due to perception of the exposure to common macro-financial risks. Interest rate risks, movements in credit spreads, equity market falls and valuation of investment portfolios can thus lead to common losses. In other words, market-based interdependence can occur not only due to underwriting or retrocession linkages, but also due to the role of reinsurers as institutional investors. This is why equity-return correlations and ΔCoVaR estimates can be considered as measures of systemic relevance while keeping in mind the caveat that such measures do not indicate any contractual linkages. These channels explain why reinsurance is relevant from a macroprudential perspective, even if it does not generate systemic risk in the same way as banking. As discussed above (Section 1.3), the absence of bank-like liquidity runs does not make reinsurers systemically irrelevant. In reinsurance specifically, systemic relevance may arise through retrocession chains, concentration of risk among large global reinsurers, common underwriting exposures, correlated investment portfolios, and the dependence of primary insurers on reinsurance capacity (Bierth, Irresberger, and Weiß, 2015; Weiß and Mühlnickel, 2014). Because of this, the reinsurance industry has a natural aptitude for a systemic risk analysis that takes into account both the institution-based approach and network methods. The appropriate query is not merely whether the given reinsurer itself is exposed to systemic risk, but whether the particular firm holds a significant place within the framework of market interdependence. The given reinsurer may become systemically relevant due to the absorption of significant amounts of risk, as well as its connection with other reinsurers via retrocession, influence on primary insurers, and similar risks among firms.

1.5 Implications for the Empirical Strategy

The discussion developed in this chapter has direct implications for the empirical strategy adopted in the remainder of the thesis. Sections 1.3 and 1.4 show that the systemic relevance of reinsurance does not depend only on the risk profile of individual institutions at a given point in time, but also on how their interdependence evolves, particularly through retrocession chains, common underwriting exposures, correlated investment portfolios and the dependence of primary insurers on major reinsurers (Cummins and Weiss, 2014; Park and Xie, 2014; Bierth, Irresberger, and Weiß, 2015). This double nature of the problem, cross-sectional and dynamic, motivates the combined use, in Chapters 3 and 4, of a DCC-GARCH model to capture the time-varying behaviour of volatilities and correlations (Engle, 2002) and of a ΔCoVaR framework, estimated within the same dynamic setting, to translate this dependence structure into institution-level measures of Systemic Contribution and Systemic Vulnerability (Adrian and Brunnermeier, 2016). Girardi and Ergün (2013) show that embedding CoVaR estimation within a multivariate GARCH framework improves the ability to capture time-varying systemic risk relative to static approaches, which further supports this methodological choice.

A second implication concerns the choice of a market-based rather than a purely contractual approach. As the LMX spiral illustrates (Bell, 2014), and as the modelling results of Klages-Mundt and Minca (2020) confirm more formally, the detailed structure of retrocession chains is generally not observable from outside the industry, and reconstructing it would require proprietary contractual data that are not available for a broad, internationally diversified sample of listed groups. Equity returns on a daily basis, however, are directly observable, current and based on a sufficiently long time series data set, capturing the overall market perception about the firm's risk profile in terms of underwriting, investment and counterparty risks. This explains why this research uses equity return co-movements, estimated using the DCC-GARCH approach, and the correlation network introduced in Chapter 3 as a proxy for interdependence. Consistently with Forbes and Rigobon (2002), these co-movements are interpreted throughout the thesis as evidence of statistical interdependence rather than as direct proof of contractual contagion, an interpretive caution that is restated whenever the empirical results are discussed.

Third, Section 1.4 shows that reinsurers may become systemically relevant through channels that are not limited to bilateral risk transfer, for instance through common exposures to catastrophe, cyber or liability risk, or through shared positions in global capital markets. This suggests that institution-level measures of Systemic Contribution and Vulnerability should be complemented with information on the overall structure of interdependence within the sector, rather than analysed in isolation. Following Billio et al. (2012) and, specifically for insurance and reinsurance, Denkowska and Wanat (2020) and Clemente, Grassi, and Pederzoli (2022), the thesis therefore complements the ΔCoVaR analysis with a correlation-based network approach, examining centrality, community structure and the Minimum Spanning Tree in Chapters 3 and 5. The directional distinction between Systemic Contribution and Systemic Vulnerability, introduced in Chapter 3, is also consistent with Diebold and Yilmaz's (2012) argument that measuring what an institution transmits to the system and what it receives from the system captures different, and equally relevant, aspects of interconnectedness.

Finally, the discussion in Section 1.2 justifies the composition of the empirical sample. Since large integrated insurance groups may be as relevant as specialised reinsurers for the transmission and absorption of market-wide shocks (IAIS, 2019), restricting the analysis to pure reinsurers would provide an incomplete picture of the global reinsurance ecosystem. The empirical sample is therefore composed of listed global reinsurers and reinsurance-related insurance groups, and the results are interpreted, throughout the thesis, as market-based evidence on the systemic relevance of this broader set of institutions rather than as a direct assessment of individual reinsurance subsidiaries. On this basis, Chapter 2 reviews the literature on systemic risk that underlies the empirical framework, before Chapter 3 presents the data and the DCC-GARCH, ΔCoVaR and network methodologies in detail.

CHAPTER 2

Literature Review

This chapter reviews the literature on systemic risk that underpins the analysis of the global reinsurance sector. It first defines systemic risk and its main transmission channels, then discusses its cross-sectional and time dimensions, and finally reviews the literature on systemic risk in insurance and reinsurance and on network-based approaches.

2.1 Systemic Risk: Definitions and Transmission Channels

A useful starting point for defining systemic risk is provided by De Bandt and Hartmann (2000), who describe systemic risk as the risk of experiencing a systemic event in the financial system. Under their approach, a systemic event can be defined as a shock that affects one or more financial institutions and markets and has such serious implications that disrupt the function of a substantial portion of the financial system. The above definition is very important because it focuses on the consequences that may arise from the initial shock, rather than the size of the shock. In other words, the shock becomes systemically relevant not due to its size but due to the way it has been transmitted, amplified, or shared. In turn, de Bandt and Hartmann (2000) provide an even further classification of a systemic event and differentiate between a systemic event in the narrow and broad senses. According to the former, a systemic event happens when the problem of one institution or market becomes a problem of others through the contagion mechanism. At the same time, according to the latter, a systemic event might happen when several institutions or markets are shocked at once due to some common reason. The difference is also important because systemic risks do not necessarily imply the collapse of one organization to lead to the collapse of others, but can arise due to the shared exposure of organizations to the same source of stress.

In addition, the approach explains the difference between individual and systemic risk. Individual risk means the probability of losses or financial problems of an organization. Systemic risk, in its turn, means the probability that the problem or financial difficulty is not isolated within one organization or market, but is transmitted to another organization, market, or sector of the economy. In this way, systemic risks are relational, that is they are associated not only with the vulnerability of individual organizations but with their mutual connections and common exposures to shocks. This distinction is central for the present thesis, because the reinsurance sector may be exposed to both mechanisms. A large reinsurer may transmit distress through risk-transfer relationships, while several reinsurers may also be affected simultaneously by common underwriting losses, global financial market shocks, or correlated investment portfolios.

Therefore, systemic risk should not be interpreted as a synonym for large losses. Large losses are relevant only when they have implications beyond the individual institution. The critical issue for a systemic perspective is whether there are any externalities created by the losses, whether such losses spread due to direct or indirect connections, and whether they

undermine the financial system's capacity to fulfill its core functions. Systemic risk assessment requires a macroprudential approach because it is not enough to determine if particular entities are solvent, but rather to know the distribution of vulnerabilities and their transmission across the system. This macroprudential perspective also reflects a fallacy-of-composition problem. Actions that may be prudent for a single institution, such as reducing risk exposures or selling assets during a downturn, can become destabilising when many institutions behave in the same way at the same time. For this reason, a regulatory approach focused only on individual soundness may fail to capture sources of instability that emerge at the level of the system as a whole (Brunnermeier et al., 2009).

After defining systemic risk, it is necessary to explain the main channels through which it can materialise. A first channel is contagion. In the systemic risk literature, contagion refers to the transmission of distress from one institution or market to others through financial linkages. These linkages may be direct, for example through contractual exposures and counterparty relationships, or indirect, through market prices, information effects, and changes in confidence. De Bandt and Hartmann (2000) distinguish this mechanism from broader systematic shocks, while Allen and Gale (2000) show that the structure of financial connections determines whether a shock remains local or spreads across the system. More recently, Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) show that financial networks may be robust to small shocks but fragile when shocks become sufficiently large. Therefore, contagion highlights that systemic risk depends not only on the initial shock, but also on the structure of interconnections through which the shock can be transmitted. However, contagion should be distinguished from interdependence. As Forbes and Rigobon (2002) argue, higher co-movement during crises does not automatically imply contagion, because part of the observed increase in correlation may reflect pre-existing linkages or the effect of higher volatility on correlation estimates. This distinction is important for the present thesis, since the empirical network is based on estimated correlations. For this reason, correlations are interpreted as measures of statistical interdependence rather than as direct evidence of causal contagion.

A second channel is common exposure. In this case, systemic risk does not arise because one institution directly transmits distress to another, but because several institutions are vulnerable to the same underlying source of risk. De Bandt and Hartmann (2000) refer to this mechanism when distinguishing between narrow systemic events, which originate from the distress of one or few institutions, and broader systemic events caused by systematic shocks affecting several institutions or markets at the same time. Similar exposures can occur when there are common asset holdings, strategies of investing, or conditions prevailing among the various organizations in financial markets. For the insurance and reinsurance industry, this form of channel through which vulnerability arises is very common because companies are exposed to catastrophes, liabilities, underwriting cycles, interest rates and shocks in financial markets. Moreover, the stress and downgrade of a large reinsurer company can affect many primary insurers who use it as a way of transferring risk, making yet another channel of vulnerability (Park and Xie, 2014).

The third channel is tail dependence. Tail dependence occurs where the level of dependence increases in extremely bad times. In ordinary times, the correlations will be considered low indicating the existence of diversification. However, during crises, the benefits of diversification will be lost since institutions which were previously loosely coupled will begin moving together. Longin and Solnik (2001) show that international equity markets tend to

display stronger dependence during extreme negative market movements, while Embrechts, McNeil, and Straumann (2002) emphasise the limitations of relying only on linear correlation when analysing dependence in risk management. Tail dependence is therefore important because systemic risk is primarily a phenomenon during stress periods rather than under average market conditions.

A fourth channel is liquidity amplification through liquidity spirals and fire sales. When institutions experience large losses, funding constraints, margin calls, or liquidity needs, they may be forced to sell assets quickly. If many institutions sell similar assets at the same time, prices may fall further, generating additional losses and forcing further sales. Brunnermeier et al. (2009) identify this type of feedback mechanism as one of the key channels of amplification in financial crises. Brunnermeier and Pedersen (2009) formalise this mechanism by showing how market liquidity and funding liquidity can reinforce each other, leading to liquidity spirals. Although insurers and reinsurers are generally less exposed to liquidity runs than banks, they can still be affected by market-based amplification mechanisms through their investment portfolios.

These transmission channels show that systemic risk cannot be analysed only through the solvency position of single institutions. Whereas a firm might seem sufficiently capitalized when viewed in isolation, its systemic importance will also be determined by its role in the overall system of finance. It is not only about the amount of risk each firm carries, but about how that risk is related to risk carried by other firms, whether the firms are exposed to similar shocks, and how their mutual dependence grows in times of stress.

From the macroprudential standpoint, it is especially important because if a few institutions have relations with each other directly or indirectly, and are exposed to financial market or underwriting cycle risks, losses may be correlated and spread beyond the initial institution. Systemic risk is not just a problem of balance sheet of one firm, but of the whole system of firms and banks with interrelations between them. The multidimensional nature of systemic risk also explains why the literature has developed a wide range of empirical measures: since systemic risk can arise through different mechanisms, such as direct contagion, common exposures, tail dependence, liquidity amplification, or network concentration, no single empirical indicator can capture all its dimensions at once (Bisias et al., 2012; Benoit et al., 2017). Bisias et al. (2012) emphasise that systemic risk measures differ according to the specific channel they are designed to identify, including market-based indicators, contingent-claims measures, network models, and macroeconomic stress indicators. This implies that systemic risk measurement is necessarily model-dependent: each methodology highlights one aspect of Systemic Vulnerability while leaving others less visible. For this reason, a combined empirical framework is particularly appropriate when the objective is not only to rank institutions, but also to understand how their interdependence evolves and how they are positioned within the broader structure of the financial system (Billio et al., 2012; Diebold and Yilmaz, 2014; Hautsch, Schaumburg, and Schienle, 2015).

2.2 Cross-Sectional and Time Dimensions of Systemic Risk

The transmission channels discussed in the previous section show that systemic risk is not a static or one-dimensional concept. From a macroprudential perspective, systemic risk develops both across institutions and over time. Borio (2003) makes this distinction clear by identifying two complementary dimensions of financial instability: the cross-sectional dimension, which concerns how risk is distributed across the financial system at a given point in time, and the time dimension, which concerns how vulnerabilities build up and evolve through the financial cycle.

The cross-sectional dimension asks which institutions are more relevant for the stability of the system at a given point in time. In this perspective, the objective is not only to measure whether a single firm is risky in isolation, but also to understand whether its distress is associated with larger losses for the financial system as a whole. This distinction is essential because the most individually risky institution is not necessarily the most systemically important one. While a company may have a very high stand-alone risk profile, if it is relatively isolated from the rest of the system, then it would remain relatively idiosyncratic. On the other hand, while an institution may be moderately risky, it may have a significant systemic risk relevance owing to the fact that it is highly interconnected, hard-to-replace, or has similar risks as many other institutions.

The cross-sectional dimension would, thus, be related to the distribution of systemic risks among institutions. The emphasis here would be on determining those institutions that make the system vulnerable as well as those that would suffer if there was trouble in the system. This would be especially pertinent for sectors where the institutions are highly interconnected, where firms with the same balance sheet structure may have different roles in the systemic risk of the sector based on their size and interconnectedness. In the macroprudential world, the question that needs to be asked would not just be about whether the firm is solvent or not.

The time dimension, on the other hand, relates to the evolution of systemic risks over time. In terms of macroprudential considerations, financial risks do not occur suddenly, nor are they independent of the previous state of markets. On the contrary, financial risks can develop over quiet times when the combination of low volatility, liquidity, and correlation levels creates an impression of low risk. Borio (2003) emphasises precisely this temporal dimension of systemic risk, arguing that macroprudential surveillance should focus not only on the distribution of risk across institutions, but also on the build-up of vulnerabilities over the financial cycle. This aspect is particularly important because volatility and dependence between institutions are not constant over time. Financial markets are characterised by periods of calm followed by phases of stress, during which volatility increases and correlations tend to rise. At such times, diversification effects tend to be less effective just when they are needed most. For instance, Longin & Solnik (2001) reveal that international equities experience greater dependence in case of extremely negative market moves. Likewise, Forbes & Rigobon (2002) argue that market comovements actually increase in times of crisis, even as they emphasize that this does not necessarily imply contagion. This literature therefore implies that it is impossible to appreciate systemic risks by considering only static or unconditional correlations.

Both dimensions are necessary for a complete analysis. A purely cross-sectional measure can identify which institutions are more systemically important, but it may fail to capture how their relevance changes during different market regimes. Conversely, a purely dynamic

correlation model can show when dependence increases, but it does not directly indicate which institutions contribute most to system-wide distress.

This combined approach is also consistent with the broader macroprudential literature, which emphasises that effective systemic risk monitoring should provide information on both the build-up of vulnerabilities over time and their distribution across institutions. According to Borio (2003), systemic risk has both temporal aspects, associated with the buildup of vulnerabilities within the financial cycle, and cross-sectional aspects, associated with the risk distribution in the financial system at any point in time. Hence, an empirical approach based on either of these aspects alone may not be comprehensive enough. On one hand, the model will be able to reveal periods of instability without understanding which firms or entities are more important in this regard. On the other hand, the model will classify different institutions by their systemic relevance without considering how this relevance evolves during periods of stress. This distinction motivates the empirical strategy adopted in this thesis: dynamic conditional correlations are used to study the time dimension of interconnectedness, while ΔCoVaR rankings are used to study the cross-sectional distribution of Systemic Contribution and Vulnerability.

2.3 Market-Based Measures of Systemic Risk

Within the broader systemic-risk literature, market-based measures were developed specifically to translate the transmission channels discussed in Section 2.1 into indicators that can be estimated from observable price data, without requiring detailed balance-sheet or contractual information. Several alternative measures have been proposed. The Marginal Expected Shortfall (MES) of Acharya, Pedersen, Philippon, and Richardson (2017) measures an institution's expected equity loss conditional on the market experiencing a severe downturn, and is used as a building block of SRISK, the capital-shortfall measure of Acharya, Engle, and Richardson (2012), which combines MES with leverage and firm size to estimate the capital an institution would need in a systemic crisis. These measures are particularly useful for ranking institutions by their expected contribution to system-wide capital shortfalls, but they are primarily designed for large, highly leveraged institutions, and their capital-shortfall interpretation is less directly applicable to the insurance and reinsurance business model, in which capital requirements and loss-absorption mechanisms differ substantially from banking.

For the purpose of this thesis, a CoVaR-based approach is therefore more suitable than a capital-shortfall measure. The objective is not to estimate the amount of capital that each institution would need in a systemic crisis, but to measure how the distress of each listed reinsurance-related group is associated with the risk of the broader insurance market. This makes ΔCoVaR particularly appropriate for comparing Systemic Contribution and Vulnerability across institutions within a market-based framework.

A related family of measures builds instead on quantile-based conditional risk, following the CoVaR approach originally proposed by Adrian and Brunnermeier (2008) and later published as Adrian and Brunnermeier (2016). Following this line of reasoning, Adams, Füss, and Gropp (2014) develop a value at risk-based methodology for state-dependent sensitivity which accounts for the varying relationship between the institution and the system depending on the state of the market. Furthermore, Girardi and Ergün (2013) extend the CoVaR literature by embedding conditional systemic-risk measurement within a multivariate GARCH framework, thereby allowing volatility and dependence to vary over time. Their

contribution provides an important methodological motivation for the present thesis, which likewise relies on a dynamic variance-covariance structure. However, rather than replicating their exact CoVaR estimator, this study uses the conditional covariance matrix generated by a DCC-GARCH model to construct market-based measures of Systemic Contribution and Systemic Vulnerability inspired by the directional intuition of the ΔCoVaR framework. This approach allows institution-specific tail risk to be combined with time-varying dependence with the global insurance market.

Metrics such as ΔCoVaR have been developed to evaluate how the distress of one institution is associated with changes in the risk of the broader financial system. According to Adrian and Brunnermeier (2016), CoVaR is defined as the Value-at-Risk of the financial system conditional on the state of a specific institution, while ΔCoVaR captures the change in conditional system risk between a distress state and a benchmark state. In the present thesis, this directional intuition is used to distinguish two dimensions: Systemic Contribution, capturing the association between institution-specific tail risk and system-wide market risk, and Systemic Vulnerability, capturing the association between market-wide distress and institution-specific risk.

Adrian and Brunnermeier (2016) primarily estimate CoVaR through quantile regressions, but they also provide a GARCH-based alternative in their robustness analysis. Under a bivariate Gaussian specification with time-varying second moments, they show that ΔCoVaR admits a closed-form representation determined by the institution-system correlation, system volatility and the relevant Gaussian tail quantile. This result provides the theoretical benchmark for the covariance-based construction used in the present thesis. Girardi and Ergün (2013) develop a different and more fully distributional multivariate-GARCH implementation, in which CoVaR is recovered from the joint conditional distribution. Their contribution remains relevant as evidence that dynamic GARCH models can be used for systemic-risk measurement.

Taken together, these contributions motivate the combined empirical framework adopted in this thesis. Static correlations would only provide an average measure of co-movement over the sample period, while systemic risk in financial markets is inherently time-varying and tends to intensify during stress episodes. The use of DCC-GARCH, thus, allows us to measure the time dimension of systemic risk by computing daily conditional volatilities and correlations between various reinsurance groups listed in the sample and the market factor. The DCC-GARCH-based measures developed in this thesis further translate this dynamic dependence structure into institution-specific indicators of Systemic Contribution and Systemic Vulnerability. In this way, the empirical framework combines the time dimension of market-based interconnectedness with a cross-sectional comparison of institutions according to their estimated association with system-wide tail risk.

2.4 Systemic Risk in Insurance and Reinsurance

The insurance-specific literature generally adopts a more nuanced view of systemic risk than the banking literature. Empirical studies show that insurance groups may become systemically relevant through size, interconnectedness, non-core financial activities, common asset exposures, and their role in absorbing and redistributing large risks across the financial system (Weiß and Mühlnickel, 2014; Bierth, Irresberger, and Weiß, 2015).

This nuanced view is also reflected in the regulatory debate on insurance systemic risk. Between 2013 and 2016, the IAIS identified a list of Global Systemically Important Insurers (G-SIIs) on the basis of an assessment methodology built around indicators of size, interconnectedness, non-traditional and non-insurance activities, substitutability, and global activity (IAIS, 2013). This methodology was subsequently replaced by the Holistic Framework, which shifted the focus from a fixed list of individually systemic insurers towards a sector-wide, activities-based assessment of systemic risk (IAIS, 2019). This evolution is consistent with the insurance-specific literature discussed above: systemic relevance in insurance appears to depend less on the size of an individual balance sheet, as in the classical too-big-to-fail argument for banks, and more on the type of activity undertaken and on the degree of interconnectedness with the rest of the financial system.

The asset side of insurers' and reinsurers' balance sheets provides a further, complementary channel of systemic relevance. Koijen and Yogo (2015) show that life insurers facing financial frictions may reprice their liabilities and alter their investment behaviour in ways that can affect the pricing of long-term insurance products and the stability of the sector. Berends, McMenamin, Plestis, and Rosen (2013) find that the balance sheet of life insurers is very sensitive to changes in the level of interest rates, due to the long maturity of the liabilities. While such results apply mostly to the life insurance business, they are still valid for the reinsurance business, since large reinsurers are also big institutional investors, which makes their portfolios subject to the same interest rate and credit market risks even in the absence of any loss from the underwriting activities introduced in Section 2.1 and the discussion of correlated investment portfolios in Section 1.4.

Reinsurance differs from primary insurance because its systemic relevance is linked not only to the size, interconnectedness and investment behaviour of individual groups, but also to their role in redistributing underwriting risk across the insurance sector. A reinsurer may therefore matter systemically even when it is not the original holder of the insured risk, because it provides capacity, absorbs peak losses and may act as a counterparty to multiple primary insurers (Cummins and Weiss, 2014; Park and Xie, 2014). This makes the reinsurance sector particularly suitable for an analysis that combines market-based systemic-risk measures with indicators of interdependence (Bierth, Irresberger, and Weiß, 2015).

Despite the growing literature on systemic risk in the insurance sector, the reinsurance industry remains less extensively studied than banks and large diversified insurers. Existing contributions have examined systemic risk among insurers, the impact of reinsurer downgrading, and the role of reinsurance networks in loss propagation (Park and Xie, 2014; Weiß and Mühlnickel, 2014; Bierth, Irresberger, and Weiß, 2015; Klages-Mundt and Minca, 2020). However, less attention has been devoted to listed global reinsurers as a distinct group and to the combination of dynamic market-based systemic-risk measures with network analysis.

2.5 Reinsurance Networks and Network-Based Approaches

For this reason, several contributions in the systemic risk literature rely on combined methodological frameworks rather than on a single risk indicator. Billio et al. (2012) show that systemic risk can be studied through multiple econometric measures of connectedness

across financial institutions, while Diebold and Yilmaz (2014) demonstrate how econometric measures of spillovers can be translated into a network representation of financial connectedness. In a similar direction, Hautsch, Schaumburg, and Schienle (2015) emphasise that systemic risk contributions should be analysed together with the financial network in which institutions are embedded, while Härdle, Wang, and Yu (2016) develop a quantile-based network approach to systemic risk. These contributions support the idea that systemic risk is better understood when institution-level risk measures are combined with information on the structure of interdependence across the system. This logic is particularly relevant for insurance and reinsurance. Denkowska and Wanat (2020), in their study of systemic risk in the European insurance sector, show the usefulness of combining dependence-based measures with network tools in order to capture both the evolution of financial interconnectedness and the structural organisation of the market. For the reinsurance sector, this is especially important because risks are not concentrated only within individual firms, but are distributed through risk-transfer relationships, common underwriting exposures, and correlated investment portfolios.

Among these references, however, a subset of studies are concerned with the network structure of the reinsurance and large-claims insurance markets in particular. In particular, Kley, Klüppelberg, and Reinert (2016) analyze the large-claims insurance market through the use of bipartite networks connecting insurers and reinsurers and demonstrate the influence that the structure of such networks has on extreme losses propagation. Clemente, Grassi, and Pederzoli (2022) make use of network theory in the context of the insurance market by employing correlation networks to measure systemic risk and determine centrality of the institutions involved. Additionally, Huang and Chen (2021) prove, by analyzing the banking sector, that community structure of the correlation network is informative in terms of systemic risk, because highly interconnected clusters of the institutions might be exposed to common risks; therefore, community detection becomes another important tool for measuring systemic risk next to centrality measures in the context of network analysis in Chapters 3 and 5. Overall, these studies provide evidence that network tools have become more common as an additional means to analyze institution-level systemic risks in insurance industries, whereas reinsurance industry is a relatively neglected field of study.

It must be distinguished between networks based on contractual reinsurance arrangements and networks based on correlations in the market. Networks based on contractual arrangements include real connections between the insurer and reinsurer, including treaties and retrocession contracts; however, they need detailed information at an exposure level, which is typically not accessible to the public. Networks based on correlation include the interdependencies observed through the movement of market prices. Such networks cannot uncover actual contractual exposures, yet they can be useful to find out if certain firms are listed institutions moving together in equity markets. This distinction is central to the present thesis, which adopts a market-based network approach rather than a contractual reconstruction of the global reinsurance market.

This is particularly important for the global reinsurance sector. Reinsurers operate as risk absorbers, but also as nodes in a global risk-transfer system. Their systemic relevance may therefore depend not only on their own level of risk, but also on their position within the network of interdependence. A reinsurer-related institution with high Systemic Contribution and a central position in the network may have a different macroprudential relevance from a reinsurer with similar stand-alone risk but weaker connections to the rest of the sector. For

this reason, combining dynamic dependence modelling, systemic risk measures, and network analysis provides a more complete framework for assessing systemic risk in reinsurance.

2.6 Literature Gap and Contribution

The literature reviewed in this chapter points to three main gaps. First, while systemic risk has been extensively studied in banking and, more recently, in large insurance groups, listed global reinsurers and reinsurance-related insurance groups remain a less developed object of empirical analysis. This is because reinsurance plays a particular role in the economy through its financial activities by absorbing and allocating underwriting risk, creating capacity for primary insurers, being involved in retrocession markets, and potentially sharing common asset-side risk exposures.

Secondly, research on systemic risks often examines either institution-level systemic-risk indicators or the network structure itself, with fewer studies considering both aspects in one empirical framework. On the one hand, market-based indicators, such as ΔCoVaR, help rank institutions in terms of systemic importance and vulnerability, but fail to capture the actual network structure of relationships between firms. On the other hand, the network analysis approach can detect central institutions, bridge institutions, and clusters of highly related firms, but fails to estimate systemic importance and vulnerability indicators. Combining these approaches therefore provides a more complete view of systemic relevance.

Third, the reinsurance literature has examined contractual risk transfer and loss propagation, but the detailed reconstruction of global reinsurance and retrocession networks requires exposure-level contractual data that are generally not publicly available. For a broad international sample of listed groups, a market-based approach offers an alternative way to study interdependence. Equity return co-movements will not provide any direct information on institutional exposures in contracts, but they can reflect how the market incorporates common underwriting risks, exposures, and stress dependence.

This thesis addresses these gaps by applying an integrated empirical framework to listed global reinsurers and reinsurance-related insurance groups. The DCC-GARCH model captures the time-varying evolution of volatilities and correlations; the ΔCoVaR framework translates this dynamic dependence structure into institution-level measures of Systemic Contribution and Systemic Vulnerability; and the correlation-based network analysis examines whether institutions identified as systemically relevant also occupy central or bridging positions in the estimated dependence structure.

CHAPTER 3

Data and Methodology

3.1 Sample Selection and Data Description

The empirical analysis uses a sample of 20 listed global insurance and reinsurance groups selected to represent the main publicly traded institutions in the global reinsurance ecosystem. The first criterion for inclusion in the sample is related to reinsurance gross written premiums and the ranking of the world's largest reinsurers according to the annual AM Best ranking. Reinsurance gross written premiums are used instead of market capitalization or total assets since the former variable is closer to the measure of the volume of risks assumed through reinsurance transactions.

The sample comprises both specialized reinsurers and large integrated insurance companies with reinsurance activities. The difference between these two categories of firms is crucial since specialized reinsurers should be included as being the key participants in the reinsurance market, since reinsurance is the core of their business. Large integrated insurance companies with reinsurance activities should be included in the sample as well since although they engage in both reinsurance and other types of businesses, they still offer reinsurance capacity. Since the empirical analysis is based on listed equity returns, the unit of observation is the publicly traded corporate group rather than the individual reinsurance subsidiary. The results should therefore be interpreted as market-based evidence on listed reinsurance-related groups, not as direct evidence on pure reinsurance legal entities alone. This is particularly important for diversified groups, whose equity returns may reflect not only reinsurance activity, but also primary insurance, investment portfolios and other business lines. For this reason, the distinction between pure reinsurers and integrated insurance groups is retained in the sample description and in the interpretation of the empirical results.

Region	Institution	Type
Europe	Munich Re	Reinsurance-led Insurance Group
Europe	Swiss Re	Specialised Global Reinsurer
Europe	Hannover Re	Specialised Global Reinsurer
Europe	SCOR	Specialised Global Reinsurer
Europe	MAPFRE	Large integrated Insurance Group with relevant reinsurance activities
Europe	Assicurazioni Generali	Large integrated Insurance Group with relevant reinsurance activities

Europe	Zurich Insurance Group	Large integrated Insurance Group with relevant reinsurance activities
Europe	Legal & General	Large integrated Insurance Group with relevant reinsurance activities
North America & Bermuda	Berkshire Hathaway	Diversified conglomerate with major reinsurance operations
North America & Bermuda	Reinsurance Group of America	Specialised life and health reinsurer
North America & Bermuda	Everest Re Group	Reinsurance-led Insurance Group
North America & Bermuda	RenaissanceRe Holdings	Specialised Property and Casualty reinsurer
North America & Bermuda	Arch Capital Group	Insurance and Reinsurance Group
North America & Bermuda	Axis Capital Holdings	Insurance and Reinsurance Group
APAC	Ping An Insurance Group	Large integrated insurance group with relevant reinsurance-related activities
APAC	Korean Re	Specialised reinsurer
APAC	QBE Insurance Group	Large integrated insurance group with relevant reinsurance-related activities
APAC	Tokyo Marine Holdings	Large integrated insurance group with relevant reinsurance-related activities
APAC	Central Reinsurance Corporation	Specialised reinsurer
APAC	MS&AD Insurance Group	Large integrated insurance group with relevant reinsurance-related activities

Table 1: Sample Description

To estimate the dynamic correlations and compute subsequent systemic risk metrics via the DCC-GARCH framework, the econometric model strictly requires high-frequency market data. Daily adjusted closing equity prices for the selected institutions were extracted using an R script that downloaded data directly from Yahoo Finance. The observation period spans from January 1, 2010, to December 31, 2024.

The ΔCoVaR methodology employed by this study also requires an external market factor as a reference for the broader insurance sector. The MSCI ACWI Insurance Index was selected as a reliable proxy for the global insurance sector within which reinsurers operate. This choice was made because it is a sector-specific index that covers both developed and

emerging countries; moreover, being insurance-specific, it better isolates the systemic linkages that characterise the (re)insurance industry, rather than those of the financial sector as a whole. The use of a sector-specific index as the market state variable in CoVaR-based systemic risk models is well established in the literature: Bierth et al. (2015) employ the MSCI World Insurance Index, together with a broad insurer index, to estimate the Marginal Expected Shortfall and ΔCoVaR of a global sample of insurers, finding that the results remain consistent regardless of the index used. Unlike the MSCI World Insurance Index, which is restricted to developed economies, the MSCI ACWI Insurance Index also includes emerging markets, thereby providing a more comprehensive representation of the global reinsurance industry, whose participants are increasingly based outside traditional developed economies.

The sensitivity of the results to this choice is assessed in Robustness Check 2, where MSCI ACWI Insurance is replaced with the MSCI World Insurance. The reason for choosing the MSCI ACWI Insurance Index as the base benchmark index is that it offers a more comprehensive benchmark, which is in line with the international nature of the sample. However, the MSCI World Insurance Index, on the other hand, limits the benchmark to the developed market economies. The robustness test, thus, will test whether the results are robust to the addition of emerging markets to the market factor benchmark. Daily prices for MSCI World Insurance were downloaded from Bloomberg Terminal over the same period, bringing the total dataset to 21 variables: 20 institutions plus the market factor. Logarithmic returns were computed for all series, as asset returns are generally much closer to covariance-stationary processes than price levels and constitute the standard input for GARCH-type models (Engle, 1982; Bollerslev, 1987).

For the network analysis in Chapter 5, the average DCC correlation matrix estimated across the 20 sampled institutions is used as the weighted adjacency matrix of the network. The market factor is required for the ΔCoVaR estimation, but it is not treated as a node in the correlation-based network. The network therefore represents pairwise statistical relationships among the 20 listed insurance and reinsurance groups.

Finally, some data quality filters were applied. The sample is limited to publicly listed companies with continuous trading activity over the full period. Since different exchanges have different national holidays, only overlapping trading days across all markets were retained to ensure that the covariance matrix is estimated on a consistent set of observations. However, restricting the dataset to common trading dates removes mismatches generated by market holidays but does not fully eliminate nonsynchronous closing-time effects across geographical regions. Since Asian, European and North American exchanges close at different times, same-calendar-day returns may incorporate partially different information sets, potentially affecting contemporaneous cross-market dependence estimates (Scholes and Williams, 1977; Dimson, 1979). Consequently, particularly low APAC–Western daily correlations may partly reflect time-zone alignment and should be interpreted cautiously. Moreover, the sample is restricted to companies that were listed and active throughout the entire 2010–2024 period, which introduces some survivorship bias. This restriction is necessary to obtain a balanced panel suitable for DCC-GARCH estimation.

As a final methodological transparency note, generative artificial intelligence was used as a supporting tool during the preparation of this thesis. Specifically, ChatGPT (OpenAI), using

the GPT-5.6 Sol model, was employed during 2026 for the revision and refinement of selected portions of the written text, primarily to improve clarity, coherence, and academic English. Particular attention was devoted to the revision of expressions that could imply causal relationships not supported by the market-based methodology adopted in the thesis. ChatGPT was also used as a supporting tool in the development and refinement of selected sections of the R code employed in the empirical analysis. The coding process was based on functions and packages documented in the relevant R libraries and their online documentation, while generative AI assistance was used to help organise, adapt and combine selected functions for the specific empirical procedures implemented in the thesis. The principal functions and model specifications used in the final code were subsequently checked against the corresponding package documentation, and the resulting outputs were verified for consistency with the methodology and empirical analysis described in the thesis. ChatGPT was not used as an autonomous source of empirical or academic evidence. AI-assisted textual revisions and code were critically reviewed, verified, and, where necessary, reworked by the author before being incorporated into the final thesis. The author therefore assumes full responsibility for the accuracy, quality, and scientific integrity of the work.

3.2 Dynamic Conditional Correlation (DCC) GARCH Model

3.2.1 Theoretical Framework and Economic Rationale

To measure systemic risk in the global reinsurance sector, we need an econometric model that can capture how financial dependencies change over time. Many of the early models examining financial contagion used the static view of the network links between the institutions (Allen & Gale, 2000). This approach has obvious advantages; however, its main disadvantage is that it considers the relationships to be unchanging. As Billio et al. (2012) and Diebold & Yilmaz (2012) prove, the level of interconnection between the financial institutions is changing; it grows significantly during the crisis period and falls during the tranquil period.

This econometric dynamism is particularly critical when analyzing the reinsurance sector, a specialized node within the global financial network. The stability of the broader financial system heavily relies on the sustained "intermediation capacity" of these institutions to absorb extreme tail-risks and distribute them globally (Cummins and Weiss, 2014). Reinsurers are highly interconnected not only through direct liabilities, such as complex retrocessional linkages (where reinsurers insure one another), but also through the asset side of their balance sheets via overlapping investment portfolios. If a large reinsurer suffers a capital shock, it may be forced to reduce the amount of risk it accepts from primary insurers. This can reduce the overall risk-transfer capacity of the market and have real consequences for the broader economy.

Because of these structural linkages, we need a model that tracks how interconnectedness evolves.

Longin and Solnik (2001) demonstrate that asset correlations are fundamentally dynamic, showing a distinct tendency to spike during market downturns and recede during tranquil

periods. This dynamic structural shift is exactly what a static model fails to capture. When markets enter a distressed regime, volatility clustering drives a sudden increase in joint tail-risk dependencies, meaning that multiple institutions are likely to suffer simultaneous capital depletion. Under such conditions, relying on a static model would risk underestimating these co-movements and would fail to reflect how dependence among reinsurers intensifies during periods of market stress (Engle, 2002).

To address these limitations, this study uses the Dynamic Conditional Correlation (DCC) GARCH model proposed by Engle (2002). The DCC framework is chosen for two reasons. First, unlike rolling-window correlations, whose estimates depend heavily on the arbitrary choice of window length and adjust only gradually as new observations enter the sample and suffer from arbitrary window-length selection, the DCC framework provides a data-driven estimate of time-varying conditional correlations, allowing the model to capture changes in financial dependence more flexibly than rolling-window estimators. Second, and most importantly for this thesis, the DCC model generates a time-varying conditional covariance matrix H_t from which conditional volatilities and correlation are extracted. These quantities constitute the key input for the dynamic estimation of the ΔCoVaR systemic risk metrics in Section 3.3. While the original ΔCoVaR methodology proposed by Adrian and Brunnermeier (2016) relied on quantile regressions, subsequent literature has proposed alternative approaches that explicitly account for time-varying dependence structures. As illustrated by Girardi and Ergün (2013), the estimation of CoVaR via multivariate GARCH model produces better, forward-looking estimates of systemic risks. With the use of the DCC-GARCH method, which takes into consideration conditional volatilities and conditional correlations, daily estimation of the systemic risk of a reinsurer becomes possible in order to ensure that ΔCoVaR captures changes in market regimes.

3.2.2 Limitations of Simple Moving Averages (SMA) and Rolling Correlations

Before explaining the DCC model, it is useful to understand why simpler alternatives are not appropriate for this study. A common approach in practice is to use Simple Moving Average (SMA) rolling correlations. However, Andersen, Bollerslev, Christoffersen, and Diebold (2006) note that historically rolling estimators suffer from important limitations when used to forecast volatility and risk.

Assuming a mean return of zero, the SMA estimate of conditional variance (and similarly, covariance) is typically expressed as:

$$\hat{\sigma}_t^2 = \frac{1}{\tau}\sum_{k=1}^{\tau} {r_{t-k}}^2 \tag{3.1}$$

Where τ is the length of the rolling window, and r_{t-k} represents the historical returns.

While computationally simple, rolling window estimators suffer from two severe structural defects that make them particularly dangerous to use during periods of financial distress.

First, the fundamental mathematical flaw of the SMA formula is that it applies a flat, equal weight ($\frac{1}{\tau}$) to all observations within the designated window. This means that returns from 99

days ago have the same effect on today's risk measure as yesterday's return. In practice, financial markets experience volatility clustering where recent financial information is far more important in forecasting today's volatility compared to an event that happened some time ago (Engle, 1982). As a result, rolling windows can react too slowly when there is a sudden market stress period. In case of a shock, rolling window will average it with several previous calm months. By the time the rolling correlation metric finally reflects the high level of systemic risk, the crash has often already peaked, limiting its usefulness as a timely indicator of systemic risk.

The second limitation of SMA models is the "ghost effect" (Alexander, 2008). Suppose a massive, isolated market shock occurs on day *t*. The rolling volatility and correlation estimates will correctly jump on that day. However, exactly τ days later, that specific extreme observation will mechanically drop out of the rolling sample window. When it does, the estimated volatility will drop sharply, creating a spurious shift in the risk metric. This sudden drop is entirely artificial: it is not caused by any new stabilizing event in the market, but merely by the "ghost" of a past shock exiting the mathematical window (Andersen et al., 2006).

A partial solution to these problems initially evolved toward the Exponentially Weighted Moving Average (EWMA), popularized by J.P. Morgan's RiskMetrics system (J.P. Morgan/Reuters, 1996). Unlike the flat weighting of SMA, EWMA applies declining weights to historical observations using a decay factor (λ):

$$\sigma_t^2 = (1-\lambda) r_{t-1}^2 + \lambda \sigma_{t-1}^2 \tag{3.2}$$

This reduces the ghost effect significantly, since observations fade out gradually rather than dropping off a cliff. However, EWMA has its own limitation: the decay factor λ is typically imposed ex ante rather than estimated within the model (0.94 for daily data in the original RiskMetrics specification) rather than estimated from the data itself.

The DCC-GARCH model of Engle (2002) solves both problems. Rather than assuming a fixed, arbitrary decay factor, it empirically estimates the data-driven decay parameters directly from the historical time series of the data, giving a fully data-driven, dynamic description of volatility and correlation.

3.2.3 Model Specification and Mathematical Framework

From univariate to multivariate GARCH

Extending dynamic volatility modelling from a single asset to a large set of assets requires dealing with an important mathematical challenge: ensuring that the estimated variance-covariance matrix remains positive definite at every point in time. This is a necessary mathematical condition because, without it, the matrix cannot be interpreted as a valid covariance structure.

Early multivariate GARCH models such as the VEC model of Bollerslev, Engle, and Wooldridge (1988) addressed this through parameter restrictions, but these became computationally impractical as the number of assets grew. With 21 variables as in this study, directly estimating the full parameter matrix would require thousands of parameters.

To resolve the problem, Bollerslev (1990) proposed the Constant Conditional Correlation (CCC) GARCH model. The basic idea of the CCC approach was to split the covariance matrix into individual volatilities and correlation matrix. By construction, the variance-covariance matrix would automatically remain positive definite with the assumption of the positive-definite correlation matrix (. In this model specification, the only source of the dynamic pattern in the conditional covariances is the asset volatilities alone.

Although this model is both convenient for computation and important in building multivariate volatility models, the basic assumption of constant correlations in the CCC model specification is decisively refuted empirically. Numerous studies have found out that dependencies between assets in financial markets are highly dynamic and asymmetric; most importantly, correlations rise sharply during crises (Longin and Solnik, 2001; Ang and Bekaert, 2002).

The DCC model of Engle (2002)

To bridge the gap between mathematical stability and empirical reality, Engle (2002) introduced the Dynamic Conditional Correlation (DCC) model. Engle's DCC framework overcomes the limitations of the CCC model by explicitly allowing the correlation matrix to be dynamically time-variant while utilizing a two-step estimation procedure to guarantee positive definiteness.

Let r_t represent the vector of mean-adjusted asset returns. In the first step, the model decomposes the conditional variance-covariance matrix H_t into conditional standard deviations and a conditional correlation matrix, as follows:

$$H_t = D_t R_t D_t \tag{3.3}$$

Where D_t is the $k \times k$ diagonal matrix of conditional standard deviations obtained from univariate GARCH models: $D_t = diag(\sqrt{h_{11,t,}}, \dots, \sqrt{h_{kk,t,}}$, and R_t is the time-variant conditional correlation matrix (Engle, 2002). It follows directly that the diagonal elements of H_t recover the conditional variances: the (i,i)-th element of $H_t = D_t R_t D_t$ equals $h_{ii,t} = \sigma_{i,t}^2$ as required.

For each individual asset *i*, the conditional variance $h_{ii,t}$ is estimated using a standard univariate GARCH (1,1) process:

$$h_{ii,t} = \omega_i + \alpha_i r_{i,t-1}^2 + \beta_i h_{ii,t-1} \tag{3.4}$$

Where $\omega_i > 0, \alpha_i \geq 0, \beta_i \geq 0, and\ \alpha_i + \beta_i < 1$ to ensure stationarity of the individual volatilities.

To model the dynamic evolution of R_t, the second step of the estimation uses the standardized residuals from the univariate models, defined as $\varepsilon_t = {D_t}^{-1} r_t$. Rather than modelling R_t directly, which makes it difficult to mathematically guarantee that the matrix always remains positive definite, the DCC framework models the dynamic process of a proxy matrix, Q_t.

The dynamic process of Q_t is defined as:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha(\varepsilon_{t-1}\varepsilon'_{t-1}) + \beta Q_{t-1} \quad (3.5)$$

Where $\bar{Q}$ is the unconditional correlation matrix of the standardized residuals ε_t, the parameters α (the innovation parameters) capture the short-term impact of recent shocks on the dynamic correlation, and the parameter β governs the persistence or long-term memory of past correlations. For the model to remain mean-reverting and stable, ensuring that the dynamic correlations eventually return to their unconditional average $\bar{Q}$ after a shock, the condition $\alpha + \beta < 1$ (with $\alpha \geq 0$ and $\beta \geq 0$) must be strictly satisfied.

Finally, because the elements of the proxy matrix $Q_t$are not mathematically constrained to behave strictly as correlation coefficients, Q_t must be rescaled. The proxy matrix is scaled to obtain the proper correlation $(\rho_{ij,t})$ correctly lie within the [-1,1] interval:

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2} \quad (3.6)$$

Specifically, the dynamic correlation between asset i and asset j at time t is expressed as:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \quad (3.7)$$

The final output is a full time-varying conditional covariance matrix H_t for every day in the sample. The off-diagonal elements of H_t contain the conditional covariances $h_{i,sys,t}$ between each institution and the market factor, while the corresponding conditional volatilities and correlations derived from H_t constitute the key inputs for the ΔCoVaR estimation.

3.2.4 Preliminary Testing and Estimation Strategy

Before estimating the DCC-GARCH model, preliminary diagnostic tests are performed to assess whether the return series exhibit statistical properties that motivate conditional-volatility modelling.

Stationary Testing: The Augmented Dickey-Fuller Test

A standard prerequisite for GARCH modelling is that the return series should be covariance-stationary. That is, its mean, variance, and autocovariance structure must remain constant over time. A non-stationary series, characterized by a stochastic trend or unit root, would compromise the validity and interpretation of the estimated volatility dynamics. To formally test for this property, the Augmented Dickey-Fuller (ADF) test is applied to each institution's log-return series (Dickey and Fuller, 1979).

The ADF test is a regression-based procedure that tests the null hypothesis H_0: the series contains a unit root (it is non-stationary) against the alternative hypothesis H_1: the series is stationary. The augmented regression takes the form:

$$\Delta y_t = \alpha + \delta y_{t-1} + \sum_{j=1}^{p} \gamma_j \Delta y_{t-j} + \varepsilon_t \quad (3.8)$$

where Δy_t is the first difference of the series, δ is the coefficient of interest (a unit root exists if δ=0), and p lagged differences are included to whiten the residuals. Rejection of the unit-root null at conventional significance levels provides evidence that the series does not contain a unit root and is therefore compatible with the stationarity requirement of the subsequent GARCH modelling. The lagged difference terms are included to remove serial autocorrelation in the residuals.

Heteroskedasticity Testing: The ARCH-LM Test

A second preliminary diagnostic concerns the presence of conditional heteroskedasticity. If the residuals of a return series exhibit volatility clustering, a constant-variance specification may fail to capture an important feature of the data, providing a motivation for modelling conditional variance dynamically. To test for this feature formally, Engle's (1982) ARCH Lagrange Multiplier (ARCH-LM) test is applied to the residuals of a preliminary mean equation for each return series.

The ARCH-LM test is constructed by regressing the squared residuals $\hat{\varepsilon}_t^2$ on a constant and *q* of their own lags:

$$\hat{\varepsilon}_t^2 = \beta_0 + \beta_1 \hat{\varepsilon}_{t-1}^2 + \cdots + \beta_q \hat{\varepsilon}_{t-q}^2 + u_t \quad (3.9)$$

The null hypothesis H_0 states that there are no ARCH effects ($\beta_1 = \cdots = \beta_q = 0$), implying that the conditional variance is constant. The test statistic, distributed as $\chi^2(q)$ under the null, is computed as $LM = T \cdot R^2$, where T is the number of observations and R^2 is the coefficient of determination from the auxiliary regression. Rejection of the null hypothesis provides evidence of ARCH effects and hence of time variation in conditional variance, supporting the use of a GARCH-type framework to model volatility clustering (Engle, 1982). Importantly, this preliminary test does not by itself establish the adequacy of the specific GARCH specification subsequently adopted; this must also be assessed on the basis of model estimation, parameter admissibility and post-estimation diagnostics.

Two-Step Estimation Procedure

Following these preliminary diagnostics, the DCC-GARCH model is estimated through a computationally efficient two-step procedure, as originally proposed by Engle (2002).

Engle (2002) formalizes the two-step estimation by decomposing the DCC log-likelihood into a volatility component and a correlation component:

$$L(\theta, \phi) = L_V(\theta) + L_C(\theta, \phi) \quad (3.10)$$

where θ denotes the parameters entering the conditional-volatility matrix, while ϕ denotes the additional parameters governing the conditional-correlation matrix. The first stage estimates the volatility parameters by

$$\hat{\theta} = \arg\max_{\theta}\{L_V(\theta)\} \tag{3.11}$$

The resulting estimates are treated as given in the second stage and the correlation parameters are obtained from

$$\max_{\phi}\{L_C(\hat{\theta}, \phi)\} \tag{3.12}$$

The link between the two stages is provided by the standardized residuals

$$\varepsilon_t = D_t^{-1} r_t \tag{3.13}$$

Equations (3.10)–(3.12) reproduce the original estimation architecture of Engle (2002) and are reported here to illustrate the sequential separation between volatility and correlation estimation. The standardized residuals in Equation (3.13), obtained from the first-stage univariate volatility models, provide the link to the dynamic correlation estimation. The empirical implementation retains this two-stage architecture while adopting Student-t innovations in the univariate GARCH stage and a multivariate Student-t distribution in the DCC stage.

In the first step, a GARCH(1,1) model is estimated independently for each of the 21 return series. The GARCH(1,1) specification for the conditional variance is chosen deliberately, based on the extensive empirical evidence surveyed by Hansen and Lunde (2005), who evaluated 330 competing ARCH-type models across a broad range of financial assets and found that, in terms of out-of-sample forecasting performance, no specification significantly outperforms the simple GARCH(1,1), a result they describe as a benchmark that "is surprisingly difficult to outperform". The parsimony and robustness of this specification make it the standard choice in the systemic risk literature (Girardi and Ergün, 2013).

A critical modelling decision at this stage concerns the distributional assumption for the innovations. GARCH models estimated under Gaussian innovations tend to underestimate tail probabilities because financial returns exhibit excess kurtosis, a phenomenon whereby extreme events occur far more frequently than a normal distribution would predict (Bollerslev, 1987). To account for these fat tails, a Student-t distribution is employed for the innovations at this stage, following Bollerslev (1987), who introduced Student-t innovations as a heavy-tailed alternative to Gaussian innovations for financial time series. The degrees-of-freedom parameter v, estimated alongside the GARCH parameters, controls the tail thickness: lower values of v imply heavier tails. If the return distribution additionally exhibits skewness (asymmetric tails), a skewed distribution (Hansen, 1994) can be substituted to further improve the fit.

In the second step, the DCC(1,1) parameters (α and β) are estimated using the standardized residuals $u_t = D_t^{-1} r_t$ extracted from Step 1. At this multivariate stage, a multivariate Student's t distribution (mvt) is preferred over a Gaussian assumption. This choice is

theoretically motivated: the mvt distribution, unlike the multivariate normal, generates non-zero tail dependence, the property that extreme negative events across multiple assets occur simultaneously with positive probability. Since the purpose of this study is precisely to measure the systemic spillover of tail-risk events via ΔCoVaR, adopting a distribution that structurally models joint extreme co-movements is essential (Embrechts, McNeil, and Straumann, 2002). Estimating the DCC model under Gaussian innovations would not capture asymptotic tail dependence and may therefore underestimate the probability of joint extreme events.

Assessment of Model Output

Once the two-step estimation is complete, a set of estimation and admissibility checks is considered before the resulting conditional variance-covariance matrices are used in the subsequent analysis.

First, the Convergence of the Maximum Likelihood Estimator. The DCC-GARCH model is estimated using Maximum Likelihood Estimator (MLE) based on the specified Student-t and multivariate Student-t log-likelihood functions. While financial studies often employ Quasi-Maximum Likelihood Estimation (QML) under a normal distribution assumption to gain robustness against general misspecification (Bollerslev and Wooldridge, 1992), this study directly maximizes the fat-tailed Student-t likelihoods. This allows the degrees-of-freedom parameters to be estimated directly, enabling the specification to accommodate the leptokurtosis and heavy-tailed dependence observed in the return series. Convergence of the estimation process is determined using two tests. Firstly, the numerical optimizer should succeed and not face any constraint violations or diverging paths of the parameters. As an additional numerical check, the estimated standard errors are inspected to verify that they are finite; non-finite standard errors could indicate numerical instability or an ill-conditioned likelihood surface.

Second, the interpretation of the Innovation (α) and Persistence (β) Parameters. Both of these parameters have exact economic meanings which play an important role in analyzing the processes of system interconnections. In particular, the innovation parameter α describes the sensitivity of the correlation structure to the last joint shock. Thus, a large value of α means that the correlation structure is quick to respond to any new information entering the market. On the other hand, the persistence parameter β determines the memory of the correlation process; hence, a large value of β (close to 1) suggests that a shock-driven rise in the level of correlations will decay very slowly. When α is small relative to β, correlations decay slowly, meaning the system remains in an elevated state of interconnectedness for a long time after a disturbance. This property of slow mean reversion is a well-documented feature of financial correlation processes (Engle, 2002)

Third, the Stationarity Constraint $\alpha + \beta < 1$. This condition, derived by Engle (2002), ensures that the correlation process is mean-reverting: after any shock, correlations eventually return to their long-run average $\bar{Q}$, rather than drifting without bound. In case of this restriction ($\alpha + \beta$) being violated, the process would be either an integrated or explosive process which does not revert back to equilibrium, making the economic interpretation of the model impossible due to the absence of a finite unconditional correlation matrix. The very fact that the sum is very close but less than 1 (for instance, $\alpha + \beta = 0.97$) implies that even though the stationarity

condition holds, correlations are extremely persistent, that is, the effect of a shock on the correlation structure lasts for a long period of time.

3.3 Systemic Risk Measurement: ΔCoVaR

3.3.1 Limitations of Value-at-Risk

Value-at-Risk (VaR) is the standard risk measure in financial regulation and internal risk management. It is used in the Basel Accords for banks and in the Solvency II directive for European insurers (Jorion, 2007). VaR is a loss threshold that is exceeded with probability q over a specified time horizon.

Formally, let $R_{i,t}$ denote the return of institution *i* at time *t,* and *q* denote the target probability level (e.g., *q*=5%). Throughout this section, returns are expressed as gains (positive=profit, negative=loss), and VaR is defined as a positive threshold such that $VaR_{q,t}^{i} > 0$ represents the maximum loss magnitude at confidence level 1-q. The negative sign in the VaR formula below ensures that this sign convention is preserved consistently throughout the ΔCoVaR derivation.

The Value-at-Risk is defined as the strictly positive threshold loss such that the probability of the institution experiencing a return worse than this threshold is exactly equal to *q*:

$$\Pr\left(R_{i,t} \leq -VaR_{q,t}^{i}\right) = q \tag{3.14}$$

Within the GARCH framework used in this study, the VaR is time-varying and conditioned on the current state of volatility. The conditional VaR at time t is mathematically expressed as:

$$VaR_{q,t}^{i} = -(\mu_{i,t} + \sigma_{i,t} \cdot z_q) \tag{3.15}$$

Where $\mu_{i.t}$ is the conditional mean, $\sigma_{i,t}$ is the conditional standard deviation derived from the GARCH equation, and z_q represents the q-th empirical quantile of the standardized residuals.

However, VaR is primarily a stand-alone risk measure and does not, by itself, capture the externalities or dependence structures that are central to a macroprudential assessment. This limitation reflects the distinction between microprudential and macroprudential perspectives: the former focuses primarily on the risk and soundness of individual institutions, whereas the latter considers system-wide interactions and externalities (Borio, 2003). VaR summarises the tail risk of an individual return distribution but does not, by itself, quantify how the distress of that institution is associated with the risk of the broader financial system. As the 2008 Global Financial Crisis made clear, an institution can look well-capitalized by its own VaR while still posing enormous systemic risk through its connections to other firms, for example through derivatives, retrocession agreements, or common investment exposures (Adrian and Brunnermeier, 2016).

Brunnermeier et al. (2009) identify a deeper problem: systemic risk is endogenous. When multiple institutions simultaneously try to reduce their individual VaR by selling assets, they collectively drive prices down, which increases the losses of all institutions. The actions

taken to improve individual safety can make the system as a whole more dangerous. VaR models cannot capture this feedback.

VaR also cannot answer the macroprudential question that regulators really care about: *what happens to the broader market when a specific institution fails?* (Benoit et al., 2017). This requires a conditional, rather than unconditional, measure of risk, which is exactly what CoVaR provides.

3.3.2 Concept and Definition of ΔCoVaR

To address the limitations of traditional VaR, Adrian and Brunnermeier (2016) introduced the Conditional Value-at-Risk (CoVaR). Instead of measuring the risk of an institution in isolation, CoVaR measures the risk of the broader financial system conditional on a specific institution being in distress.

Formally, let X^i be the return loss of institution *i* and X^{sys} be the return loss of the overarching financial system. The $CoVaR_q^{sys|i}$ is defined as the Value-at-Risk of the system given that institution *i* is exactly at its *q-th* quantile VaR:

$$\Pr\left(X^{sys} \leq CoVaR_q^{sys|i} \middle| X^i = VaR_q^i\right) = q \tag{3.16}$$

This conditional probability allows researchers to observe how the tail risk of the broader market behaves when a specific node within the network collapses. However, as Adrian and Brunnermeier point out, the absolute CoVaR is an insufficient measure of Systemic Contribution. If the global market is experiencing a period of high unconditional volatility, the CoVaR will inherently be high, regardless of whether institution *i* is failing or operating normally. Relying only on absolute CoVaR makes it impossible to determine if the system is in danger because of the institution, or if the system is simply risky by nature.

To isolate the marginal contribution of an institution *i*, Adrian and Brunnermeier (2016) define the ΔCoVaR. This metric is defined as the difference between the CoVaR of the system when the institution is in extreme distress (at the q-th quantile, e.g. *q*=5%) and the CoVaR of the system when the institution is in its normal state (at the 50th percentile, i.e., its median):

$$\Delta CoVaR_q^{sys|i} = CoVaR_q^{sys|i} - CoVaR_{50\%}^{sys|i} \tag{3.17}$$

By subtracting the baseline systemic risk ($CoVaR_{50\%}^{sys|i}$), the $\Delta\mathrm{CoVaR}$ isolate the additional risk that the system bears because of institution *i*'s distress. Consequently, institutions exhibiting the highest $\Delta\mathrm{CoVaR}$ are those associated with the largest marginal increase in system-wide risk under distress conditions. Unlike standalone risk measures, ΔCoVaR explicitly incorporates the dependence structure between institutions and the broader financial system, making it particularly suitable for identifying systemically important institutions (Adrian and Brunnermeier, 2016; Benoit et al., 2017).

While ΔCoVaR is conceptually defined as the difference between the system's Value-at-Risk under distress and normal states of institution i, several subsequent studies have proposed

dynamic implementations based on multivariate GARCH models. These approaches exploit the time-varying covariance structure of asset returns to obtain daily measures of systemic risk contributions, thereby extending the original static framework to a dynamic setting (Girardi and Ergün, 2013)

3.3.3 DCC-GARCH-Based Construction of Systemic Contribution and Vulnerability Measures

Adrian and Brunnermeier (2016) originally proposed ΔCoVaR within a quantile regression framework, where the conditional risk of the financial system is derived directly from the conditional quantile distribution of market returns. While theoretically appealing, this approach typically relies on relatively long estimation windows and does not explicitly model time-varying volatility and correlation dynamics, which are key features of financial markets. For the purposes of the present thesis, the DCC-GARCH approach is preferred because it explicitly models the evolution of conditional volatilities and correlations, which are central to the analysis of time-varying interconnectedness in RQ1.

The present thesis retains the directional economic intuition of the CoVaR literature but implements it through a different empirical construction. Rather than estimating the exact conditional CoVaR formulations proposed by Adrian and Brunnermeier (2016) or Girardi and Ergün (2013), the study uses the time-varying conditional variance-covariance matrix produced by the DCC-GARCH model to construct two covariance-based systemic-risk measures. The first captures the association between institution-specific tail risk and the risk of the global insurance market and is referred to as Systemic Contribution. The second reverses the direction and captures the association between market-wide tail risk and institution-specific risk, and is referred to as Systemic Vulnerability. The DCC-GARCH model provides a daily conditional variance-covariance matrix, which contains the time-varying variance of each institution, the time-varying variance of the market factor and the time-varying covariance between each institution and the market factor. These quantities make it possible to construct a dynamic systemic beta that maps the distress of one institution into the conditional risk of the broader insurance market.

This DCC-GARCH-based construction relies on three main assumptions.

First, the return series must be suitable for GARCH modelling. In particular, they should be stationary and should display conditional heteroskedasticity, since GARCH models are designed to capture time-varying volatility rather than trends in price levels. Stationarity is assessed through the Augmented Dickey-Fuller test, while the presence of ARCH effects is assessed through the ARCH-LM test. These diagnostics are reported in Appendix A and provide the empirical justification for modelling the return series with a GARCH-type specification (Dickey and Fuller, 1979; Engle, 1982; Bollerslev, 1987).

Second, the DCC-GARCH model must generate a valid time-varying conditional covariance matrix. This requires successful model convergence, positive conditional variances and a stationary DCC process. In particular, the DCC parameters must satisfy $(\alpha+\beta<1)$, so that conditional correlations are mean-reverting rather than explosive. This condition ensures that, after a shock, correlations eventually return towards their long-run level instead of drifting without bound. The use of the DCC-GARCH framework is appropriate in this context

because it provides a parsimonious way to estimate time-varying conditional variances, covariances and correlations within a valid multivariate volatility structure (Engle and Kroner, 1995; Engle and Sheppard, 2001; Engle, 2002).

Third, the link between the DCC-GARCH covariance matrix and the systemic-risk measure requires an explicit statistical assumption connecting the conditional covariance structure to the conditional distribution used for CoVaR. The key output of the DCC-GARCH model is the conditional variance-covariance matrix:

$$H_t = D_t R_t D_t \tag{3.3}$$

Where D_t is a diagonal matrix of time-varying conditional standard deviations and R_t is the time-varying conditional correlation matrix (Engle, 2002). For any institution *i* and the system *sys,* the relevant elements of H_t are:

$$h_{i,i,t} = \sigma_{i,t}^2 \tag{3.18}$$

$$h_{sys,sys,t} = \sigma_{sys,t}^2 \tag{3.19}$$

$$h_{i,sys,t} = \rho_{i,sys,t}\sigma_{i,t}\sigma_{sys,t} \tag{3.20}$$

representing respectively the conditional variance of institution *i*, the conditional variance of the system, and their conditional covariance.

Under the assumption that the joint conditional distribution belongs to the elliptical family, which includes both the Gaussian benchmark of Adrian and Brunnermeier (2016, Appendix II.A) and the multivariate Student-t distribution used in this study, the conditional expectation of one variable given another is linear in the conditioning variable (Embrechts, McNeil and Straumann, 2002). Elliptical distributions are particularly attractive in risk management because they preserve this linear conditional expectation and admit tractable dependence structures while accommodating fat-tailed specifications such as the multivariate Student's t distribution (McNeil, Frey and Embrechts, 2015). The slope coefficient of this conditional expectation is the ratio between the conditional covariance and the conditional variance, which can therefore be interpreted as a time-varying systemic beta:

$$\beta_t^{sys|i} = \frac{Cov_t(X^{sys}, X^i)}{Var_t(X^i)} = \frac{h_{i,sys,t}}{h_{ii,t}} = \rho_{i,sys,t}\frac{\sigma_{sys,t}}{\sigma_{i,t}} \tag{3.21}$$

Economically, this coefficient measures the time-varying sensitivity of system-wide returns to movements in institution *i*, conditional on the prevailing volatility regime. Since both conditional volatilities and correlations evolve over time, $\beta_t^{sys|i}$ is inherently time-varying and captures changes in financial interconnectedness across market regimes.

Under the zero-mean Gaussian benchmark of Adrian and Brunnermeier (2016), and using the median state as the reference, the conditional-dispersion term cancels because

$\Phi^{-1}(0.5) = 0$. After adapting their loss convention to the lower-tail return and positive-loss VaR convention adopted here, ΔCoVaR reduces exactly to:

$$\Delta\mathrm{CoVaR}_{q,t}^{sys|i} = \beta_t^{sys|i} VaR_{i,t} = -\Phi^{-1}(q)\rho_{i,sys,t}\sigma_{sys,t} \tag{3.22}$$

The empirical implementation below retains this beta-times-tail-risk mapping but does not compute the explicit distress-minus-median conditional-quantile difference. The resulting measures are therefore treated as ΔCoVaR-inspired operational systemic-risk scores rather than exact ΔCoVaR estimates. The ΔCoVaR notation is retained only for continuity with the motivating literature. This Gaussian result provides the theoretical benchmark for the covariance-based construction adopted in this thesis. However, the baseline specification used here is not Gaussian: both the univariate GARCH innovations and the multivariate DCC innovations are modelled using Student-t distributions. Under a multivariate Student-t distribution, the conditional location retains the same linear covariance-based structure, so $\beta_t^{sys|i}$ remains the relevant linear conditional-sensitivity coefficient. The linearity of the conditional expectation, however, does not by itself justify obtaining the conditional quantile through the same linear shift. For the multivariate Student-t distribution, the conditional distribution of X^{sys}given $X^i = x_i$ is itself Student-t, but with modified ($v + 1$) degrees of freedom and, importantly, a conditional scale that depends on the realised value of the conditioning variable (Ding, 2016; Aste, 2021). Formally, the exact analytical Student-t CoVaR would take the form

$$CoVaR_{q,t}^{sys|i} = \mu_{sys,t} + \beta_t^{sys|i}\left(x_{i,t} - \mu_{i,t}\right) + \sigma_{sys,t}\sqrt{\left(1 - \rho_{i,sys,t}^2\right)\frac{v - 2 + d_i^2}{v + 1}}\, t_{v+1}^{-1}(q) \tag{3.23}$$

where $d_i = \frac{(x_{i,t} - \mu_{i,t})}{\sigma_{i,t}}$ denotes the standardized conditioning distance, $t_{v+1}^{-1}(q)$ is the q-quantile of a standard Student-t distribution with $v + 1$ degrees of freedom, and $v > 2$ ensures the existence of finite second moments (Ding, 2016; Aste, 2021). Consequently, the beta-times-VaR identity derived under Gaussianity does not constitute the exact analytical Student-t CoVaR: it omits the scale-inflation term above. Since the covariance-based beta is constructed from conditional second moments, this interpretation additionally requires finite second moments of the Student-t distribution, i.e. a degrees-of-freedom parameter $v > 2$ (Aste, 2021), which is a condition satisfied by the multivariate Student-t specification used in the DCC estimation.

Rather than implementing this exact analytical Student-t correction, the present thesis adopts a semi-parametric volatility-filtering approach. Conditional location and volatility are estimated parametrically through the GARCH specification, while the tail component is obtained from the empirical distribution of the resulting standardized residuals. This construction follows the logic of volatility-filtered historical simulation, in which past innovations are first standardized for time-varying volatility before their empirical distribution is used for risk measurement (Hull and White, 1998; Barone-Adesi, Giannopoulos and Vosper, 1999). More broadly, the separation between parametric conditional-volatility estimation and subsequent tail modelling is consistent with the two-stage approach advocated by McNeil and Frey (2000), although their original implementation models the tail

of the standardized innovations parametrically through Extreme Value Theory rather than using the empirical residual quantile adopted here.

This choice is motivated by two considerations. First, the exact conditional scale of a multivariate Student-t distribution depends on the realised value of the conditioning variable through the Mahalanobis-distance term $d_{i,t}$. Implementing the analytical correction would therefore require relying on the multivariate Student-t specification not only as a convenient model for heavy-tailed innovations, but also as an exact representation of how the conditional tail scale changes with the realised conditioning state. The operational approach adopted here imposes a weaker distributional requirement: the DCC-GARCH model determines the time-varying conditional second-moment structure, whereas tail severity is inferred from the observed standardized innovations.

Second, estimating tail severity from standardized residuals reduces reliance on a single parametric distribution for the entire innovation distribution. McNeil and Frey (2000) similarly motivate separating volatility dynamics from tail estimation, although they use Extreme Value Theory to model the standardized-residual tail explicitly. Their results show that accounting jointly for stochastic volatility and heavy-tailed innovations improves the estimation of conditional tail-risk measures relative to approaches that neglect either feature (McNeil and Frey, 2000). The present construction therefore sacrifices the analytical exactness that would follow from imposing a fully specified conditional Student-t distribution in favour of a more flexible empirical treatment of the standardized-innovation quantile. This trade-off is consistent with the broader literature on volatility-filtered and semi-parametric risk measurement (Hull and White, 1998; Barone-Adesi, Giannopoulos and Vosper, 1999; McNeil and Frey, 2000).

The empirical implementation therefore retains the covariance-based structure of the Gaussian GARCH ΔCoVaR benchmark while deliberately not implementing this exact analytical scale correction. Instead of the analytical Student-t conditional quantile, the institution-specific VaR is estimated semi-parametrically from the empirical q-quantile of the standardized GARCH residuals. Following Section 3.3.1, the conditional VaR of institution *i* at time *t* is defined as:

$$\mathrm{VaR}_{q,t}^{i} = -(\mu_{i,t} + \sigma_{i,t}\mathrm{z}_{q}^{i}) \tag{3.24}$$

where $\mu_{i,t}$ is the conditional mean, $\sigma_{i,t}$ is the conditional volatility from the GARCH model, and z_q^i denotes the empirical q-quantile of the standardized GARCH residuals of institutions *i.* For a given value of q, z_q^i is estimated from the full standardized-residuals series of institution i and is therefore institution-specific, although it does not vary over time.

Analogously, the tail-risk measure of the system is obtained from the standardized residuals of the global insurance-market factor:

$$\mathrm{VaR}_{q,t}^{sys} = -(\mu_{sys,t} + \sigma_{sys,t}\mathrm{z}_{q}^{sys}) \tag{3.25}$$

where z_q^{sys} denotes the empirical q-quantile of the standardized residuals of the market factor. Consequently, the institution-specific and system-wide tail quantiles are estimated

separately and need not coincide, i.e. $z_q^i \neq z_q^{sys}$ in general. Using the empirical distribution of standardized residuals for tail estimation follows the logic of GARCH-filtered historical simulation (Hull and White, 1998; Barone-Adesi, Giannopoulos and Vosper, 1999). More generally, separating conditional-volatility estimation from subsequent tail modelling of standardized innovations is consistent with semi-parametric GARCH risk measurement (McNeil and Frey, 2000).

Combining the time-varying systemic beta with the institution-specific VaR yields the operational Systemic Contribution measure used in this study:

$$\Delta\mathrm{CoVaR}_t^{sys|i} = \beta_t^{sys|i} \times VaR_{q,t}^i = \frac{h_{i,sys,t}}{h_{ii,t}} \times VaR_{q,t}^i \qquad (3.26)$$

This specification combines institution-specific tail severity with the institution's time-varying conditional dependence with the system. A high Systemic Contribution score can therefore arise from a relatively large institution-specific tail loss, strong conditional dependence with the market factor, or a combination of both. This process yields a daily time series of the operational Systemic Contribution measure for each institution; the daily series are averaged over the sample period to construct the rankings presented in Chapter 4. The same covariance-based logic is subsequently applied in the reverse direction to construct Systemic Vulnerability.

The use of a GARCH(1,1)-DCC(1,1) specification is motivated by both parsimony and empirical robustness. Hansen and Lunde (2005) show that more complex volatility models do not systematically outperform the standard GARCH(1,1) benchmark, while Girardi and Ergün (2013) demonstrate how a multivariate GARCH framework can be used to estimate CoVaR dynamically.

Throughout the empirical analysis, the terms Systemic Contribution and Systemic Vulnerability refer specifically to the DCC-GARCH-based covariance measures defined above. While their directional interpretation is inspired by the CoVaR and ΔCoVaR literature, they should not be interpreted as exact replications of the original conditional-quantile estimators, nor as causal effects of one institution on the system or evidence of direct contractual contagion. They are market-based measures of conditional risk derived from equity-return co-movements, conditional volatilities and conditional covariances, and their purpose is to rank institutions according to their average Systemic Contribution and Vulnerability within the estimated DCC-GARCH framework.

3.3.4 Directional Asymmetry: Systemic Contribution vs Vulnerability

Standard correlation matrices are symmetric by construction: the correlation between institution *i* and institution *j* is identical regardless of the direction in which the relationship is considered. Correlation alone therefore cannot distinguish the direction of conditioning or the relative sensitivity of one variable to movements in another. This motivates the use of directional systemic-risk measures that separately examine institution-to-system and system-to-institution associations. More generally, the directional connectedness literature

shows that outward- and inward-oriented measures need not provide the same institutional ordering (Diebold and Yilmaz, 2012; Billio et al., 2012). To capture this directional asymmetry, the ΔCoVaR framework is applied in two distinct directions for each institution *i.*

3.3.4.1 Systemic Contribution ($\Delta CoVaR_t^{sys|i}$)

As defined in Section 3.3.3, Systemic Contribution is the covariance-based operational measure that combines institution-specific tail risk with the time-varying sensitivity of system returns to institution i. It is computed as:

$$\Delta CoVaR_t^{sys|i} = \beta_t^{sys|i} \times VaR_t^i = \frac{h_{i,sys,t}}{h_{i,i,t}} \times VaR_t^i \tag{3.27}$$

Here, the beta is scaled by the conditional variance of institution i. Consequently, the contribution measure captures how strongly movements in institution i are associated with movements in the broader market. A high value arises when the conditional covariance between the institution and the system is large relative to the institution's own conditional variance. Institutions ranking highest according to this metric are therefore those whose distress is associated with the largest deterioration in system-wide conditions.

3.3.4.2 Systemic Vulnerability ($\Delta CoVaR_t^{i|sys}$)

Systemic Vulnerability applies the same covariance-based construction in the opposite direction. It combines the market tail-risk measure with the conditional sensitivity of institution i to movements in the market factor.

Applying the same covariance-based mapping with the market as the conditioning variable gives:

$$\Delta CoVaR_t^{i|sys} = \beta_t^{i|sys} \times VaR_t^{sys} = \frac{h_{i,sys,t}}{h_{sys,sys,t}} \times VaR_t^{sys} \tag{3.28}$$

The key difference from the Contribution formula is in the denominator: here we divide by the variance of the market $h_{sys,sys,t}$ rather than the variance of institution *i*. This ratio captures the conditional sensitivity of institution i to movements in the aggregate market. A high Systemic Vulnerability score therefore arises when the institution exhibits strong conditional dependence with the market and the market itself is characterised by substantial tail risk. The measure should be interpreted as a market-based indicator of exposure to aggregate stress rather than as an exact change in the institution's conditional VaR or as evidence of balance-sheet amplification. The VaR used to scale the ratio is that of the market, and not that of the institution.

Although both measures share the same conditional covariance in the numerator, they differ in both the denominator and the tail-risk multiplier. Their rankings therefore need not coincide. Systemic Contribution may be relatively high when institution-specific tail risk is strongly associated with aggregate market conditions, while Systemic Vulnerability may

remain comparatively low, and vice versa. This directional asymmetry is precisely the reason why both measures are reported throughout the empirical analysis.

3.3.5 Robustness Setup

To check that the main findings are not driven by specific modelling choices, three robustness checks are implemented. The first changes the distress quantile threshold, the second replaces the market factor, and the third modifies the distributional assumption of the DCC-GARCH model. These tests are designed to assess whether the institution-level ΔCoVaR rankings remain stable when key modelling choices are varied.

Robustness Check 1: Alternative Distress Quantile (q)

The baseline specification measures the financial stress using q = 0.05, following the common convention introduced by Adrian and Brunnermeier (2016) and used later in CoVaR models (Girardi and Ergün, 2013). It should be emphasised that the choice of q does not affect the DCC-GARCH estimation procedure. The GARCH and DCC parameters are estimated from the full return distribution and remain unchanged across quantile specifications. The parameter q enters only the subsequent systemic-risk calculation through the empirical residual quantile used in the VaR component. Nevertheless, the choice of 5% as the baseline threshold can be challenged on the grounds that systemic risk analysis should capture catastrophic, rather than merely adverse, market events.

To address this concern and evaluate the stability of the systemic risk hierarchy under extreme conditions, the ΔCoVaR measures are recomputed using q=1% while keeping the estimated DCC-GARCH parameters unchanged. Operationally, the robustness exercise replaces the baseline 5% empirical standardized-residual quantiles with their 1% counterparts in the VaR components, while leaving the estimated GARCH and DCC parameters unchanged.

By comparing the resulting rankings of the sampled listed reinsurance-related groups under q=0.05 and q=0.01, this test verifies whether the cross-sectional vulnerability and contribution patterns are invariant to the depth of the tail threshold.

Robustness Check 2: Alternative Market Factor Specification

The second critical choice in the baseline model is the selection of the market factor proxy, which utilizes the MSCI ACWI Insurance as the 21st variable representing the aggregate system.

To eliminate this potential geographical distortion and test the invariance of the network's directional asymmetry, the entire multivariate DCC-GARCH model is re-estimated by replacing with the MSCI World Insurance. Because the systemic-risk measures are defined relative to a reference system, replacing the market factor provides a direct sensitivity analysis of the extent to which the resulting rankings depend on the definition of the aggregate insurance market.

Robustness Check 3: Alternative Distributional Assumption

The third robustness check modifies the distributional assumption of the model. The baseline specification uses Student-t innovations in the univariate GARCH step and a multivariate Student-t distribution in the DCC step, because financial returns typically exhibit excess kurtosis and tail dependence. This choice follows Bollerslev (1987), who shows the relevance of Student-t innovations for modelling the fat-tailed behaviour of financial returns, and Embrechts, McNeil, and Straumann (2002), who emphasise the importance of accounting for dependence in the tails when measuring financial risk. As an alternative benchmark, the full DCC-GARCH and ΔCoVaR procedure is re-estimated using Gaussian innovations, while keeping the sample, time period, market factor, GARCH(1,1)-DCC(1,1) specification and 5% distress threshold unchanged. The objective is not to replace the baseline Student-t model, but to assess whether the systemic-risk rankings are robust to a less fat-tailed distributional assumption. The comparison focuses primarily on the stability of the Contribution and Vulnerability rankings, using rank changes and Spearman rank correlations, while also comparing model fit through log-likelihood, AIC and BIC.

Remaining Limitations of the Robustness Strategy

Although the three robustness checks implemented in this thesis assess the sensitivity of the ΔCoVaR rankings to the distress threshold, the market factor proxy and the Student-t versus Gaussian distributional assumption, they do not exhaustively cover all possible sources of model uncertainty. Another limitation lies in the specification of the volatility process. In the baseline estimation, the use of a symmetric GARCH(1,1) process is kept constant throughout the estimation procedure. Such a model is preferred due to its simplicity, as well as empirical results reported by Hansen and Lunde (2005), which reveal that complex volatility models do not necessarily perform better than the common GARCH(1,1) model in terms of predictive power. It should be noted that the volatility process in equity returns may be asymmetric. Alternative specifications such as EGARCH, introduced by Nelson (1991), or GJR-GARCH, associated with Glosten, Jagannathan, and Runkle (1993), are specifically designed to capture this type of asymmetry. Re-estimating the DCC-GARCH-ΔCoVaR framework with asymmetric volatility models could therefore provide an additional robustness check, particularly for institutions whose equity returns exhibit pronounced leverage effects.

A second remaining limitation concerns the range of alternative innovation distributions considered. The Gaussian benchmark implemented in this thesis provides a useful comparison with the baseline Student-t specification, but it does not cover asymmetric fat-tailed distributions. In particular, a skewed Student-t distribution, such as the one proposed by Hansen (1994), could capture both excess kurtosis and skewness in conditional return distributions. This may be relevant because some insurance and reinsurance-related groups may exhibit asymmetric downside risk that is not fully captured by either the symmetric Student-t or the Gaussian specification. Future research could therefore extend the present robustness analysis by comparing the baseline Student-t model with skewed Student-t or other asymmetric fat-tailed innovation distributions.

These remaining limitations do not invalidate the empirical findings, but they define the boundary of the robustness evidence provided in this thesis. The results can be interpreted

as robust to changes in the distress threshold, market factor and Gaussian-versus-Student-t distributional assumption, but not as exhaustive with respect to all possible volatility specifications or asymmetric innovation distributions.

3.4 Correlation Networks and Minimum Spanning Tree (MST)

3.4.1 Rationale for a Network Approach

The DCC-GARCH model and the ΔCoVaR framework developed in Sections 3.2 and 3.3 provide two complementary perspectives on systemic risk. The former captures time-varying dependence structures at the pairwise level, while the latter quantifies the marginal contribution of individual institutions to system-wide risk. However, both approaches remain fundamentally local in nature, as they focus either on bilateral relationships or on institution-specific risk measures.

As highlighted in Newman (2010), many complex systems cannot be fully understood only by analysing their individual components in isolation, since their behaviour emerges from the pattern of interactions among their elements. Network theory provides a natural framework for studying such systems by representing entities as nodes and their relationships as edges, allowing both the characteristics of individual components and the overall structure of their interactions to be analysed simultaneously. In this sense, the financial system can be naturally represented as a network in which financial institutions are nodes and statistical dependencies define weighted edges. This representation makes it possible to move beyond pairwise analysis and investigate higher-order structural properties of the system, such as centrality, clustering, and connectivity, which cannot be inferred from bilateral relationships alone. As a result, network analysis provides a system-wide perspective on financial interconnectedness and offers insights into structural vulnerabilities that may not be evident from institution-level measures alone (Newman, 2010).

A network framework makes it possible to identify structural properties that are inherently collective, such as the presence of highly interconnected clusters, central intermediaries, and the overall pattern of connections linking institutions. Unlike standard econometric measures, which primarily quantify bilateral dependence or institution-specific risk, network analysis characterises the architecture of the financial system as a whole. This makes it possible to identify structural features such as highly connected hubs, bridge institutions connecting otherwise weakly linked groups, and cohesive communities of closely interconnected firms, all of which may influence the potential transmission of shocks across the system (Billio et al., 2012; Diebold and Yilmaz, 2014; Newman, 2010).

More generally, the financial network literature argues that systemic risk is an emergent property of the network, arising not only from the magnitude of individual exposures but also from the way these exposures are organised across the system (Newman, 2010; Hautsch, Schaumburg, and Schienle, 2015). Consequently, institutions with similar individual risk characteristics may play very different systemic roles depending on their position within the network. A network perspective therefore complements institution-level measures such as

ΔCoVaR by revealing the structural context in which systemic risk is generated, identifying the institutions that occupy central positions, the groups that form tightly connected communities, and the backbone of interconnections through which shocks may potentially spread.

3.4.2 Weighted Network Construction

The input to the network analysis is the average conditional correlation matrix $\bar{R}$, obtained by averaging the daily conditional correlation matrix R_t, from the global DCC-GARCH model over the full 2010-2024 sample:

$$\bar{\rho}_{i,j} = \frac{1}{T}\sum_{t=1}^{T} \rho_{ij.t} \tag{3.29}$$

The objective of the network analysis is to characterize the long-run structural organization of the global reinsurance market rather than its day-to-day evolution. Taking the average of conditional correlation gives a consistent way to measure the interconnectedness over a long period of time despite being derived from the time-varying dependence of the DCC approach.

In this approach, the edges do not signify any kind of contractual relationship or exposure that exists between the institutions. Rather, the edges indicate the dependence that is statistically inferred from the market data.As noted by Newman (2010), network edges may represent many different types of relationships depending on the system under study; in the present application, they capture the intensity of financial interdependence inferred from the estimated correlation structure.

This 20x20 matrix serves as the weighted adjacency matrix for the network. In this framework, each institution represents a node, and the weight of the edge connecting nodes *i* and *j* is determined by their average pairwise correlation $\bar{\rho}_{i,j}$. A stronger edge means the two institutions co-move more closely on average over the sample period.

Following Newman (2010), many real-world networks are more appropriately represented as weighted rather than binary graphs, since interactions between nodes generally differ in intensity rather than being simply present or absent. A weighted representation therefore preserves substantially more information about the underlying system by accounting for the relative strength of each connection. Representation of the network using weighted edges according to average DCC correlations would offer a better description of the structure of dependence, compared to the unweighted graph. It would enable further analysis to differentiate strong from weak dependencies as opposed to giving all relationships the same weight. Weighted representation enables network statistics to take into account the strength of financial connections. For this reason, measures of centrality are calculated by considering edge weights, instead of taking only the number of connections into account.

The network is structured as an undirected graph, reflecting the symmetry of the conditional correlation matrix derived from the DCC-GARCH model, where the dynamic dependence between institutions *i* and *j* satisfies: $\bar{\rho}_{ij} = \bar{\rho}_{ji}$. Within this topological setup, edges do not

represent directional causal spillovers; instead, they capture the intensity of mutual co-movements and statistical interdependence. This approach is standard practice in financial econometrics when mapping the systemic backbone of a market through a Minimum Spanning Tree (MST), as the mathematical transformation of correlation coefficients into a metric distance matrix requires perfect symmetry (Mantegna, 1999).

While the network topology is undirected, the baseline ΔCoVaR framework is inherently directional, as it distinguishes between an institution's Systemic Contribution and its Systemic Vulnerability. To bridge these two methodological perspectives, the time-averaged ΔCoVaR scores computed in Section 3.3.4 are incorporated into the graph as node-specific attributes. Specifically, the size of each node is scaled proportionally to the institution's Systemic Contribution, while different node shapes are used to classify specific risk profiles. As a result, the final graph provides a joint representation of the network structure and institution-level systemic risk. The edges describe the pattern of statistical interdependence among institutions, while node-specific attributes summarize their average Systemic Contribution and Vulnerability.

The decision to combine directional node attributes with an undirected correlation network is supported by a macroprudential rationale. In the global reinsurance sector, systemic risk is unlikely to materialise as a simple, unidirectional domino effect. Rather, it may arise through a complex structure of retrocession agreements, pool arrangements, overlapping asset portfolios, and common market exposures. Therefore, an undirected edge filtered via the MST algorithm does not imply a lack of causal direction. Instead, it provides a simplified representation of the structural pathways along which shocks may potentially spread (Mantegna, 1999). By scaling node sizes according to each institution’s average Systemic Contribution (ΔCoVaR) the resulting graph simultaneously conveys structural importance and systemic relevance. The visual topology immediately exposes which core, highly-connected hubs also possess the highest potential systemic importance within the network.

Before including an edge in the network, each pairwise correlation is tested for statistical significance. Significance filtering reduces the influence of estimation noise and improves the interpretability of financial networks by removing weak relationships that are more likely to arise from sampling variability (Tumminello et al., 2010). A non-zero sample correlation can arise by chance in a finite sample, and including statistically unreliable edges would distort the network topology. To reduce the influence of spurious correlations, the elements of the average correlation matrix were subjected to a Pearson significance test. Although this test assumes independent observations and should therefore be interpreted cautiously in financial time series, it provides a simple empirical filter for excluding statistically weak relationships prior to visualization. To test whether each $\bar{\rho}_{ij}$ is significantly different from zero, the standard Pearson t-test is applied:

$$t_{ij} = \frac{\bar{\rho}_{ij}\sqrt{n-2}}{\sqrt{1-\overline{\rho_{ij}^2}}} \tag{3.30}$$

Where n is the number of overlapping trading days in the global dataset. Under the null hypothesis $H_0: \rho = 0$, this statistic follows a Student-*t* distribution with *n* − 2 degrees of freedom. The test is bilateral. Only edges with p-value < 0.05 are retained in the network

used for visualization and community detection, consistent with standard practice in the empirical finance literature (Tumminello, Lillo, and Mantegna, 2010)

3.4.3 Minimum Spanning Tree

The full correlation network, even after the significance filter, remains dense, making its structural interpretation difficult. To extract its essential backbone, this study applies the Minimum Spanning Tree (MST) methodology.

The MST approach in financial markets was first introduced by Mantegna (1999), who demonstrated that stock return correlations in the Dow Jones Industrial Average generate a hierarchical structure consistent with industrial classifications, despite no sectoral information being imposed ex ante. Since then, the MST has become a standard tool in financial network analysis for reducing complex correlation structures into their most informative backbone (Onnela et al., 2003).

In the context of systemic risk, the MST is particularly valuable because it identifies the subset of relationships that form the structural backbone of the network: the edges that survive the pruning are precisely those that cannot be removed without disconnecting some part of the system. This makes the MST a natural complement to the ΔCoVaR analysis: while the ΔCoVaR scores identify institutions with higher Systemic Contribution or Vulnerability, the MST provides a simplified representation of the structural connections through which shocks may potentially propagate.

The MST is obtained using Prim's algorithm. Mantegna (1999) uses Prim's algorithm in his original implementation, and subsequent studies in financial network analysis have followed the same convention (Onnela et al., 2003). Starting from a single node, the algorithm iteratively adds the shortest available edge that connects a new node to the growing tree, until all 20 nodes have been included. This greedy procedure is guaranteed to produce an optimal spanning tree.

Standard optimization and graph-theoretic algorithms require distance metrics rather than correlation coefficients, as they operate under the convention that smaller values represent higher proximity, which is the opposite convention from correlation. To convert correlations into proper distances, the metric proposed by Mantegna (1999) is used:

$$d_{ij} = \sqrt{2(1 - \bar{\rho}_{ij})} \tag{3.31}$$

Prim's algorithm builds the spanning tree by always selecting the shortest edge available. The Mantegna distance transformation ensures a proper metric space representation of correlations, preserving absolute geometric and topological consistency (Mantegna, 1999; Onnela et al., 2003). Under this metric, a correlation of 1.0 gives a distance of 0, a correlation of 0 gives a distance of $\sqrt{2} \approx 1.41$, and a correlation of −1 gives the maximum geometric distance of 2. The most correlated pairs of institutions are therefore the closest nodes in the MST.

Given the resulting distance matrix, the MST is the spanning tree, which is a connected, cycle-free subgraph that minimizes the total sum of edge distances. For n = 20 nodes, the MST always contains exactly $n - 1 = 19$ edges. This pruning retains only the most relevant connections in terms of minimal total distance, providing a clearer representation of the network backbone.

Finally, for ease of economic interpretation, the edge labels in the MST visualization display the original DCC correlation value $\bar{\rho}_{ij}$ rather than the Mantegna distance.

Two centrality metrics are computed for each node to characterize its role in the network.

Node Strength is the sum of all edge weights connected to institution i:

$$S_i = \sum_{j \neq i} \bar{\rho}_{ij} \tag{3.32}$$

Strength measures the total connectivity of each institution. A high value means the firm has strong average correlations with many others, making it a well-integrated hub in the network. Strength is the weighted analogue of degree centrality (Barrat et al., 2004). In financial networks, institutions with high strength are often interpreted as occupying highly connected positions within the system and may therefore play a more important role in the transmission of shocks (Billio et al., 2012). A high-strength node is not only connected to many other institutions, but is connected to them strongly, which may indicate a more central position in the structure of financial interdependence.

Betweenness centrality is defined as the extent to which a node sits on the shortest path between any two other nodes. As the computation of shortest paths is dependent on the distance measure, the Mantegna index becomes an immediate choice of edge weight measure consistent with the MST approach. High betweenness centrality implies that the node serves as a structure link in the network, and hence its deletion can result in changes in the inter-cluster links. Billio et al. (2012) highlight the importance of bridge institutions within financial networks, as they connect otherwise weakly linked segments of the financial system.

Rank-Based Comparison with ΔCoVaR

After computing the network centrality measures, the analysis implements a rank-based comparison between ΔCoVaR indicators and network position. The purpose of this step is to assess whether institutions that are more systemically relevant according to the DCC-GARCH ΔCoVaR framework also occupy more central positions within the correlation-based network. This follows the broader systemic-risk literature, which emphasises that institution-level risk measures should be interpreted together with information on the structure of financial interconnectedness (Billio et al., 2012; Hautsch, Schaumburg, and Schienle, 2015).

The two families of indicators should not, however, be interpreted as statistically independent measures. The Systemic Contribution and Systemic Vulnerability scores are constructed from the conditional covariance between each institution and the market factor, while the correlation network is built from the dependence structure among institution-level

equity returns. Strength centrality, in particular, aggregates the correlation weights attached to each institution. Consequently, both approaches contain information derived from the co-movement of equity returns, and a positive association between the systemic-risk measures and Strength is therefore partly expected rather than constituting independent validation. The measures remain distinct, however: Systemic Contribution and Vulnerability combine institution–market dependence with tail-risk components, whereas network centrality characterises the institution's position within the multilateral structure of firm-to-firm dependence (Engle, 2002; Barrat et al., 2004; Billio et al., 2012; Hautsch, Schaumburg, and Schienle, 2015).

The comparison focuses on four quantitative indicators: Systemic Contribution, Systemic Vulnerability, Strength centrality and Betweenness centrality. Systemic Contribution and Systemic Vulnerability capture the two directional dimensions of ΔCoVaR, while Strength and Betweenness capture two different aspects of network position. Strength measures the weighted embeddedness of an institution in the correlation network, since it sums the intensity of its connections with all other institutions (Barrat et al., 2004; Newman, 2010). Betweenness centrality, instead, identifies institutions that lie on shortest paths between other nodes and therefore occupy potential bridging positions in the network (Freeman, 1977; Newman, 2010).

For each quantitative indicator, institutions are ranked from highest to lowest value, with rank 1 assigned to the institution with the largest value. The relationship between the ranks is then tested through the Spearman rank correlation, and the choice of the latter is due to the reason that what the aim is not to compare the value of indicators on different scales in absolute sense, but rather test if institutions with high rank in one category have high ranks in another (Spearman, 1904). Specifically, Systemic Contribution is compared to Strength and Betweenness, while Systemic Vulnerability is compared to Strength and Betweenness, as well as two ΔCoVaR rankings. Strength and Betweenness are also compared to evaluate whether broad embeddedness and bridging position capture similar or distinct aspects of network centrality.

Community membership is reported in the joint comparison table but is not included in the rank-correlation calculation, since it is a categorical classification rather than an ordinal or continuous variable. The rank-based comparison is therefore descriptive and interpretative rather than a test of independent validation. Spearman coefficients are used to summarize the degree of rank concordance across measures expressed on different scales. Given the partially shared dependence information entering the indicators, particular emphasis is placed on the magnitude of concordance, on differences across centrality concepts, and on institution-specific ranking divergences.

3.4.4 Community Detection

Beyond the MST, a community detection analysis is performed on the significant correlation network. The goal is to identify groups of institutions that are more densely connected to each other than to the rest of the network purely from the correlation data, without imposing any geographical or sectoral classification in advance.

In the context of financial market networks, community detection has a direct economic interpretation. A community in a correlation network represents a group of institutions whose

returns co-move more tightly with each other than with the broader market, a pattern that may reflect shared underwriting exposures, common reinsurance counterparties, geographic concentration of catastrophe risk, or herding behaviour in portfolio allocation (Billio et al., 2012; Huang and Chen, 2021). Importantly, community structure is not a fixed property of the financial system: empirical studies of stock-market networks have documented that modularity often changes substantially during crisis periods depending on the market structure, as institutions retreat into sectoral or regional clusters, reflecting the reorganization of market structure into different clustering patterns (Vodenska et al., 2016). In systemic risk analysis, the community partition is informative because it identifies groups of institutions with stronger internal co-movement. These clusters may indicate segments of the network within which shocks could propagate more intensely than across communities (Newman, 2006). High modularity may therefore suggest a clearer separation between clusters, although stronger within-community dependence can also imply greater intra-cluster vulnerability (Bardoscia et al., 2016; Galstyan and Ghosh, 2013).

The Louvain algorithm (Blondel et al., 2008) is selected for three reasons that make it particularly well-suited to this application. First, it operates directly on weighted edges: in the present network, the weights are the DCC correlation coefficients, so the community partition is informed by the actual strength of each link rather than treating it as binary. Second, it is computationally efficient for networks of this size, exhibiting good empirical scalability even for very large networks with rapid convergence even for large weighted graphs (Blondel et al., 2008), which makes it one of the most widely used methods in applied financial network studies (Billio et al., 2012; Huang and Chen, 2021). Third, benchmarking studies have consistently found that Louvain produces higher-quality partitions, as measured by modularity (Lancichinetti and Fortunato, 2012), which explains its widespread adoption in the systemic-risk network literature.

The Louvain algorithm identifies the optimal network partition by maximizing the modularity metric (*Q*), defined mathematically as:

$$Q = \frac{1}{2m}\sum_{ij}\left[A_{ij} - \frac{k_i k_j}{2m}\right]\delta(c_i c_j) \tag{3.33}$$

Where A_{ij} is the edge weight between nodes *i* and *j,* k_i is the total strength of node *i, m* is the sum of all edge weights, and $\delta(c_i c_j)$=1 if nodes *i* and *j* belong to the same community and 0 otherwise (Blondel et al., 2008; Newman and Girvan, 2004). Modularity measures how much the density of within-community connections exceeds what would be expected by chance in a random graph with the same degree sequence. The term $\frac{k_i k_j}{2m}$ is the null-model expectation: the expected edge weight between nodes i and node j in a configuration model that preserves degree sequence but randomises all connections (Newman, 2006).

The Louvain algorithm operates in two phases. In the first phase (local optimization), each node is initially assigned to its own community. The algorithm then iterates over all nodes and, for each node i evaluates the modularity gain ΔQ that would result from reassigning i to each of its neighbours' communities; the move yielding the largest positive ΔQ is applied, and the pass is repeated until no single-node reassignment improves Q. In the second phase (aggregation), all nodes belonging to the same community are collapsed into a single

node, and the inter-community edge weights are aggregated accordingly. The algorithm terminates when no further modularity improvement is achievable at any resolution (Blondel et al., 2008).

To assess the statistical significance of the detected community structure, a null-model based validation procedure is implemented. Rather than relying on absolute modularity thresholds, the observed community partition is evaluated relative to an ensemble of degree-preserving random graphs, in line with the standard approach in network science (Guimerà, Sales-Pardo, and Amaral, 2004; Fortunato, 2010). In particular, the null model is constructed by generating randomised networks that preserve the empirical degree sequence through a rewiring procedure (Maslov & Sneppen, 2002), while destroying any higher-order community structure. To extend this framework to weighted networks, edge weights are independently permuted across the rewired topology, following the general principle of decoupling network topology from weight distribution in weighted network randomisation (Serrano, Boguñá, and Vespignani, 2007). This procedure generates a distribution of networks that preserve first-order properties of the empirical system while eliminating any systematic association between edge weights and community structure.

The procedure is as follows: the observed modularity obtained from the Louvain run on the empirical network is recorded. A null distribution of modularity values is then generated by producing 5000 rewired copies of the original network using the rewiring algorithm implemented in the igraph package in R (Csárdi and Nepusz, 2006). This ensures that the first-order connectivity properties of the network are retained while randomizing the network topology, and that the weights are independently randomized so that there is no relationship between the structure and weights of the communities. As a result of randomizing the topology but not the weights, the edge weight vector of the network is independently randomly permuted in each iteration among the set of edges in the rewired network; this ensures that there is no community structure in the edge weights while retaining their distribution. The Louvain algorithm is then used on the 5000 rewired networks to get a null distribution of Q values. The empirical p-value is calculated based on the proportion of the null Q-values that are greater than or equal to the observed modularity value and a z-score is calculated.

However, the Louvain algorithm is also subject to limitations. First, modularity is subject to the resolution limit (Fortunato and Barthélemy, 2007), which implies that the algorithm may fail to detect communities below a network-dependent scale. This arises from the global nature of the modularity objective function: the null-model term $\frac{k_i k_j}{2m}$ assigns a non-negligible expected weight to all node pairs, which can lead to the absorption of small but internally dense groups into larger communities during the maximisation of Q. As a consequence of the above, small communities may remain unnoticed based on the size and density of the network. Second, the Louvain method is stochastic and thus may be subject to run-to-run variation due to the random selection of nodes at each stage. This may result in minor variations in the partitions formed with slightly varied modularity scores. Furthermore, in some cases, the method may generate low connectivity communities. In order to resolve these problems, the Leiden method has been developed as an extension with an extra refinement phase to ensure high connectivity of communities (Traag, Waltman, and van Eck, 2019). However, this is not implemented in this precise study but could be explored in future research. Finally, the interpretation of absolute modularity values is limited, particularly in

small, dense networks such as the one analysed in this study. Common heuristic benchmarks (e.g., Q>0.3) are not generally informative outside the sparse networks for which they were originally discussed (Fortunato, 2010). In dense correlation networks, the distribution of modularity values becomes compressed, making absolute values less informative. Consequently, even economically meaningful community structure may correspond to relatively low modularity levels. This issue is particularly relevant in highly interconnected financial systems, where elevated edge density compresses the range of attainable modularity values (Clemente et al., 2022). For this reason, inference should rely on comparison with an appropriate null model rather than absolute thresholds, as implemented in the permutation-based significance test described in the previous section.

The community structure is applied to both the full network visualization and the MST. The geographical region of each institution is shown separately, as a convex hull background in the MST plot (as implemented via the *ggraph* and *ggplot2* in R), so that the emergent community partition can be visually compared with the geographical classification. This allows the reader to assess directly how much of the network structure is explained by geography versus by actual co-movement patterns in the data.

CHAPTER 4

Empirical Results

Before discussing the empirical results, all regional and global return series were tested for stationarity and conditional heteroskedasticity. The ADF tests reject the unit-root null at the 1% level for all institutions, while the ARCH-LM tests indicate significant conditional heteroskedasticity in almost all cases. These preliminary diagnostics support the use of dynamic conditional-volatility modelling. The specific GARCH(1,1)-DCC(1,1) specification is motivated by the parsimony and empirical evidence discussed in Section 3.2.4, together with the estimation and admissibility checks described therein. The full diagnostic tables are reported in Appendix A.

4.1 Regional Evidence

4.1.1 Europe

Correlation Persistence and Network Structure

The DCC model converged successfully. The model estimated an innovation parameter (α) of 0.0127 and a decay parameter (β) of 0.9614. The sum of these parameters (a + b = 0.9741) strictly satisfies the necessary stationary condition (a + b < 1) derived by Engle (2002).

Parameter	Value	Interpretation
Innovation (α)	0.0127	Short-term shock impact
Decay (β)	0.9614	Long-term memory/ Persistence
(α + β)	0.9741	High persistence (Stationary)

Table 2: DCC Parameters -Europe

This high persistence means that once equity correlations rise during a market shock, they remain elevated for an extended period before reverting to normal. Economically, this implies that the European reinsurance market tends to stay highly co-moving well after a crisis has passed, so that diversification benefits across these institutions' equity holdings recover only slowly, which is consistent with Billio et al. (2012), who link growing insurance-sector interconnectedness to more persistent episodes of elevated systemic risk.

The full-sample time-averaged conditional correlation matrix (Figure 5) gives a picture of the baseline network structure across the 2010–2024 period.

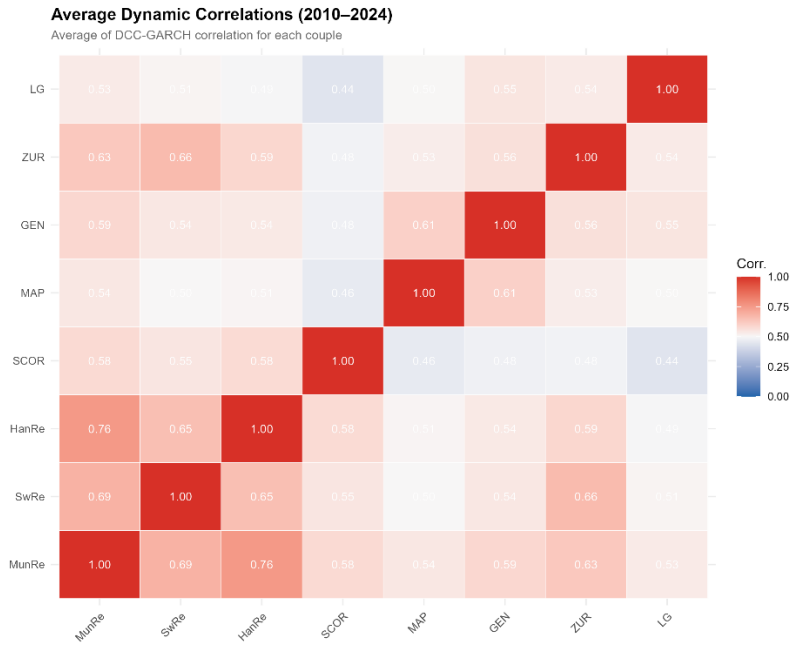

Figure 5: Time-Averaged DCC Correlation Matrix Heatmap -Europe.

Each cell reports the full-sample (2010-2024) average conditional DCC correlation between a pair of eight European institutions. Diagonal elements equal one. Warmer colours indicate stronger positive co-movement, while cooler colours indicate weaker co-movements.

The network is anchored by what can be called a 'German-Swiss core' encompassing Munich Re, Hannover Re, and Swiss Re, which show the highest average pairwise correlations in the sample, consistently above 0.65. This pattern may reflect shared exposure to European macro-financial conditions, partly overlapping supervisory environments, correlated underwriting cycles, and other common sectoral factors. On the other hand, more diversified groups such as MAPFRE and Legal & General show lower baseline correlations with the rest of the European sample, typically in the 0.44–0.54 range, suggesting that different business models still provide some structural diversification during calm periods.

Dynamic Interconnectedness During Stress Episodes

The Average Dynamic Correlation (ADC), computed as the average of all 28 pairwise correlations at each point in time, shows how interconnectedness changes during the sample period. The historical average ADC is 0.557, but this number masks large swings driven by major macro-financial events. This pattern supports the findings of Kenourgios et

al. (2011), who show that correlations tend to rise sharply during crises and recover more slowly afterwards.

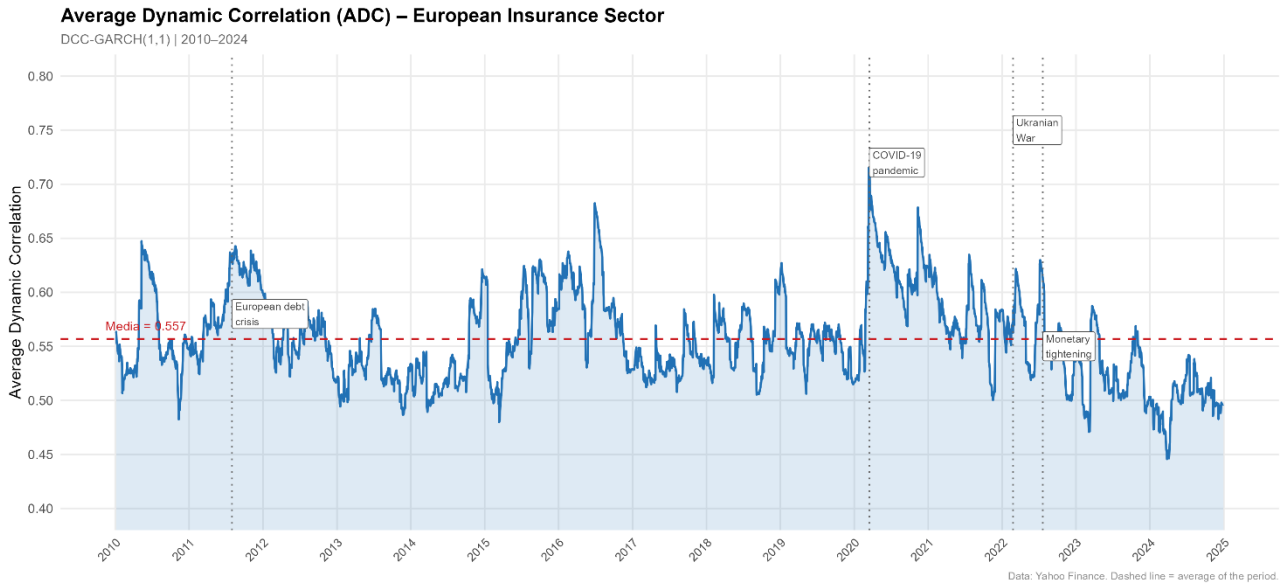

Figure 6: Average Dynamic Correlation (ADC) -Europe.

The blue line reports the daily average of the 28 pairwise DCC correlations among the eight European institutions over 2010–2024. The red dashed line indicates the full-sample mean ADC, while the dotted vertical lines and labels identify selected stress episodes.

The plot reveals four distinct stress episodes over the sample period worth discussing:

Early 2010, Pre-Crisis Elevated Correlations. The European ADC begins the sample already at a moderately elevated level, fluctuating around 0.55 and rising temporarily to about 0.64–0.65 in early 2010. This indicates that European insurance-sector co-movement was already substantial at the start of the sample, consistent with the lingering effects of the post-crisis financial environment.

The European Sovereign Debt Crisis (August 2011). A clear stress episode appears around the European sovereign debt crisis, when the ADC again rises to approximately 0.64–0.65. This pattern is consistent with a temporary increase in sector-wide co-movement during a period of intensified sovereign and financial stress in Europe (EIOPA, 2012; De Bruyckere et al., 2013).

Following this peak, the ADC enters a gradual declining phase through 2012–2014, as the ECB's intervention ("whatever it takes") progressively stabilized sovereign markets and allowed correlations to revert toward the full-sample mean.

The COVID-19 Pandemic (March 2020). The largest shock in the whole dataset is observed in March 2020 when the ADC rises to about 0.72, which is the highest value throughout the whole 2010-2024 timeframe. This is an empirical example of the phenomenon described by Kenourgios et al. (2011) as the diversification breakdown: both financial and insurance-related shocks affected all pairwise correlations at once. The value of the ADC fell quite fast after the peak in the second half of 2020, which might be perceived as a signal that the market regarded the pandemic as a temporary shock.

The Ukraine War and ECB Monetary Tightening (2022). The war in Ukraine is associated with a moderate and short-lived increase in the ADC in early 2022. Subsequently, during the ECB monetary tightening phase, the ADC generally moves below its historical average and trends downward through much of 2023–2024. This suggests that higher interest rates did not produce a sustained increase in co-movement across the European sample and may instead have been associated with more differentiated market responses across institutions. (Berends et al., 2013).

4.1.2 North America & Bermuda

Correlation Persistence and Network Structure

The multivariate DCC (1,1) estimation for the US and Bermuda network converged successfully. The innovation parameter (α) is 0.0178 and the decay parameter (β) is 0.9528, resulting in a sum (α + β = 0.9707) that strictly satisfies the stationarity condition.

Parameter	Value	Interpretation
Innovation (α)	0.0178	Short-term shock impact
Decay (β)	0.9528	Long-term memory/ Persistence
(α + β)	0.9707	High persistence (Stationary)

Table 3: DCC Parameters -US & Bermuda

The slightly higher innovation parameter than Europe (0.0178 vs. 0.0127) indicates somewhat greater short-run sensitivity of the estimated correlation process to recent standardized shocks.(Cappiello, Engle, and Sheppard, 2006)

Examining the full-sample time-averaged conditional correlation matrix (Figure 7) reveals a structurally differentiated network architecture.

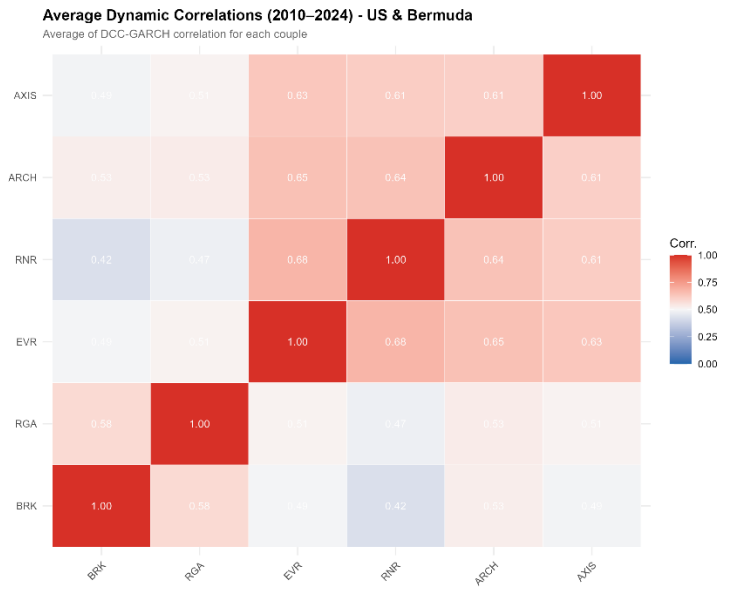

Figure 7: Time-Averaged DCC Correlation Matrix Heatmap -US & Bermuda.

Each cell reports the full-sample (2010-2024) average conditional DCC correlation between a pair of six US/Bermuda institutions. Diagonal elements equal one. Warmer colours indicate stronger positive co-movement, while cooler colours indicate weaker co-movements.

Unlike the European "DACH core," the North American network is anchored by a "Bermuda Catastrophe Core" comprising Everest Re (EVR), RenaissanceRe (RNR), Arch Capital (ARCH), and Axis Capital (AXIS). These four firms show the highest average pairwise correlations in the sample, with EVR and RNR averaging around 0.68. This makes sense: these institutions share exposure to catastrophe-oriented reinsurance markets and may therefore respond to common underwriting, pricing and financial-market conditions. The observed correlations do not, however, identify direct retrocession relationships among them. When a large catastrophe event occurs, all four tend to suffer losses at the same time, pulling their equity prices together. Shared catastrophe-oriented exposures and common underwriting conditions are plausible channels through which co-movement may increase during major loss events (Cummins and Weiss, 2014).

Conversely, Berkshire Hathaway (BRK) consistently exhibits the lowest baseline correlations across the network (for example only 0.42 with RenaissanceRe). This is because BRK is a highly diversified conglomerate with major businesses in railroads, energy, and technology, not just insurance. This dilutes its co-movement with pure-play reinsurers. Similarly, RGA, being a specialist life and health reinsurer, shows lower integration with the P&C-oriented Bermudian firms.

Dynamic Interconnectedness During Stress Episodes

The Average Dynamic Correlation for the US and Bermuda bloc, shown in Figure 8, oscillates around a mean of 0.557, approximately the same level as Europe, yet with a different temporal pattern. The US/Bermuda ADC is more volatile than its European counterpart, oscillating frequently and sharply above and below the mean over the sample. This higher short-term reactivity is consistent with the DCC parameter estimates reported in Table 3, where the slightly higher innovation parameter (α=0.0178 vs. Europe's α=0.0127) indicates somewhat greater short-run sensitivity of the estimated correlation process to recent standardized shocks.

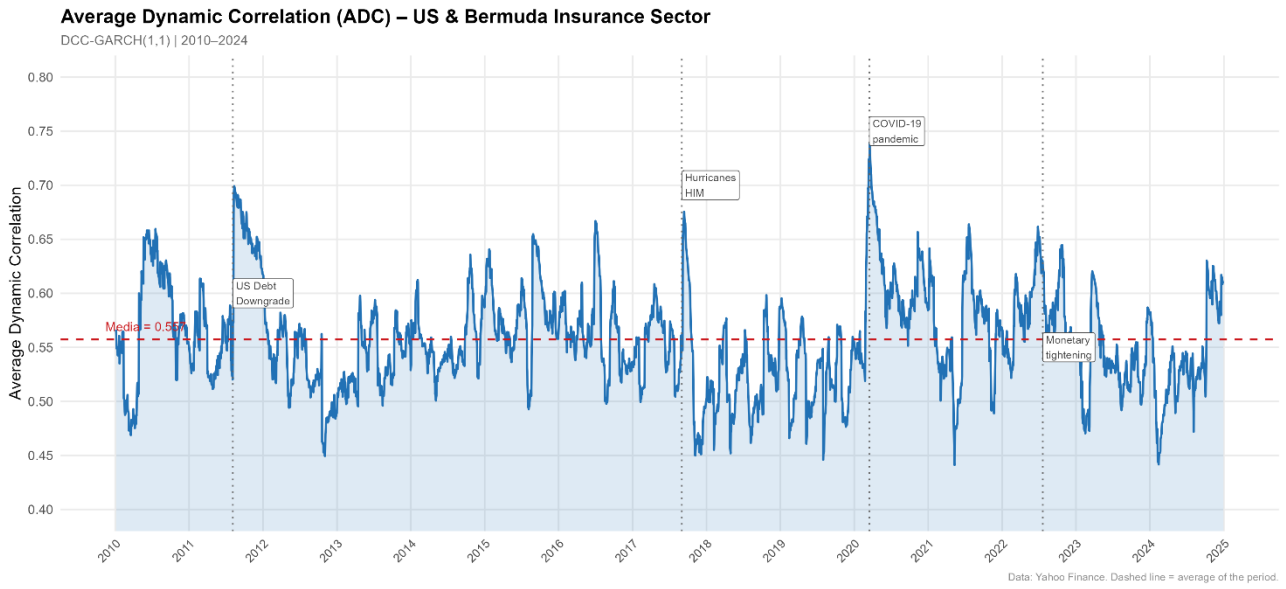

Figure 8: Average Dynamic Correlation (ADC) -US & Bermuda.

The blue line reports the daily average pairwise DCC correlations among the six US/Bermuda institutions over 2010–2024. The red dashed line indicates the full-sample mean ADC, while the dotted vertical lines and labels identify selected stress episodes.

Early 2010. Baseline Volatility. The ADC begins the sample already at a moderately elevated level, fluctuating around 0.55–0.60, and shows frequent short-run movements from the outset. Compared with Europe, the US/Bermuda bloc displays a persistently higher and more volatile pattern of co-movement throughout the sample.

The US Sovereign Debt Downgrade (August 2011). Following the US sovereign downgrade, the ADC reached about 0.70. Since US Treasuries represent a major component of insurers' investment portfolios, the shock affected institutions simultaneously and increased co-movement across the sector (Koijen and Yogo, 2015).

The 2012–2013 Decline. Following the 2011 spike, the ADC declines and, by late 2012 and early 2013, moves closer to the lower end of its sample range, around 0.45–0.50. This phase suggests a temporary reduction in common dependence relative to the preceding stress period.

Hurricanes Harvey, Irma, and Maria, "HIM" (September 2017). The 2017 Atlantic hurricane season is associated with a sharp rise in the ADC to around 0.67–0.68, marking one of the clearest event-related spikes in the US/Bermuda series. Correlations then fall back towards levels closer to the full-sample average.

The COVID-19 Pandemic (March 2020). Mirroring the European experience, the pandemic triggers the highest ADC spike in the US/Bermuda sample, reaching over 0.70 in March 2020. The magnitude is comparable to the HIM event.

Monetary Tightening (2022–2023). As in Europe, the tightening cycle did not increase interconnectedness. Differences in business models led to heterogeneous responses to higher interest rates, contributing to slightly lower correlations during 2023 (Berends et al., 2013).

4.1.3 APAC

Correlation Persistence and Network Structure

The multivariate DCC (1,1) estimation for the APAC network converged successfully. The model yielded an innovation parameter (α) of 0.0131 and a decay parameter (β) of 0.9424, resulting in a sum (α + β = 0.9555) that satisfies the stationarity condition.

Parameter	Value	Interpretation
Innovation (α)	0.0131	Short-term shock impact
Decay (β)	0.9424	Long-term memory/ Persistence
(α + β)	0.9555	High persistence (Stationary)

Table 4: DCC Parameters -APAC

While the network remains stationary, the persistence parameter (β= 0.9424) remains slightly lower than that of the US/Bermuda (0.9528) and Europe (0.9614). This means that after a shock, correlations in the APAC bloc tend to decay somewhat faster. The system

does not stay locked into elevated interconnectedness for quite as long as in the Western blocs.

The mean correlation matrix (Figure 9) shows substantially stronger within-country co-movement than cross-border co-movement across the sampled APAC institutions.

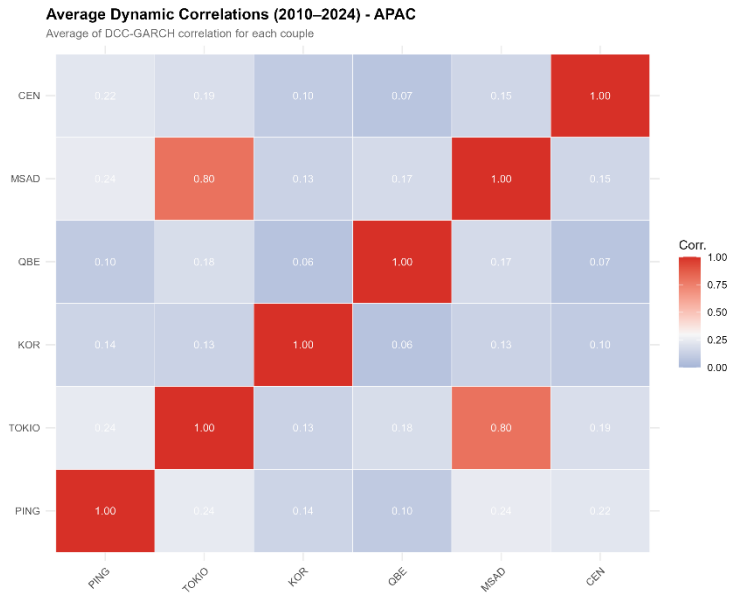

Figure 9: Time-Averaged DCC Correlation Matrix Heatmap -APAC.

Each cell reports the full-sample (2010-2024) average conditional DCC correlation between a pair of six APAC institutions. Diagonal elements equal one. Warmer colours indicate stronger positive co-movement, while cooler colours indicate weaker co-movements.

The highest pairwise correlation in the APAC sample is between the two Japanese integrated insurance groups, Tokio Marine (TOKIO) and MS&AD Insurance (MSAD), at 0.80. This is a domestic effect: they operate in the same market, face the same regulatory environment, and are exposed to similar Japanese macroeconomic conditions. Outside this domestic Japanese pair, correlations drop sharply. The lowest baseline correlation in the network, just 0.06, is between QBE and Korean Re (KOR). This is not surprising: QBE is a globally diversified Australian insurance and reinsurance group with significant P&C exposure with exposure to Lloyd's of London and North American liability risks, while Korean Re is focused almost entirely on the domestic South Korean market. The two firms operate in essentially separate business worlds, and their equity prices reflect completely different sets of drivers (Phylaktis and Ravazzolo, 2005). However, the particularly low cross-border correlations should not be interpreted entirely as economic segmentation, since nonsynchronous closing times across APAC markets may also reduce contemporaneous daily-return correlations.

Dynamic Interconnectedness During Stress Episodes

The Average Dynamic Correlation for the APAC bloc, shown in Figure 10, oscillates around a mean of 0.195, less than one-third of the corresponding European and North American means. This pattern is consistent with a comparatively lower degree of market-based integration among the sampled APAC institutions. For extended periods, the ADC remains between approximately 0.15 and 0.20. The low level of co-movement may reflect heterogeneous national market environments, business models and macroeconomic exposures. At the same time, as discussed in Section 3.1, part of the difference may also reflect nonsynchronous closing times across the underlying equity markets.

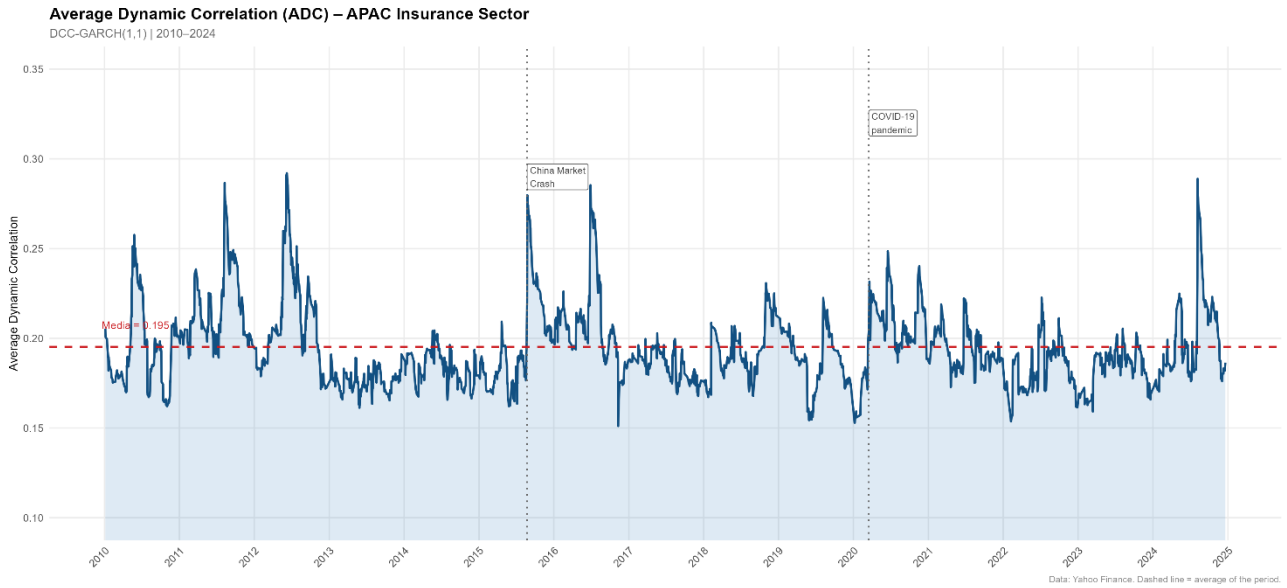

Figure 10: Average Dynamic Correlation (ADC) -APAC.

The blue line reports the daily average of the pairwise DCC correlations among the six APAC institutions over 2010–2024. The red dashed line indicates the full-sample mean ADC, while the dotted vertical lines and labels identify selected stress episodes.

Early 2010–2015. Moderate Baseline Oscillations. During the first part of the sample, the APAC ADC fluctuates mostly around 0.17–0.22, although several temporary increases above 0.25 are visible, particularly between 2010 and 2012. These movements indicate intermittent episodes of stronger regional co-movement rather than a persistently high level of dependence. Some of these fluctuations coincide with periods of heightened global financial uncertainty, including the European sovereign debt crisis, although the correlation dynamics alone cannot identify the precise drivers of individual peaks.

The China Market Crash (August 2015). One of the most visible pre-COVID movements in the APAC ADC coincides with the Chinese equity-market turmoil of August 2015, when the indicator rises sharply to approximately 0.27–0.28 before subsequently declining towards its previous range. A second pronounced increase is visible in mid-2016, reaching a similar magnitude. Given the composition of the APAC sample, the 2015 episode is consistent with a temporary increase in regional market co-movement during the Chinese

equity-market stress. However, the ADC alone does not identify which individual institution was primarily responsible for the increase. Compared with the corresponding European and US/Bermuda dynamics, the episode appears to have been predominantly regional within the present sample rather than associated with a comparable increase in cross-regional interconnectedness.

The COVID-19 Pandemic (Early 2020). The most interesting observation in the APAC ADC during the pandemic is not the magnitude of the spike but its relative restraint. While the European and US/Bermuda ADCs reached about approximately 0.70 during March 2020, the APAC ADC only rose to around 0.23, compared with a full-sample average of about 0.195. The relatively limited increase in ADC may reflect the earlier adjustment of several Asian markets to pandemic-related risks and the heterogeneous business models represented in the sample, which reduced the likelihood of a fully synchronized response (Baker et al., 2020).

Post-2022 Stability and Late-2024 Spike. Following the pandemic period, the APAC ADC generally returns to relatively low levels, fluctuating mainly around 0.17–0.20 during 2022–2024, although several short-lived movements above this range remain visible. The series reaches a local trough close to 0.15 in early 2022 before gradually returning towards its long-run average. A particularly pronounced increase occurs in late 2024, when the ADC rises to approximately 0.28–0.29 before declining again. The precise drivers of this late-sample increase are outside the scope of the present study and are therefore not investigated further.

4.2 Global Dynamic Interconnectedness

The regional analyses provide a detailed picture of each geographical bloc, but systemic risk in the global reinsurance ecosystem is not contained within regions. Market-based co-movements may arise through retrocession chains, shared capital markets, overlapping investment portfolios and common underwriting exposures across continents (Cummins and Weiss, 2014). To capture this global dimension, a unified DCC-GARCH(1,1) model was estimated simultaneously across all 20 institutions and the market factor, treating the sampled listed reinsurance-related groups as a single market-based system.

Given the 20 sampled firms listings across twelve exchanges, from Frankfurt and Zurich to New York, Tokyo and Sydney, only days on which all global markets were simultaneously open were retained, to avoid spurious covariance estimates from asynchronous prices.

4.2.1 Correlation Persistence and Time-Varying Dependence

The global DCC-GARCH model converged successfully. The innovation parameter (α) was estimated at 0.0041, indicating that global correlations react gradually to daily standardized residuals. The low innovation parameter indicates that the estimated global correlation process responds only modestly to recent standardized shocks. The heterogeneous regional and business-model composition of the global sample may contribute to this lower short-run responsiveness, although this interpretation is not tested directly. Conversely, the persistence parameter (β) was extremely high at 0.9764. The sum of these parameters (α +

β = 0.9805) is strictly less than 1 and satisfies the stationarity condition derived by Engle (2002).

The cross-sectional network structure is best visualized through the full-sample time-averaged conditional correlation matrix, presented in Figure 11. Rather than a uniform, borderless web of dependencies, the heatmap reveals a clear block structure that follows geographical and regulatory lines.

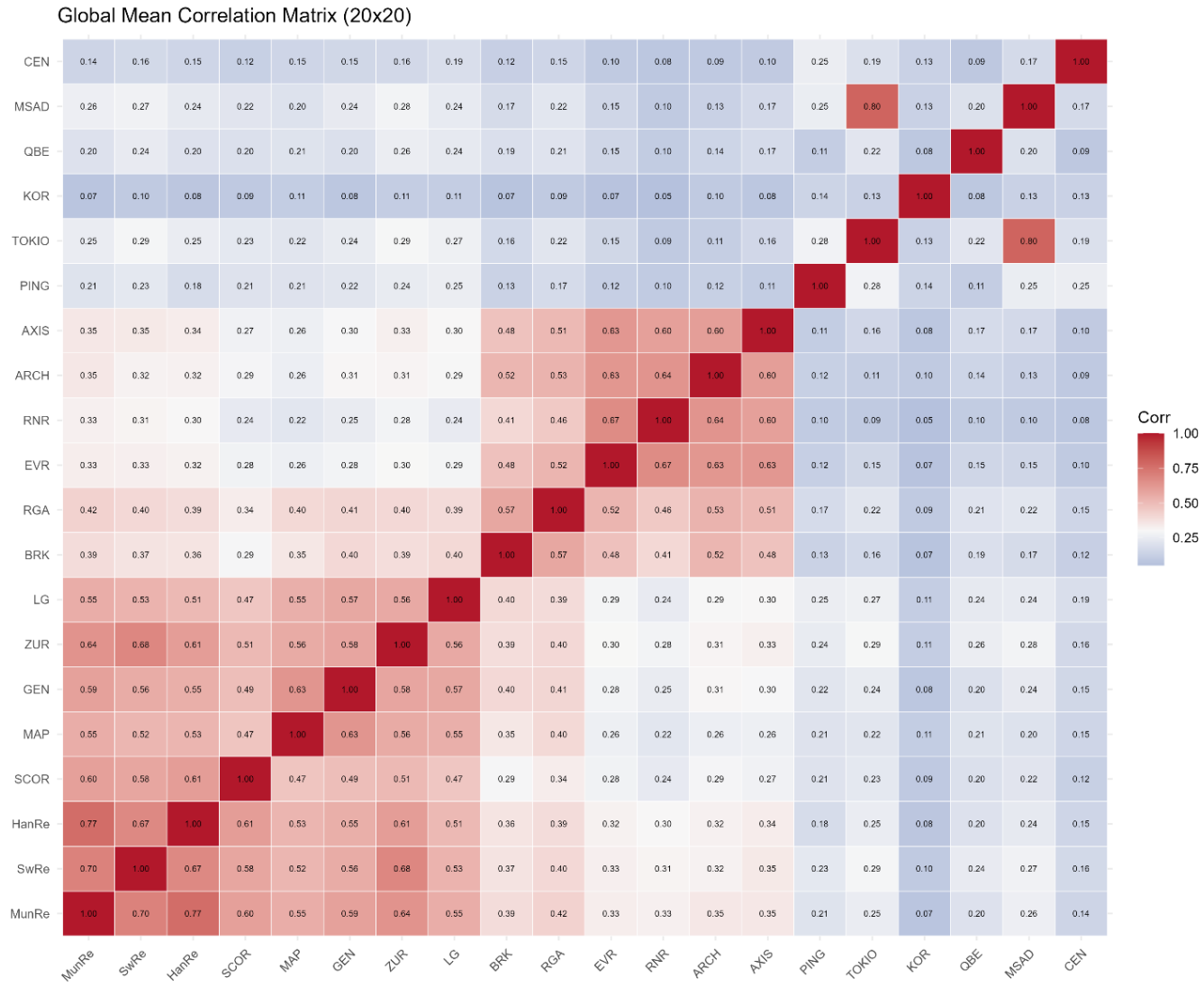

Figure 11: Time-Averaged DCC Correlation Matrix Heatmap -GLOBAL

Each cell reports the full-sample (2010-2024) average conditional DCC correlation between a pair of 20 institutions in the global sample. Diagonal elements equal one. Warmer colours indicate stronger positive co-movement, while cooler colours indicate weaker co-movements.

The European bloc is the most internally integrated, with the Germanic-Swiss core (Munich Re, Hannover Re, Swiss Re) showing average pairwise correlations above 0.70. Their high co-movement may reflect shared exposure to European macro-financial conditions, partly

overlapping supervisory environments, correlated underwriting cycles and other common sectoral factors.

The US/Bermuda bloc shows moderate-to-high internal integration, anchored by the Bermuda catastrophe-oriented segment discussed in Section 3.1. There is also a clear transatlantic link between Europe and the US, for example, Swiss Re and Everest Re average 0.44. This connection may reflect two elements: the integration of Western capital markets, which exposes both regions to common financial shocks, and the shared underwriting exposure to Atlantic hurricane risks and large international liability programs, since European reinsurers actively participate in US catastrophe markets (Froot, 2001).

The APAC region, by contrast, looks like an island in the global network. Most APAC firms show near-zero correlations with European and North American counterparts. Most cross-regional coefficients fall between 0.05 and 0.20. The only significant intra-APAC link is between Tokio Marine and MS&AD (0.80), which is a domestic Japanese effect. The comparatively low measured co-movement of the APAC institutions may indicate potential geographic diversification from a market-risk perspective. However, this result should not be interpreted as evidence of a fixed diversification benefit, particularly given the possible effect of nonsynchronous market closing times and the state dependence of international correlations.

4.2.2 Dynamic Interconnectedness During Stress Episodes

The Global Average Dynamic Correlation (Figure 12) is the cross-sectional mean of all pairwise dynamic correlations across the full 20-institution sample. It oscillates around a mean of 0.302, which is much lower than the European and North American means of 0.557. This is partly because the APAC region's near-zero cross-border correlations pull the global average down. The global ADC is therefore best read not as a measure of how interconnected any specific cluster is, but as a measure of how much global shocks manage to override regional fragmentation (Forbes and Rigobon, 2002; Diebold and Yilmaz, 2012). These cross-regional differences should nevertheless be interpreted with caution, since

contemporaneous daily correlations may also be affected by nonsynchronous market closing times, as discussed in Section 3.1.

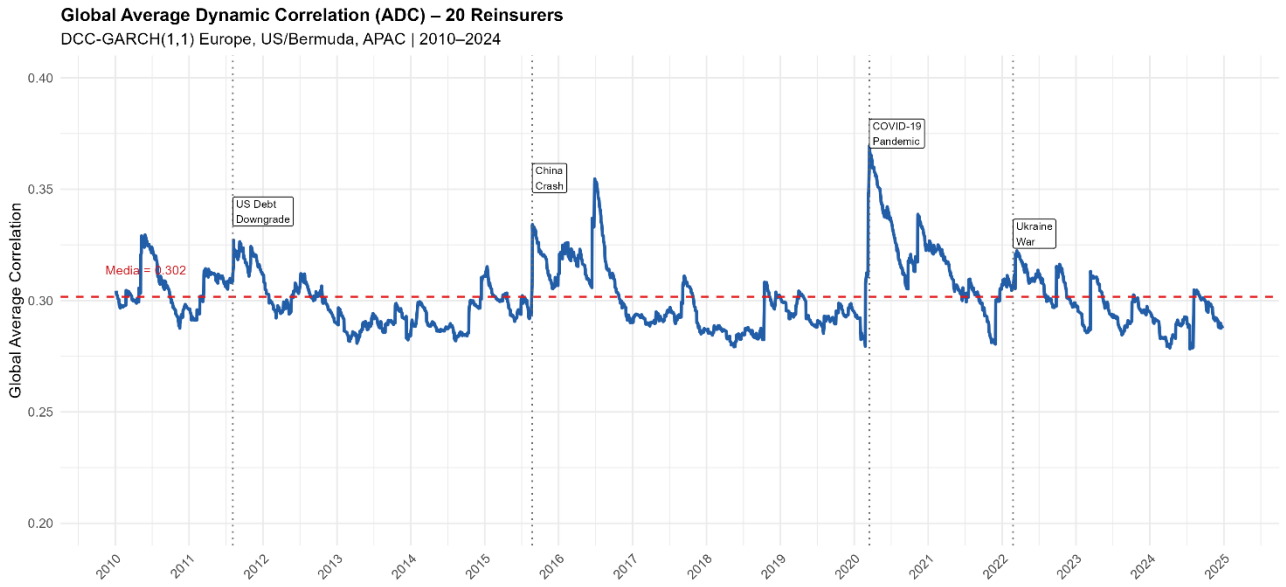

Figure 12: Average Dynamic Correlation (ADC) -Global.

The blue line reports the daily average of the pairwise DCC correlations among the 20 institutions in the global sample over 2010–2024. The red dashed line indicates the full-sample mean ADC, while the dotted vertical lines and labels identify selected stress episodes.

The US Debt Downgrade (August 2011). The first pronounced stress-period increase occurs around August 2011, when the global ADC rises to approximately 0.32. This movement coincides with heightened financial uncertainty surrounding the US sovereign downgrade and the ongoing European sovereign debt crisis, indicating a temporary increase in global insurance-sector co-movement.

The China Market Crash (Mid-2015). The Chinese equity-market turmoil of August 2015 is associated with an increase in the global ADC to approximately 0.33. The response is visible but relatively contained, suggesting some contemporaneous cross-regional co-movement during the episode. A larger, short-lived peak of approximately 0.35 is visible in 2016.

COVID-19 Pandemic (March 2020). The pandemic generates the highest global ADC value in the entire sample, reaching approximately 0.37 in March 2020. Although substantially below the regional peaks observed in Europe and US/Bermuda, the episode represents the strongest increase in global co-movement over 2010–2024. The ADC subsequently declines, while remaining elevated for part of 2020–2021.

The Ukraine War (February 2022). The Ukrainian war caused a short, relatively mild increase to the level of about 0.31-0.32, which is just above its full-sample average. The response is considerably smaller than during COVID-19, suggesting a more limited increase in global co-movement within the sampled institutions.

Post-2022 Normalization. After the 2022 episode, the global ADC generally fluctuates around or below its full-sample average, mostly between approximately 0.28 and 0.31 throughout 2023–2024. Neither the Ukraine-war episode nor the subsequent monetary-

tightening period is associated with a sustained rise in global co-movement, and the ADC gradually returns towards lower levels by the end of the sample.

4.2.3 Regional Differences in Stress-Period Co-Movement

Stress episode	Europe	North America & Bermuda	APAC
Early 2010	Around 0.55, with temporary peaks around 0.64-0.65	Around 0.55-0.60	Moderate oscillations
Sovereign stress/US downgrade, 2011	Around 0.65	Around 0.70	Moderate oscillations
China Market Crash, 2015	Limited effect	Limited effect	Around 0.27-0.28
Hurricanes Harvey, Irma and Maria, 2017	Limited effect	Around 0.67-0.68	Limited effect
COVID-19 Pandemic, 2020	Around 0.72	Above 0.70	Around 0.23
Ukraine War and monetary tightening, 2022–2023	Moderate short-lived increase, followed by lower correlations	No persistent increase	Low and stable

Table 5: Main Stress Episodes and ADC Responses

Overall, the comparison shows that the COVID-19 pandemic is the clearest episode associated with an increase in co-movement across all three regional blocs, making it the strongest common stress episode in the sample. However, the magnitude of the increase was substantially larger in Europe and North America & Bermuda than in APAC. The Asia-Pacific bloc therefore continued to display considerably lower within-region average co-movement than the two Western blocs even during the largest global stress episode in the sample. Other episodes appear more region-specific. Sovereign stress in 2011 coincided with pronounced increases in the European and North American ADCs, whereas no comparable movement is visible in APAC. The Chinese equity-market turmoil of 2015 was associated with a clearer increase in the APAC ADC, while the response in Europe and North America & Bermuda was limited and the corresponding increase in the global ADC remained relatively modest. Similarly, the 2017 Atlantic hurricane season produced a pronounced increase in the North America & Bermuda ADC, without a comparable response in the other two regions. Finally, the Ukraine-war episode generated only a moderate and short-lived increase in European and global co-movement, while the subsequent 2022–2023 monetary-tightening period was not associated with a sustained increase in ADC across the three regional blocs. Overall, these differences are consistent with substantial heterogeneity in regional exposures and business models across the sampled institutions.

4.3 Global ΔCoVaR Results

Building on the dynamic correlation structure estimated above, this section presents the core ΔCoVaR results for the 20 sampled institutions. The analysis distinguishes between two directional measures: Systemic Contribution ($\Delta CoVaR_t^{sys|i}$) and Systemic Vulnerability ($\Delta CoVaR_t^{i|sys}$), as defined in Sections 3.3.4.1 and 3.3.4.2.

The estimates are reported as time-series averages of daily ΔCoVaR values over the full 2010–2024 sample period and are expressed as a percentage of portfolio value. Therefore, the rankings identify the average cross-sectional distribution of Systemic Contribution and Vulnerability across institutions, rather than separate rankings for each individual stress episode. Stress-period dynamics are analysed primarily through the time-varying correlation results in Sections 4.1 and 4.2, while this section focuses on which institutions appear more systemically relevant on average and whether the same firms are relevant in both directions.

A key point is that the two rankings are not symmetric: an institution with a high Systemic Contribution is not necessarily also highly vulnerable to market-wide distress, and vice versa. This distinction allows the analysis to separate institutions that mainly contribute to system-wide risk from those that are mainly exposed when the broader insurance market is under stress.

4.3.1 Systemic Contribution

As for the Systemic Contribution ($\Delta CoVaR_t^{sys|i}$), Figure 13 presents the ranking of all 20 institutions by their average Systemic Contribution color-coded by geographical region.

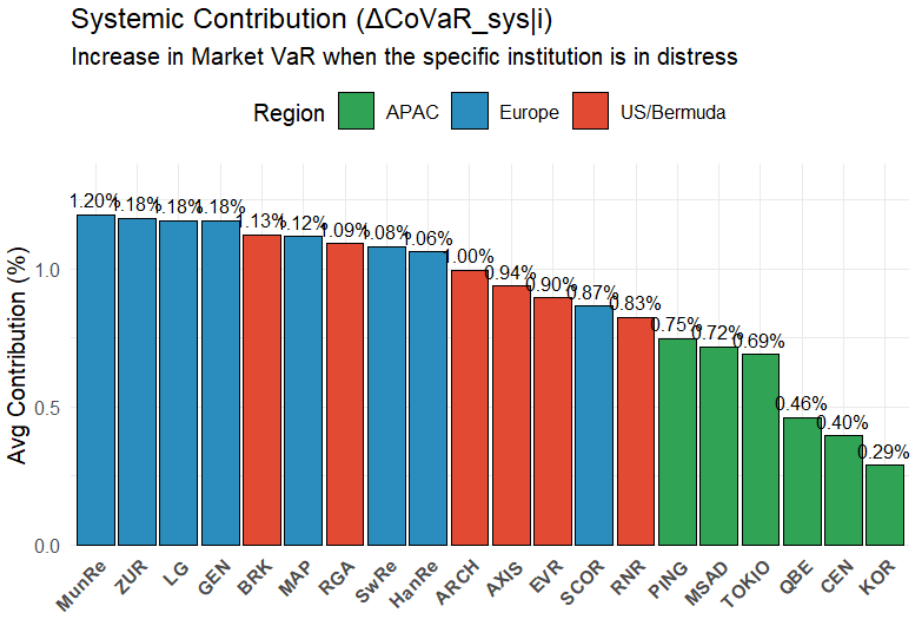

Figure 13: Systemic Contribution -Global Ranking.

Institutions are ranked in descending order according to their full-sample average Systemic Contribution under the baseline q=5% specification with the MSCI ACWI Insurance market factor. Bar labels report the average score in percentage terms; colours identify geographical regions: green for APAC, blue for Europe, red for US/Bermuda

The ranking shows a clear geographical gradient: the top nine positions, with average contributions ranging from about 1.06% to 1.20% of portfolio value, are dominated by European institutions (Munich Re, Zurich, Legal & General, Generali, Mapfre, Swiss Re, Hannover Re), interrupted only by Berkshire Hathaway and RGA among the US/Bermuda carriers. A middle tier, Arch, Axis, Everest, RenaissanceRe and SCOR, follows, with contributions between 0.83% and 1.00%, while the six APAC institutions occupy the bottom of the ranking without exception, with contributions (0.29%-0.75%) substantially below those of the leading European groups. This pattern is consistent with the view that an institution's contribution to systemic risk is driven primarily by interconnectedness and leverage rather than by underwriting size alone (Billio et al., 2012; Bierth et al., 2015), and suggests a prominent role for large, globally diversified European groups within the sample. It is important to note that the results above must be understood in relation to the listed company. It has been noted that some of the firms ranked at the top of the list are not pure reinsurers but rather insurance firms that conduct reinsurance. These firms include Zurich, Legal & General, Generali and Mapfre. It is for this reason that the firms have relatively higher contribution scores.

4.3.2 Systemic Vulnerability

Figure 14 presents the complementary ranking by average Systemic Vulnerability.

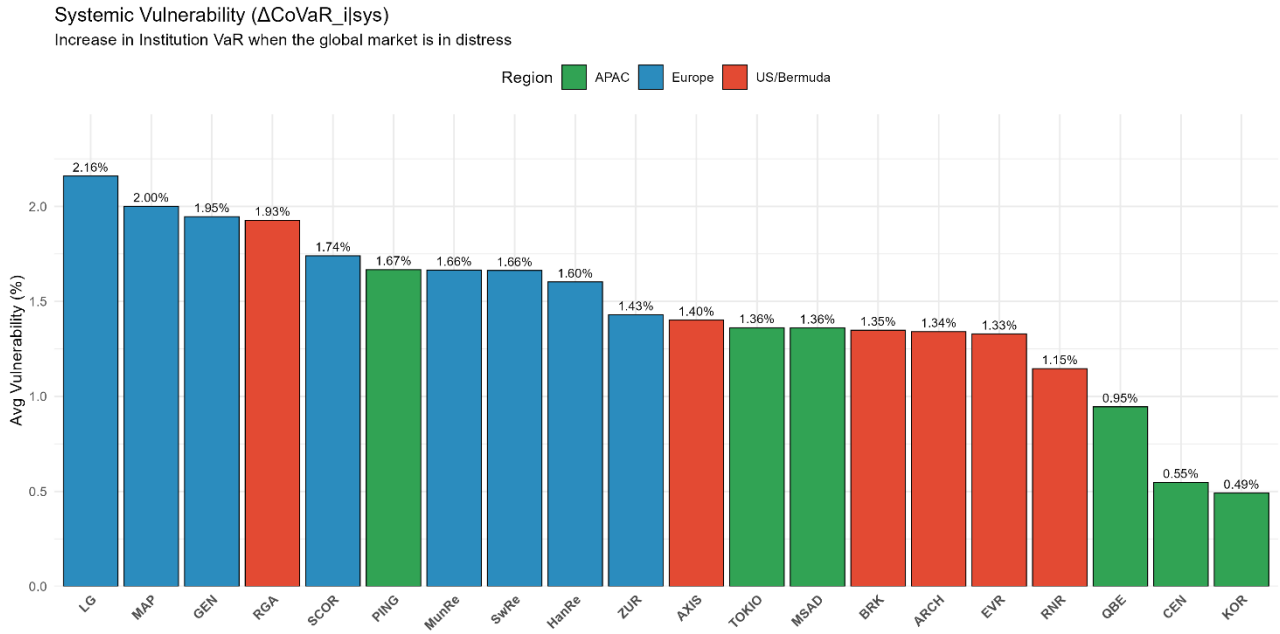

Figure 14: Systemic Vulnerability -Global Ranking.

Institutions are ranked in descending order according to their full-sample average Systemic Vulnerability under the baseline q=5% specification with the MSCI ACWI Insurance market factor. Bar labels report the average score in percentage terms; colours identify geographical regions: green for APAC, blue for Europe, red for US/Bermuda

The distribution is markedly wider, ranging from 0.49% to 2.16%, and while the top positions are again occupied mostly by European and large US/Bermuda institutions (Legal &

General, Mapfre, Generali, RGA, SCOR), the ordering changes substantially for several entities. Most notably, Ping An rises to sixth place despite ranking only fifteenth in Contribution, whereas Zurich and Berkshire Hathaway, respectively second and fifth in the Contribution ranking, fall to tenth and fourteenth place in Vulnerability. With the exception of Ping An, APAC institutions populate the lower half of the ranking, with three of them, QBE, CEN and KOR, occupying the three lowest positions overall. This interpretation is particularly important for diversified groups such as Legal & General, Mapfre, Generali, Zurich, Ping An, Berkshire Hathaway and QBE. For these institutions, the vulnerability ranking captures the sensitivity of the listed group's equity returns to distress in the broader insurance market. It should therefore be read as a group-level market-based measure, rather than as evidence that the reinsurance activity alone drives the result.

4.3.3 Contribution vs Vulnerability: Ranking Differences

Additional insights emerge from reading the two rankings jointly. Table 6 presents both metrics simultaneously for all 20 institutions, enabling a direct comparison of each entity's role as a systemic transmitter versus a systemic receiver of distress.

Institution	Region	Avg Contribution (%)	Contrib. Rank	Avg Vulnerability (%)	Vuln. Rank
MunRe	Europe	1,198413779	1	1,664787949	7
ZUR	Europe	1,184506621	2	1,429568025	10
LG	Europe	1,176606226	3	2,159780919	1
GEN	Europe	1,175188268	4	1,946147085	3
BRK	US/Bermuda	1,125652546	5	1,348461137	14
MAP	Europe	1,118392058	6	2,000602349	2
RGA	US/Bermuda	1,092613947	7	1,926773397	4
SwRe	Europe	1,082495244	8	1,662931631	8
HanRe	Europe	1,063722845	9	1,602817093	9
ARCH	US/Bermuda	0,99722767	10	1,340728142	15
AXIS	US/Bermuda	0,939274709	11	1,402073096	11
EVR	US/Bermuda	0,896514727	12	1,328628598	16
SCOR	Europe	0,867022511	13	1,740099759	5
RNR	US/Bermuda	0,82662003	14	1,146253965	17
PING	APAC	0,748097203	15	1,666880819	6
MSAD	APAC	0,718630437	16	1,360238518	13
TOKIO	APAC	0,691162157	17	1,360980237	12
QBE	APAC	0,462255805	18	0,945251217	18
CEN	APAC	0,396203528	19	0,546789995	19
KOR	APAC	0,289887258	20	0,491559807	20

Table 6: Global ΔCoVaR Rankings

Although the two measures seem to be positively correlated, the ranking is far from identical, confirming Adrian and Brunnermeier's (2016) original distinction between the two directions of ΔCoVaR. Three distinct risk profiles emerge from the joint analysis.

Profile 1) Dual-Risk Entities: High Contribution and High Vulnerability. Generali, Legal & General, Mapfre, and RGA are some of the top seven organizations that fall within the top

seven ranking of ΔCoVaR in both directions. In the case of RGA, all the other organizations are large and integrated insurance companies which also have reinsurance operations; therefore, the interpretation of the results is based on consolidated listed group level. For these organizations, the two directions of systemic risk are consistent, because distress of these organizations is accompanied by higher risk of the global market. This bidirectional pattern is broadly consistent with characteristics commonly associated with systemic importance in the IAIS framework for Global Systemically Important Insurers, and is consistent with Bierth et al.'s (2015) finding that leverage and balance-sheet interconnectedness drive both dimensions of insurer systemic risk jointly.

Profile 2) Size-Driven Transmitters with Moderate Fragility. Berkshire Hathaway, Zurich and Munich Re rank in the top five for Contribution (5th, 2nd and 1st, respectively) but only 14th, 10th and 7th for Vulnerability. These companies belong to diverse forms of institutions, where Munich Re represents reinsurance dominant group, Zurich, large and integrated insurer, while Berkshire Hathaway is a conglomerate having large reinsurance activities. Being located high on the Contribution rating may be explained by the fact that the underwriting and investment activities of these institutions are extensive and globally diversified, and not by the fact that their risk position is risky. Indeed, big and capitalised institutions may demonstrate a relatively high contribution to systemic risk indicators while being moderately vulnerable. This inconsistency can be explained by Weiß and Mühlnickel (2014) finding that the contribution of an insurer to systemic risk depends mostly on size and does not depend on exposure of institution to systemic risk.

Profile 3) Hidden Fragility: Asymmetric Receivers. SCOR and Ping An rank among the top six institutions for Vulnerability while contributing comparatively little to systemic risk (13th and 15th in Contribution, respectively). These institutions appear more exposed to market-wide distress than their Contribution ranking alone would suggest, a pattern that may be overlooked if systemic risk is assessed solely through the contribution dimension. The case of Ping An is particularly relevant because it is a large integrated Chinese insurance group rather than a specialised reinsurer. Its asymmetric vulnerability should therefore be interpreted as a market-based group-level result, partly reflecting its exposure to emerging-market insurance dynamics captured by the MSCI ACWI Insurance Index.

The remaining APAC institutions (QBE, CEN and KOR) rank near the bottom of both dimensions, suggesting a comparatively peripheral position within the sample network.

This joint view allows the 20 firms to be grouped into three distinct profiles. The idea of classifying institutions by their directional role, transmitter, receiver, or both, is grounded in the network topology literature (Billio et al., 2012; Diebold and Yilmaz, 2012) and has been used in a macroprudential context by Benoit et al. (2017), who argue that a single metric cannot capture the full picture of an institution's systemic position.

4.4 Robustness Checks

4.4.1 Alternative Quantile Threshold

As a first robustness check, the baseline 5th-percentile distress threshold is replaced with the 1st percentile, shifting the conditioning event further into the tail while leaving the model specification, market factor, and sample unchanged, so that any difference in results is attributable solely to the more extreme threshold.

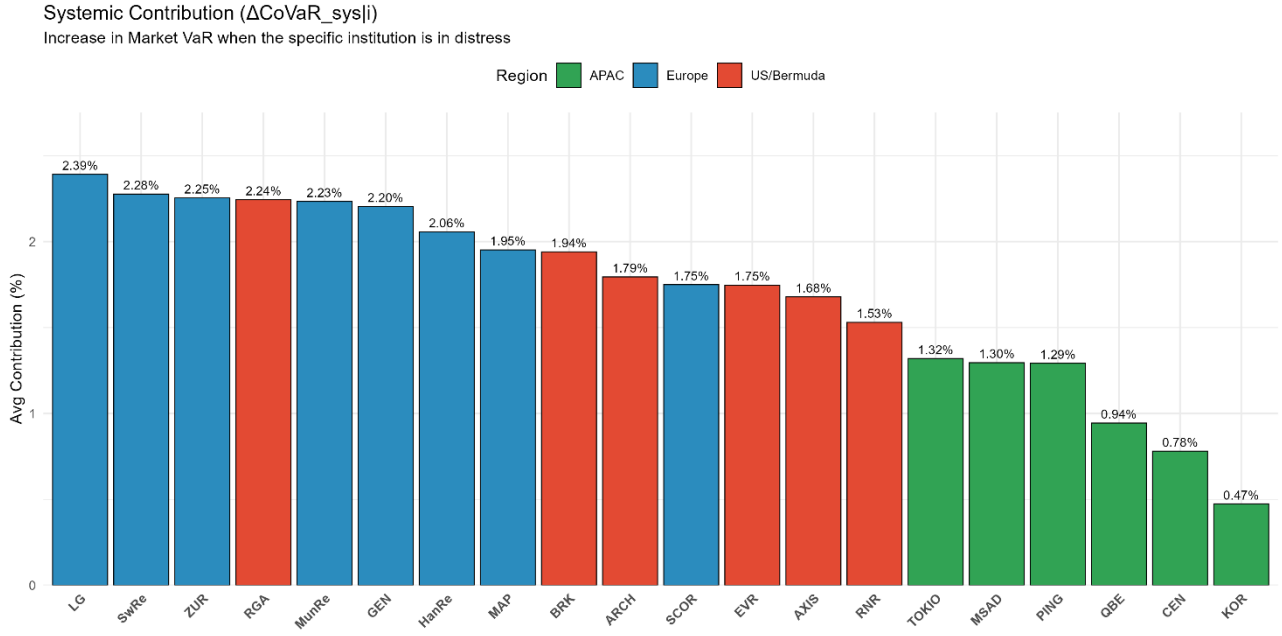

Figure 15: Systemic Contribution -Robustness Check 1 (q=1%).

Ranking of the 20 institutions by average Systemic Contribution after replacing the baseline 5% distress threshold with q=1%, while keeping the remaining baseline specification unchanged. Colours identify geographical regions and bar labels report average scores.

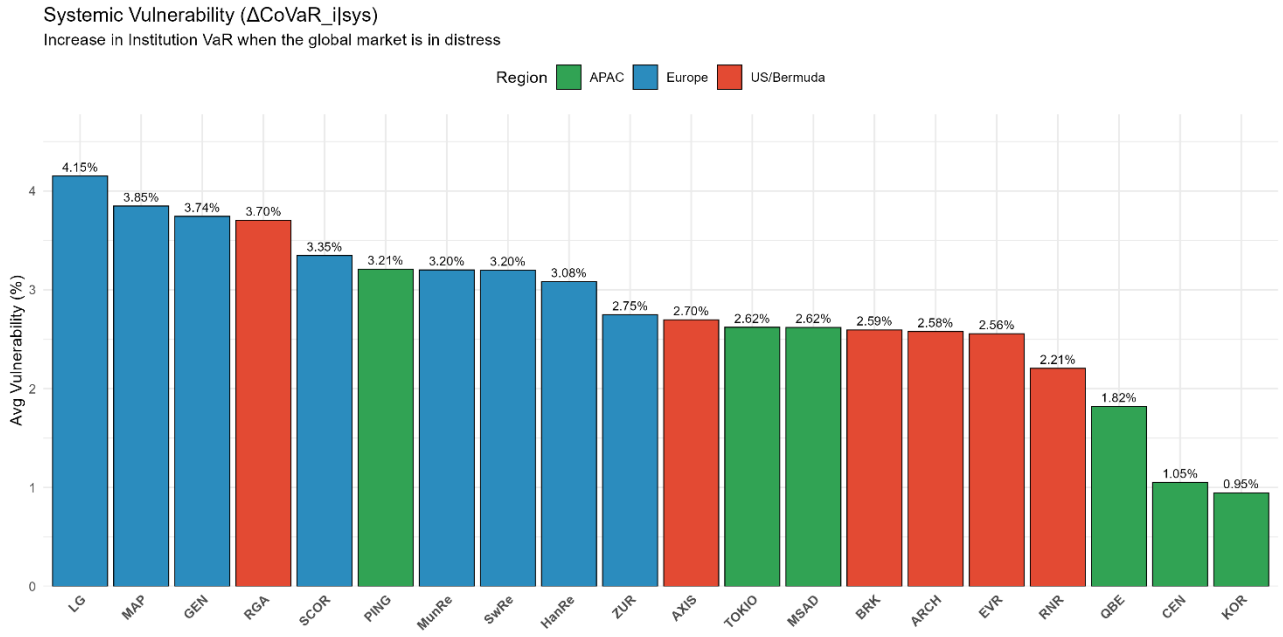

Figure 16: Systemic Vulnerability -Robustness Check 1 (q=1%).

Ranking of the 20 institutions by average Systemic Vulnerability after replacing the baseline 5% distress threshold with q=1%, while keeping the remaining baseline specification unchanged. Colours identify geographical regions and bar labels report average scores.

Figure 15 reports the Systemic Contribution ranking under the q=1% specification. As expected, all estimated values increase in magnitude relative to the baseline; in fact, average contributions now range from 0.47% (KOR) to 2.39% (LG), reflecting the larger market-wide losses associated with a more extreme distress threshold. The composition of the top and bottom segments of the ranking remains largely unchanged: the same ten institutions occupy the top half, including the European listed insurance and reinsurance groups together with Berkshire Hathaway, RGA and Arch, while the same six APAC institutions occupy the bottom six positions. Within the top group, however, the internal ordering shifts somewhat: Munich Re, the leading contributor at q=5%, drops to fifth place, while Legal & General and Swiss Re move up to first and second.

Figure 16 presents the corresponding Systemic Vulnerability ranking. Levels increase even more sharply than for Contribution, from 0.95% (KOR) to 4.15% (LG), and, unlike the Contribution ranking, the ordering of institutions is identical to the q=5% baseline at every single position, from Legal & General at the top to Korean Re at the bottom.

More importantly for the robustness assessment, the ranking structure is largely preserved, providing support for the stability of the main findings. Table 7 compares the institution-level rankings under both specifications.

Rank	Contribution q = 5%	Contribution q = 1%	Vulnerability q = 5%	Vulnerability q = 1%
1	MunRe (1.20)	LG (2.39)	LG (2.16)	LG (4.15)
2	ZUR (1.18)	SwRe (2.28)	MAP (2.00)	MAP (3.85)
3	LG (1.18)	ZUR (2.25)	GEN (1.95)	GEN (3.74)
4	GEN (1.18)	RGA (2.24)	RGA (1.93)	RGA (3.70)
5	BRK (1.13)	MunRe (2.23)	SCOR (1.74)	SCOR (3.35)
6	MAP (1.12)	GEN (2.20)	PING (1.67)	PING (3.21)
7	RGA (1.09)	HanRe (2.06)	MunRe (1.66)	MunRe (3.20)
8	SwRe (1.08)	MAP (1.95)	SwRe (1.66)	SwRe (3.19)
9	HanRe (1.06)	BRK (1.94)	HanRe (1.60)	HanRe (3.08)
10	ARCH (1.00)	ARCH (1.79)	ZUR (1.43)	ZUR (2.75)
11	AXIS (0.94)	SCOR (1.75)	AXIS (1.40)	AXIS (2.70)
12	EVR (0.90)	EVR (1.75)	TOKIO (1.36)	TOKIO (2.62)
13	SCOR (0.87)	AXIS (1.68)	MSAD (1.36)	MSAD (2.62)
14	RNR (0.83)	RNR (1.53)	BRK (1.35)	BRK (2.59)
15	PING (0.75)	TOKIO (1.32)	ARCH (1.34)	ARCH (2.58)
16	MSAD (0.72)	MSAD (1.30)	EVR (1.33)	EVR (2.56)
17	TOKIO (0.69)	PING (1.29)	RNR (1.15)	RNR (2.21)
18	QBE (0.46)	QBE (0.94)	QBE (0.95)	QBE (1.82)
19	CEN (0.40)	CEN (0.78)	CEN (0.55)	CEN (1.05)
20	KOR (0.29)	KOR (0.47)	KOR (0.49)	KOR (0.95)

Table 7: Baseline VS Robustness Check 1

Table 7 compares the two specifications directly. The Vulnerability ranking is perfectly preserved: every institution retains exactly its baseline rank. This result is consistent with what the regression-based construction of ΔCoVaR implies: Systemic Vulnerability depends on the market's own distress quantile, which is common to all 20 institutions, while each institution's loading on the market (its time-varying correlation and volatility) is unaffected by the choice of q. For the present case study, adjusting the quantile of market distress would simply rescale the estimates of all institutions by a constant factor without affecting the order. The Systemic Contribution measure, however, relies upon the quantile of each institution, which may have its own tail distribution; hence, the factor would be different for each institution (from 1.6 to 2.1 in this case). Despite the variations in the scaling factor, however, the rearrangement of institutions remains limited to a few institutions in the middle of the ranking; in other words, the top and bottom halves of the ranking remain intact and the movement of only three institutions, Swiss Re, Munich Re and Berkshire Hathaway, exceeds three positions in the list. Overall, the results in Table 7 support the robustness of the baseline findings: moving to a more extreme 1% distress threshold raises the magnitude of systemic risk uniformly, consistent with the heavier-tailed conditioning event underlying the GARCH-based CoVaR framework (Girardi and Ergün, 2013), but leaves the identification of the institutions with the highest ΔCoVaR values, and in particular the prominent position of the European cluster, essentially unchanged.

4.4.2 Alternative Market Index

The second robustness check replaces the MSCI ACWI Insurance Index with the MSCI World Insurance Index to assess whether the results depend on the inclusion of emerging-market insurers in the market factor. The main ranking structure remains stable, but the test

is economically informative because it changes the reference system against which vulnerability and contribution are measured.

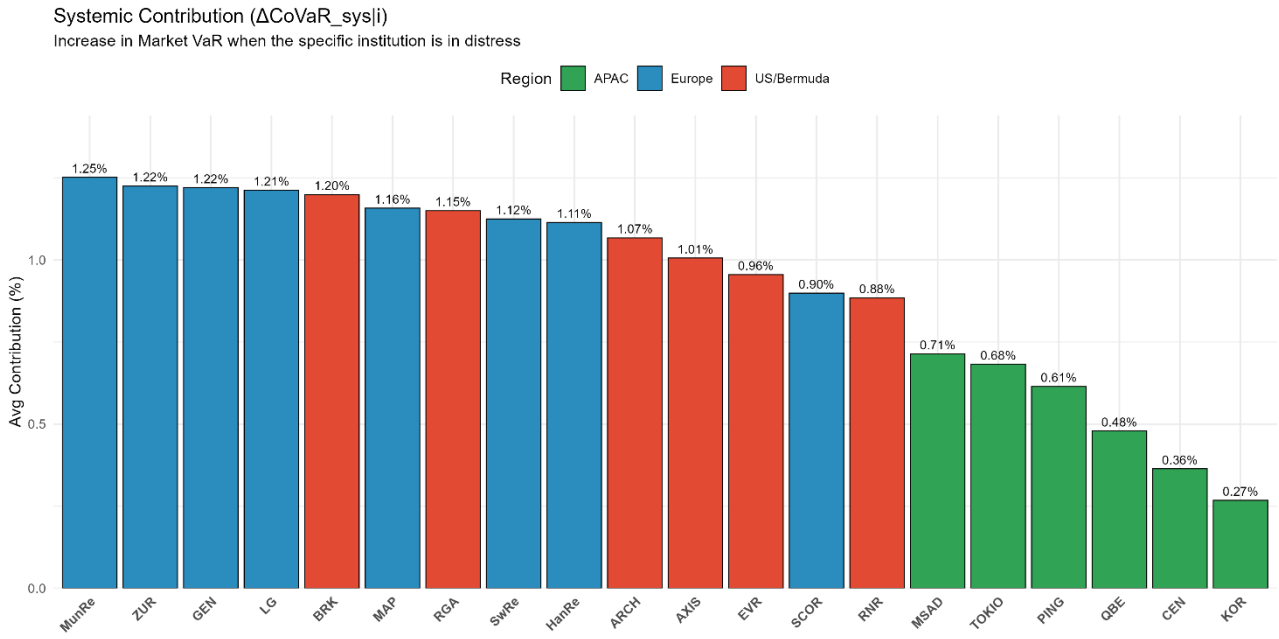

Figure 17: Systemic Contribution -Robustness Check 2.

Ranking of the 20 institutions by average Systemic Contribution after replacing the baseline MSCI ACWI Insurance market factor with the MSCI World Insurance Index. Colours identify geographical regions and bar labels report average scores.

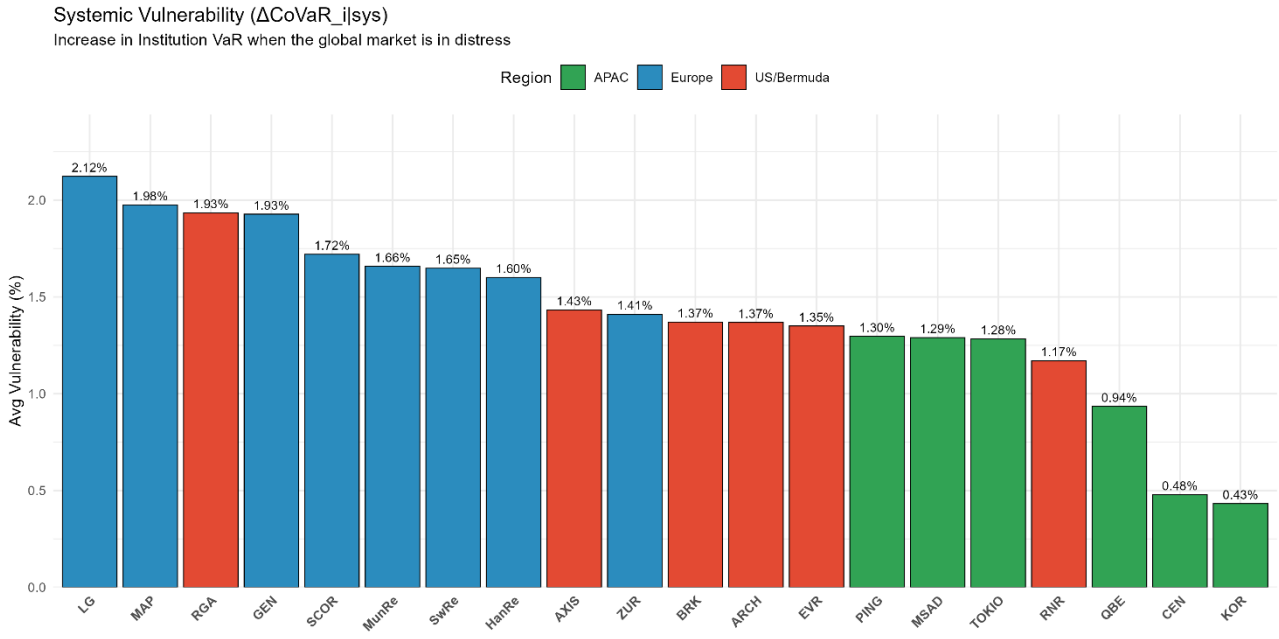

Figure 18: Systemic Vulnerability -Robustness Check 2.

Ranking of the 20 institutions by average Systemic Vulnerability after replacing the baseline MSCI ACWI Insurance market factor with the MSCI World Insurance Index. Colours identify geographical regions and bar labels report average scores.

Figure 17 reports the Systemic Contribution ranking under the MSCI World specification. The estimates themselves change by little from their baselines; the average contribution is now between 0.27% (KOR) and 1.25% (MunRe), down from 0.29%-1.20% in the baseline case. This makes sense from a theoretical perspective, since by reducing the reference set of insurance companies to those from developed markets we are reducing some of the idiosyncratic variance that was present in the market variable in the baseline case, making it more likely that the contribution estimate of the remaining, mostly developed-market institutions will be higher. The rankings remain largely unchanged; MunRe remains 1, ZUR 2, GEN and LG switching places 3 and 4.

Figure 18 displays the Systemic Vulnerability ranking for the scenario. The results are equally stable; LG remains first (2.12% vs. 2.16% baseline), MAP remains second (1.97% vs. 2.00%), and GEN/RGA again switch third and fourth (1.93% each under both specifications). SCOR, MunRe, SwRe, and HanRe maintain their positions in the top eight. The most notable deviation is PING, which declines from rank 6 under the baseline (1.67%) to rank 14 under the MSCI World specification (1.30%), a drop of eight positions. This shift is interpretable: PING An's vulnerability under the baseline partly reflects its co-movement with the emerging-market insurance dynamics captured by the ACWI; once the reference system is restricted to developed markets, that channel of vulnerability is attenuated, consistent with the dependence of the covariance-based measures on the choice of conditioning market (Forbes and Rigobon, 2002).

Table 8 compares the institution-level ranking under both specifications directly.

Rank	Contribution (Baseline, MSCI ACWI)	Contribution (MSCI World)	Vulnerability (Baseline, MSCI ACWI)	Vulnerability (MSCI World)
1	MunRe (1.20%)	MunRe (1.25%)	LG (2.16%)	LG (2.12%)
2	ZUR (1.18%)	ZUR (1.22%)	MAP (2.00%)	MAP (1.97%)
3	LG (1.18%)	GEN (1.22%)	GEN (1.95%)	RGA (1.93%)
4	GEN (1.18%)	LG (1.21%)	RGA (1.93%)	GEN (1.93%)
5	BRK (1.13%)	BRK (1.20%)	SCOR (1.74%)	SCOR (1.72%)
6	MAP (1.12%)	MAP (1.16%)	PING (1.67%)	MunRe (1.66%)
7	RGA (1.09%)	RGA (1.15%)	MunRe (1.66%)	SwRe (1.65%)
8	SwRe (1.08%)	SwRe (1.12%)	SwRe (1.66%)	HanRe (1.60%)
9	HanRe (1.06%)	HanRe (1.11%)	HanRe (1.60%)	AXIS (1.43%)
10	ARCH (1.00%)	ARCH (1.07%)	ZUR (1.43%)	ZUR (1.41%)
11	AXIS (0.94%)	AXIS (1.00%)	AXIS (1.40%)	BRK (1.37%)
12	EVR (0.90%)	EVR (0.95%)	TOKIO (1.36%)	ARCH (1.37%)
13	SCOR (0.87%)	SCOR (0.90%)	MSAD (1.36%)	EVR (1.35%)
14	RNR (0.83%)	RNR (0.88%)	BRK (1.35%)	PING (1.30%)
15	PING (0.75%)	MSAD (0.71%)	ARCH (1.34%)	MSAD (1.29%)
16	MSAD (0.72%)	TOKIO (0.68%)	EVR (1.33%)	TOKIO (1.28%)
17	TOKIO (0.69%)	PING (0.61%)	RNR (1.15%)	RNR (1.17%)
18	QBE (0.46%)	QBE (0.48%)	QBE (0.95%)	QBE (0.93%)
19	CEN (0.40%)	CEN (0.36%)	CEN (0.55%)	CEN (0.48%)
20	KOR (0.29%)	KOR (0.27%)	KOR (0.49%)	KOR (0.43%)

Table 8: Baseline VS Robustness Check 2

This methodological property is well-documented in the financial stability literature. Girardi and Ergün (2013), who pioneered the DCC-GARCH estimation of CoVaR adopted in this study, execute an analogous robustness exercise across alternative market proxies. They confirm that systemic rankings shift when the reference index changes, concluding that this variation is an expected, interpretable feature of the conditional CoVaR framework rather than a sign of parametric instability. From a topological perspective, Billio et al. (2012) show that measures of systemic importance depend on the structure of the financial network under consideration; a financial institution acting as a core systemically important hub within a specific regional system may not necessarily maintain that status on a global scale. Furthermore, Forbes and Rigobon (2002) show that covariance-based measures of financial integration are inherently sensitive to the choice of conditioning variables. Taken together, these foundational insights suggest that the market factor sensitivity documented here should therefore be viewed as an economically informative feature of the model: it provides strong evidence that the choice of reference system constitutes a substantive modelling decision with important economic implications, rather than a neutral, purely technical exercise.

The first two robustness checks lead to a common conclusion. Changing the distress threshold from 5% to 1% increases the magnitude of the ΔCoVaR estimates, as expected, but has only a limited effect on the ranking of institutions. Similarly, replacing the MSCI ACWI Insurance Index with the MSCI World Insurance Index produces some changes in the estimated values and in the position of a few firms, most notably Ping An, while leaving the overall structure of the rankings largely intact. In both exercises, the institutions identified as the main contributors to systemic risk remain concentrated within the European insurance cluster. Overall, the results suggest that the baseline findings are not driven by a particular choice of distress quantile or market factor and therefore provide a consistent picture of market-based systemic risk within the global reinsurance ecosystem, interpreted at the level of listed insurance and reinsurance groups.

4.4.3 Alternative Distributional Assumption

As a third robustness check, the baseline Student-t innovation assumption is replaced with Gaussian innovations. The purpose of this exercise is to assess whether the ΔCoVaR rankings are sensitive to the distributional assumption used in the DCC-GARCH estimation. The sample, time period, market factor, GARCH(1,1)-DCC(1,1) specification and 5% distress threshold are kept unchanged. The Student-t specification remains the preferred baseline model because financial returns typically exhibit excess kurtosis and heavier tails than the normal distribution. The Gaussian model is therefore used only as a benchmark alternative, not as a replacement for the main specification.

The Gaussian specification also has a methodological role in relation to the construction of the systemic-risk measures. Under conditional Gaussianity, the conditional variance does not depend on the realised conditioning value, and the covariance-based GARCH ΔCoVaR representation has the closed form derived by Adrian and Brunnermeier (2016). The comparison with the Student-t baseline therefore provides an indirect robustness assessment of whether allowing for heavy-tailed DCC innovations, while retaining the covariance-based operational score, materially changes the relative systemic-risk rankings. It should not be interpreted as validating the approximation exactly under Student-t, but

rather as testing whether the main cross-sectional conclusions are sensitive to the distributional specification.

Institution	Contribution Student-t	Rank Student-t	Contribution Gaussian	Rank Gaussian	Rank change
MunRe	1.198	1	1.206	1	0
ZUR	1.185	2	1.180	4	2
LG	1.177	3	1.183	3	0
GEN	1.175	4	1.203	2	-2
BRK	1.126	5	1.118	6	1
MAP	1.118	6	1.114	7	1
RGA	1.093	7	1.112	8	1
SwRe	1.082	8	1.120	5	-3
HanRe	1.064	9	1.076	9	0
ARCH	0.997	10	0.988	10	0
AXIS	0.939	11	0.956	11	0
EVR	0.897	12	0.920	12	0
SCOR	0.867	13	0.864	13	0
RNR	0.827	14	0.834	14	0
PING	0.748	15	0.781	15	0
MSAD	0.719	16	0.715	16	0
TOKIO	0.691	17	0.694	17	0
QBE	0.462	18	0.477	18	0
CEN	0.396	19	0.388	19	0
KOR	0.290	20	0.289	20	0

Table 9: Student-t vs Gaussian per Contribution

The Contribution ranking is highly stable across the two distributional assumptions. Munich Re continues to be the biggest contributor under both versions, but Zurich, Legal & General and Generali continue to stay in the top four as well. The only shifts that occur relate to shuffling inside the group of the best-ranked European contributors: Generali shifts from fourth place to second one, Zurich shifts from the second place to fourth one, and Swiss Re shifts from eighth place to fifth one.

Institution	Vulnerability Student-t	Rank Student-t	Vulnerability Gaussian	Rank Gaussian	Rank change
LG	2.160	1	2.119	1	0
MAP	2.001	2	1.971	2	0
GEN	1.946	3	1.892	4	1
RGA	1.927	4	1.893	3	-1
SCOR	1.740	5	1.763	5	0
PING	1.667	6	1.592	8	2
MunRe	1.665	7	1.625	6	-1
SwRe	1.663	8	1.622	7	-1
HanRe	1.603	9	1.576	9	0
ZUR	1.430	10	1.421	10	0
AXIS	1.402	11	1.362	11	0
TOKIO	1.361	12	1.358	12	0
MSAD	1.360	13	1.345	13	0
BRK	1.348	14	1.338	14	0

ARCH	1.341	15	1.308	15	0
EVR	1.329	16	1.294	16	0
RNR	1.146	17	1.132	17	0
QBE	0.945	18	1.022	18	0
CEN	0.547	19	0.532	19	0
KOR	0.492	20	0.481	20	0

Table 10: Student-t vs Gaussian per Vulnerability

The Vulnerability ranking is even more stable than the Contribution ranking. Legal & General and Mapfre remain the two most vulnerable institutions under both specifications, while Generali and RGA only exchange third and fourth position. SCOR remains fifth, and the bottom part of the ranking is virtually unchanged. The only noticeable movement is Ping An, which declines from sixth to eighth place under the Gaussian benchmark, although it remains in the upper half of the Vulnerability ranking.

Ranking comparison	**Spearman ρ**	**p-value**
Contribution ranking	0.985	<0.001
Vulnerability ranking	0.994	<0.001

Table 11: Ranking Spearman Comparison

The Spearman rank correlations confirm the high stability of the rankings across distributional assumptions. The coefficient is 0.985 for Systemic Contribution and 0.994 for Systemic Vulnerability, with p-values below 0.001 in both cases. This indicates that the switch from Student-t to Gaussian innovations does not materially affect the ordering of institutions by systemic relevance.

In addition to the ranking comparison, Table 12 reports the model-fit statistics for the baseline Student-t specification and the Gaussian benchmark. This comparison is useful because the Gaussian model is not intended to replace the baseline specification, but to assess whether the main results are robust to an alternative distributional assumption. The Student-t model achieves a higher log-likelihood and lower AIC and BIC values than the Gaussian benchmark, even though it includes a larger number of estimated parameters. This supports the use of the Student-t specification as the preferred baseline model.

Model	Log-likelihood	AIC	BIC
Student-t	177695	-355173	-354534
Gaussian	172900	-345628	-345119

Table 12: Model Fit Comparison: Student-t vs Gaussian

The model-fit comparison therefore confirms that the Student-t specification provides a better statistical fit than the Gaussian benchmark. This is consistent with the use of Student-t innovations in the baseline model, since financial return series are typically characterised by excess kurtosis and heavier tails than the normal distribution.

Overall, the Gaussian benchmark supports the robustness of the baseline results. The distributional assumption affects the estimated ΔCoVaR values to some extent, but it does not substantially alter the identification of the most systemically relevant institutions.

Moreover, the leading entities from the Contribution ranking still include the European insurance companies and reinsurers, with the first place still taken by Munich Re. Likewise, the leading companies of the Vulnerability ranking still include Legal & General, Mapfre, Generali, RGA and SCOR. At the same time, according to the model fit comparison, the Student-t specification is preferred to the Gaussian benchmark, being characterized by higher log-likelihood and lower information criteria. This means that the Student-t assumption makes the statistical fit of the model better, while the identification of the institutions with higher market-based systemic-risk scores is consistent under the Gaussian specification. In conclusion, the model-fit comparison supports the Student-t specification as the preferred innovation distribution for the DCC-GARCH estimation, as it achieves a substantially higher log-likelihood and lower AIC and BIC values than the Gaussian benchmark. At the same time, the very high rank correlations between the Student-t and Gaussian specifications show that the main cross-sectional conclusions are not materially affected by the choice between the two distributions. This second result is particularly informative because the covariance-based beta-times-VaR representation has an exact closed-form interpretation under the Gaussian GARCH benchmark of Adrian and Brunnermeier (2016), whereas under Student-t innovations it is used as an operational approximation because the conditional scale is state-dependent. Thus, the Gaussian robustness exercise does not validate the Student-t approximation analytically, but it shows that the resulting institutional rankings remain virtually unchanged under the distributional case in which the covariance-based representation is theoretically more direct.

CHAPTER 5

Network Structure of the Global Reinsurance Ecosystem

5.1 Correlation Networks

The DCC-GARCH and ΔCoVaR analyses are powerful tools for studying bilateral financial dependencies and institution-level systemic risk, but they have a structural limitation: they describe pairs of firms or individual nodes in isolation, without providing a view of the network as a whole. A global reinsurance ecosystem composed of 20 listed institutions involves not two but many pairwise statistical relationships simultaneously, and the market-based relevance of a shock may depend on how strongly institutions co-move, which firms occupy central positions in the correlation structure, how tightly clusters are linked, and where structural bottlenecks appear in the estimated network. To answer these questions, this chapter moves from bilateral analysis to a network theoretic framework.

The application of network theory to financial systems has a well-established academic foundation. Allen and Gale (2000) show that the topology of inter-firm connections can shape the way financial shocks are absorbed or amplified within a system. Billio et al. (2012) extend this insight empirically by showing that financial connectedness can provide useful information about systemic fragility, while Diebold and Yilmaz (2012) show that network-based connectedness measures capture dimensions of systemic risk that bilateral measures alone may miss. In the reinsurance context, network analysis is particularly useful because institutions may be linked through several economic channels, including retrocession agreements, quota shares, co-insurance arrangements, common underwriting exposures and overlapping investment portfolios. However, the empirical network constructed in this chapter is based exclusively on equity-return correlations. Retrocession and other contractual data are not observed, and any reference to these relationships is therefore interpreted only as a possible economic explanation for the observed statistical pattern, not as a direct measurement of contractual exposure.

From Correlation Matrix to Network

The empirical input to the network analysis is the full-sample time-averaged conditional correlation matrix $\bar{R}$, computed by averaging the daily conditional correlation matrix R_t from the global DCC-GARCH model over the full 2010–2024 sample:

$$\bar{\rho}_{i,j} = \frac{1}{T}\sum_{t=1}^{T} \rho_{ij.t} \tag{3.29}$$

This 20×20 matrix is used as the weighted adjacency matrix of the network: each of the 20 institutions is a node, and each pairwise average correlation defines the weight of the edge

between two nodes. Before including an edge, each correlation is tested for statistical significance using the Pearson t-statistic (see Section 3.4.2), and only edges with p-value < 0.05 are retained. This filters out weaker and statistically insignificant correlations, so that the network topology reflects statistically supported equity-return co-movements rather than sampling variability.

The resulting full weighted network is shown in Figure 19. In the figure, node color denotes Louvain community membership, while node size is proportional to each institution's ΔCoVaR Contribution as estimated in Chapter 4. The form of the node differentiates between the institutions categorized as Dual-Risk and those having a Standard category of risks, as defined in Section 4.3.3, while the thickness of the line shows the average of the DCC correlations for the particular pairing of institutions, meaning that thick lines signify strong and persistent correlations. From the graph alone one can readily appreciate the structural segregation found in the DCC correlation study in Chapter 4: a core of well-connected Western including all the European and US/Bermuda institutions and an APAC periphery in which most of the firms have limited statistical links with the core.

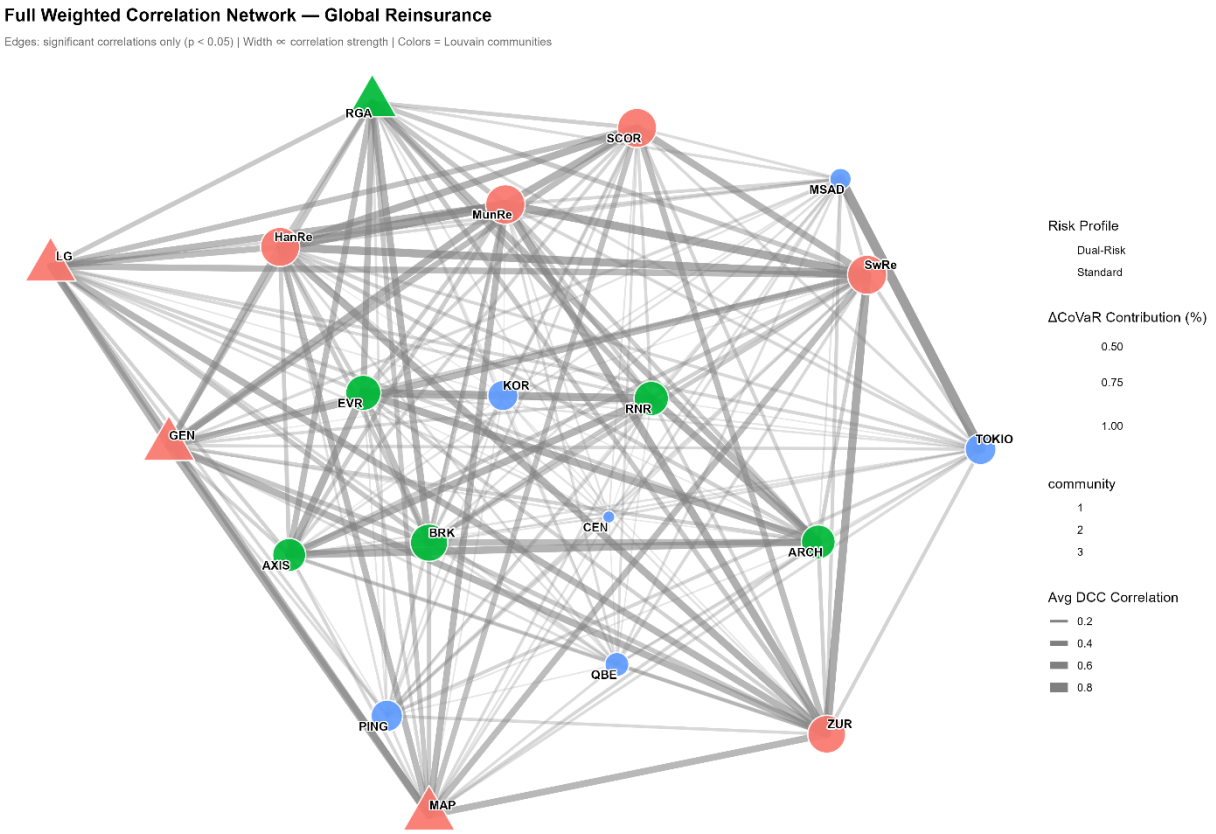

Figure 19: Full Weighted Correlation Network.

Nodes represent the institutions in the global sample, while edges represent statistically significant (p<0.05) full-sample time-averaged DCC correlations. Node colours identify the Louvain communities: red denotes Community 1, blue Community 2, and green Community 3. Node size is proportional to average Systemic Contribution, while edge thickness increases with correlation strength. Triangles identify Dual-Risk institutions, characterised by high Systemic Contribution and Vulnerability, whereas circles identify the remaining Standard-profile institutions. Edges represent statistical equity-return dependence rather than contractual reinsurance relationships.

Two centrality metrics are computed for each node: Node Strength and Betweenness Centrality, as described in Section 3.4.2. The full results are presented in Table 13.

Company	Region	Strength	Betweenness
MunRe	Europe	7,7221	0
SwRe	Europe	7,6125	0,0292
ZUR	Europe	7,5077	0,0526
HanRe	Europe	7,3763	0
GEN	Europe	7,0493	0
LG	Europe	6,9531	0,0351
RGA	US/Bermuda	6,8299	0,0468
MAP	Europe	6,6684	0
SCOR	Europe	6,4885	0
BRK	US/Bermuda	6,2691	0
AXIS	US/Bermuda	6,1032	0
ARCH	US/Bermuda	6,0703	0,0175
EVR	US/Bermuda	6,0582	0
RNR	US/Bermuda	5,4706	0
TOKIO	APAC	4,5713	0
MSAD	APAC	4,4408	0
PING	APAC	3,5355	0
QBE	APAC	3,4203	0
CEN	APAC	2,6858	0
KOR	APAC	1,8077	0

Table 13: Network Centrality Metrics

Strength centrality shows a clear regional hierarchy in the network. The first five positions are all taken by European institutions: Munich Re is in first place with a strength of 7.722, followed by Swiss Re (7.613), Zurich Insurance (7.508), Hannover Re (7.376), and Assicurazioni Generali (7.049). The US/Bermuda group is in the middle range, with RGA as the most connected North American firm, reaching a value of 6.830. The APAC companies have clearly lower values of strength: Korean Re is at the bottom with 1.808. This trend appears economically feasible since the European cluster encompasses both specialised or reinsurance-focused firms, as well as big conglomerates with insurance operations and reinsurance activities. Their high strengths may be explained by partly overlappinginvestment exposures, similar business cycles and greater integration of markets in Europe. Also, some business connections like retrocession may have an effect on this trend, although they do not play any role in the network built on correlations. These factors should therefore be interpreted as plausible explanations for the higher equity-return correlations observed among European institutions, not as directly tested transmission channels.

Betweenness centrality gives a more focused picture of the network structure. Fifteen out of twenty firms have a betweenness value equal to zero, meaning they do not lie on the shortest paths between other nodes. Only five firms display a positive betweenness value, suggesting a potential bridging role in the network: Zurich Insurance (0.053), RGA (0.047), Legal & General (0.035), Swiss Re (0.029), and Arch Capital (0.018). The fact that all positive values are concentrated in just a few nodes suggests a hub-and-spoke structure

rather than a more evenly connected network (Billio et al., 2012). In other words, the results suggest that a large share of shortest path connections is concentrated in a small number of intermediary nodes.

An interesting result in this section is Zurich Insurance's position. Zurich Insurance's network position is complementary to, rather than an independent confirmation of, the Chapter 4 results: ZUR is already the second highest institution in terms of ΔCoVaR Contribution (1.18%). The network analysis also identifies Zurich Insurance as the node with the highest betweenness centrality, suggesting a potentially important position in the network structure. As will be discussed in Section 5.2, ZUR occupies a bridging position between the European cluster and the APAC region in the correlation-based network. The MST results indicate that ZUR lies on the main path linking the APAC firms to the European core within this statistical representation. Therefore, changes in its correlation profile could potentially be associated with changes in the overall connectivity between these regions in the estimated network. In a similar way, RGA's betweenness value of 0.047 reflects its structural position as the main bridging node between the European and US/Bermuda clusters in the correlation network, a result that is also clearly visible in the MST analysis in Section 5.2.

Community Structure

The Louvain community detection algorithm, applied to the significant correlation network with DCC correlation coefficients as edge weights, identifies three communities and yields a modularity score of Q = 0.0953 (Blondel et al., 2008).

Community	Member Firms
1	MunRe, SwRe, HanRe, SCOR, GEN, LG, MAP, ZUR
2	BRK, ARCH, RGA, EVR, RNR, AXIS
3	PING, TOKIO, KOR, QBE, MSAD, CEN

Table 14: Louvain Community Membership of Global Reinsurance

The modularity score of Q=0.0953 falls below the conventional heuristic benchmark of Q>0.3 commonly cited as indicative of meaningful community structure (Newman and Girvan, 2004). However, applying this threshold uncritically to the present network would constitute a methodological error for two reasons that are well established in the literature. Although modularity values above 0.3 are often regarded as indicative of pronounced community structure, such benchmarks should not be interpreted as universal thresholds, particularly in small and dense networks (Fortunato and Barthélemy, 2007). Second, in small, compact, and homogeneous networks in terms of sectors, maximum possible modularity gets structurally compressed. Logically, in case all the firms in the network have some common exposures to systematic risks like global disaster risks, cycle of insurance and co-regulation, expected value of weight of an edge in the null model itself will be high, thereby reducing the gap which could be filled by observed modularity. Similar patterns have been documented in insurance-sector networks, where high edge density is associated with relatively low observed modularity despite the presence of economically meaningful clustering (Clemente et al., 2022). The correct inferential question is therefore not whether Q exceeds 0.3, but whether it significantly exceeds what would be produced by a random

graph preserving the empirical degree sequence and edge-weight distribution, which is a question addressed formally by the permutation test below.

To assess the statistical significance of the detected community structure, a null-model based validation procedure is implemented as described in Section 3.4.4.

Statistic	**Value**
Observed modularity	0.0953
Null distribution mean	0.0640
Null distribution SD	0.0082
Null distribution range	[0.0422, 0.0967]
Z-score	3.83
Empirical p-value	0.0004 ($\frac{2}{5000}$ $null\ Q \geq Q_obs$)
Percentile rank of Observed modularity	99.96th
Number of permutations	5000

Table 15: Results Permutation Test

The null distribution, generated from 5,000 configuration-model rewirings, ranges from Q = 0.042 to Q = 0.097, with mean = 0.064 and standard deviation = 0.008. Only 2 of the 5,000 null networks produce a modularity value equal to or greater than Q_obs = 0.0953, yielding an empirical *p*-value of 0.0004 and a *z*-score of 3.83. The community structure detected by the Louvain algorithm is therefore statistically significant at the 0.1% level. The upper tail of the null distribution is particularly informative. The largest modularity observed among the 5,000 randomised networks is Q = 0.0967, only marginally above the empirical value of Q = 0.0953. The fact that Q_obs = 0.0953 lies at the 99.96th percentile of the null distribution indicates that the detected partition captures substantially more community structure than would be expected under a degree-preserving random network. This provides strong evidence that the observed clustering reflects genuine organisation in the correlation network rather than random fluctuations.

The economic interpretation of the detected communities requires some caution. The Louvain algorithm uses only the correlation structure of equity returns and therefore has no information regarding firms' domicile, business model, underwriting portfolio, or regulatory environment. Consequently, any economic interpretation should be regarded as ex post rather than as an input to the community detection procedure itself.

Nevertheless, the resulting partition exhibits several informative patterns. Community 1 is composed predominantly of European listed insurance and reinsurance groups, including specialised or reinsurance-led groups such as Munich Re, Swiss Re, Hannover Re and SCOR, together with large integrated insurance groups such as Zurich, Generali, Mapfre and Legal & General. The classification of such entities implies that there is an implied similar return characteristic for large diversified organizations having operations across various lines of business. Community 2 is mainly composed of North American and Bermudian entities, which include Berkshire Hathaway, Arch Capital, RenaissanceRe, Everest Re, RGA, and AXIS Capital. It can be noted that compared to Community 1, this community is more inclined towards entities engaged in reinsurance business. Community 3 contains the Asia-Pacific institutions, including Ping An, Tokio Marine, MS&AD, Korean Re, QBE, and China Pacific Insurance. The emergence of this cluster suggests that regional

factors continue to influence return co-movements despite the increasing global integration of the insurance industry.

5.2 Minimum Spanning Tree (MST) Analysis

The full weighted correlation network, while informative about the density of connections, is difficult to interpret visually and analytically when nearly all significant pairwise correlations are present within the Western blocs. The many possible edges create a dense topology where distinguishing essential from redundant connections is not straightforward. To extract the structural backbone of the network, meaning the minimal set of connections that defines the system's hierarchical architecture, the Minimum Spanning Tree (MST) methodology of Mantegna (1999) is applied.

As described in Section 3.4.3, correlations are first transformed into distances using the metric $d_{ij} = \sqrt{2(1 - \bar{\rho}_{ij})}$, and Prim's algorithm is then used to construct the spanning tree that minimizes the total sum of distances across all 20 nodes. This results in a tree of exactly 19 edges, which is the smallest connected graph possible, with all edges belonging to the correlation backbone of the network. It would be wrong to view these edges as any form of contract or as a channel for causal transmissions; instead, they are simply the strongest statistically linked edges required to maintain the structure of the dependence network. Edge values shown in Figure 20 represent the initial DCC correlations. Node descriptions follow the same convention as Figure 19.

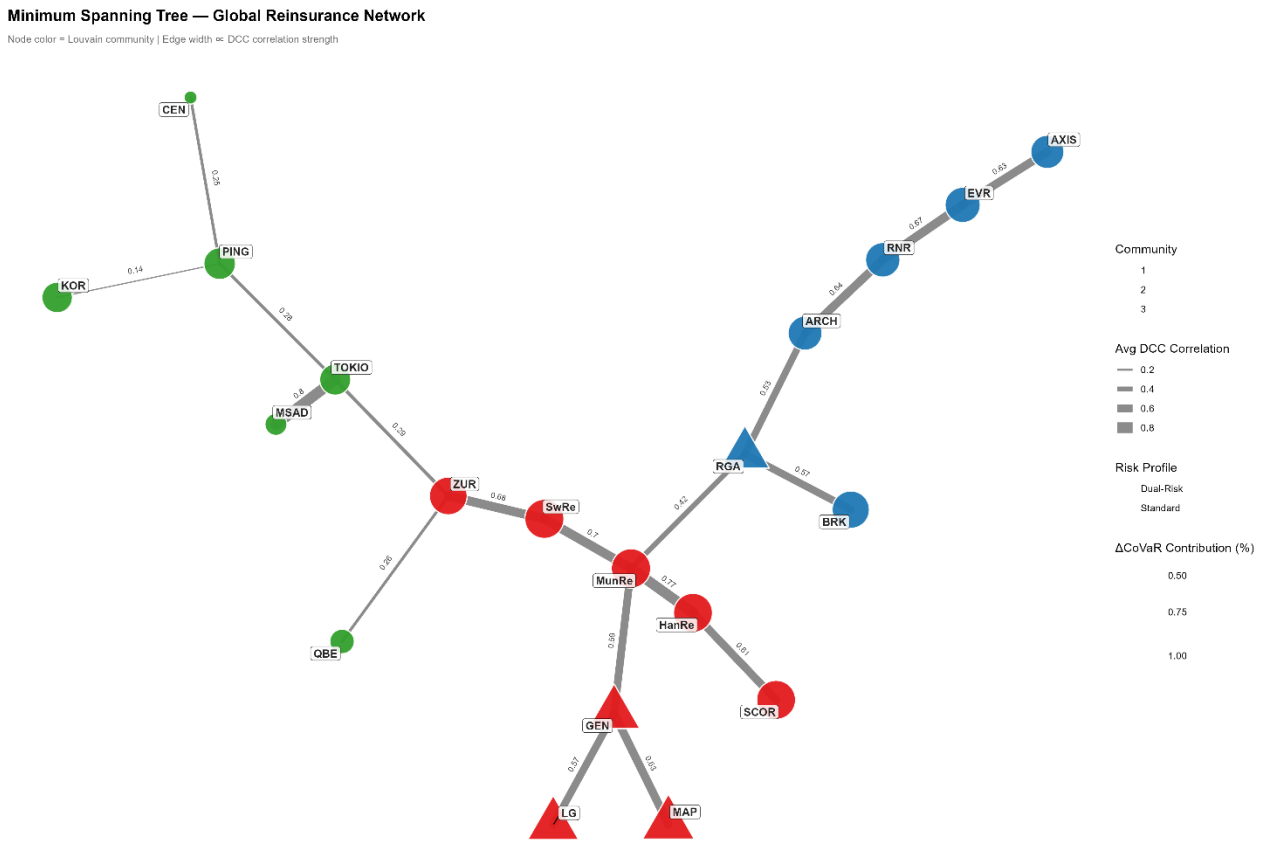

Figure 20: Minimum Spanning Tree.

The MST connects the 20 institutions through 19 edges derived from Mantegna correlation distances based on full-sample time-averaged DCC correlations. Edge labels report the original average DCC correlations, while edge thickness increases with correlation strength. Node colours identify the Louvain communities: red denotes Community 1, blue Community 2, and green Community 3. Node size is proportional to average Systemic Contribution. Triangles identify Dual-Risk institutions, while circles identify the remaining Standard-profile institutions. The MST represents the correlation-based backbone of the network rather than contractual reinsurance relationships.

The MST places Munich Re at the centre in the correlation-based network, but one notable result concerns Zurich Insurance. Rather than revealing a limitation of the bilateral risk measures, the MST supports what was already shown in Chapter 4: ZUR is the second highest institution in terms of ΔCoVaR Contribution (1.18%). The network analysis also shows that it holds a key structural role, with the highest betweenness centrality in the whole network. In particular, it occupies a bridging position between the European core and the APAC firms in the MST representation, through the correlation-based links ZUR–TOKIO and ZUR–QBE. The fact that Zurich ranks highly according to both Contribution and Betweenness is economically informative, but it should not be interpreted as independent confirmation because both measures ultimately rely on equity-return dependence. Rather, the network result adds a distinct topological dimension to the institution-to-market evidence by showing that Zurich also occupies a bridging position within the correlation structure. This result is consistent with Billio et al. (2012), who argue that network measures capture aspects of systemic importance that complement bilateral risk measures.

A similar pattern is observed for RGA within the US/Bermuda cluster. ARCH, RNR, EVR, and AXIS, the four P&C catastrophe insurers in the sample, form a strongly connected sub-group, with correlations always above 0.60 (ARCH–RNR 0.64, RNR–EVR 0.67, EVR–AXIS 0.63). This supports the idea of a common NatCat underwriting cycle described in Section 4.1.2. RGA, which is a life reinsurer rather than a catastrophe specialist, is positioned outside this core group but appears to occupy an important bridging position in the correlation network. It is connected to the catastrophe cluster (through RGA–ARCH, 0.53) and to Berkshire Hathaway (through RGA–BRK, 0.57) and, through these links, to the rest of the global network, mainly via a single connection, RGA–MunRe (0.42). This concentration of cross-regional correlation-based links in one node may indicate a potential concentration of network connectivity. This suggests that a marked change in RGA's equity-return behaviour could potentially be associated with a shift in the connectivity pattern observed in the MST.

The APAC cluster is located at the periphery of the MST and is connected to the global network through the weakest cross-regional links. This translates the qualitative isolation described in Chapter 4 into a clear structural result. Korean Re reaches Munich Re, the centre of the European core, through a path of five steps (KOR–PING–TOKIO–ZUR–SwRe–MunRe). The relatively long path suggests a lower degree of correlation-based proximity between these regions within the MST representation.

Overall, the MST adds an important dimension that cannot be captured by the ΔCoVaR framework alone: it identifies institutions whose relevance within the network appears to be mainly related to their structural position rather than purely based on risk magnitude. Munich Re, Zurich Insurance, and RGA are not central simply because of their size or risk

contribution, but because of their position in the network. Their central position suggests that changes in their equity-return correlation profiles could be associated with noticeable changes in the overall topology of the estimated correlation network.

5.3 Structural Evolution of the Network Over Time

5.3.1 Segmentation Methodology

Financial networks are inherently dynamic entities, characterized by structural properties and linkage intensities that continuously fluctuate in response to shifting macroeconomic regimes, regulatory regimes, and exogenous shocks (Diebold & Yilmaz, 2012; Billio et al., 2012). A comprehensive understanding of systemic risk and connectedness within the global reinsurance sector cannot rely solely on a full-sample, static network analysis. Estimating a single network over a multi-decade horizon risks washing out critical, time-varying structural transformations and shifts in market sentiment. To capture these underlying dynamics, the comprehensive sample has been segmented into three distinct sub-periods, each representing a homogeneous and unique macroeconomic and financial regime.

Period 1 (January 2010 to December 2019)

First, there is a period of ten years after the Global Financial Crisis. In that period, advanced countries have seen the period of low interest rates thanks to the quantitative easing measures of the Federal Reserve, European Central Bank, and the Bank of Japan. Even though some significant events happened, like the European Sovereign Debt Crisis (2011-2012) and the crash of Chinese stock market (2015), financial markets worldwide were generally marked by the absence of major system shocks. For the reinsurance industry, this period can be considered a relatively stable environment, with low investment returns and fairly regular underwriting conditions. Since it represents the longest sub-sample in the analysis, it serves as the benchmark period against which the results of the following sub-periods are compared.

Period 2 (January 2020 to December 2021)

The second sub-period includes the outbreak of the COVID-19 pandemic and its immediate aftermath. The significant fall witnessed in the international financial market during March 2020 is among the fastest market falls that have ever occurred in the recent past (Baker et al., 2020). Insurance and reinsurance firms were not immune to the growing uncertainties in the market, making it ideal to study the behavior of the network during times of stress. The government and central banks responded to the crisis through unconventional measures. Interest rates remained at very low levels, asset purchase programs were expanded, and financial conditions gradually improved during the second half of 2020. Although this is the shortest sub-period in the sample, it is included because it represents a significant exogenous shock that may have affected the structure of the network.

Period 3 (January 2022 to December 2024)

The third sub-period captures a macro-financial regime that is in many respects the structural opposite of Period 1: rapidly rising interest rates across all major developed economies, elevated inflation, and a sharp repricing of interest-rate-sensitive assets.

The DCC correlation matrices for the sub-periods are calculated through the mean of the whole sequence of daily conditional correlation matrix values obtained from the global DCC-GARCH model described in Section 3.2 over the time points in each of the regimes. The benefit of using this technique is that the methodology used here is consistent with the full sample methodology because the networks in each sub-period are calculated using the same set of DCC parameters.

5.3.2 Evolution of Network Connectivity

Table 16 presents the core topological metrics for each sub-period, and Figure 21 summarizes four key indicators graphically.

Metric	**P1**	**P2**	**P3**
Sample size (days)	1856	373	534
Average DCC correlation	0,2998	0,316	0,2981
Significant pairs (p<0.05)	190	175	181
Network density (%)	100	92,1	95,3
MST avg edge weight	0,5271	0,5398	0,5254
MunRe Strength	7,665	8,09	7,664
ZUR Strength	7,445	7,814	7,513
ZUR Betweenness	0,0468	0,0234	0,0585
MST cross-regional edges EU-US	1	1	1
MST cross-regional edges EU-APAC	2	2	2
MST cross-regional edges US-APAC	0	0	0
Louvain Modularity	0,0977	0,0859	0,094

Table 16: Topological Metrics of Network Evolution

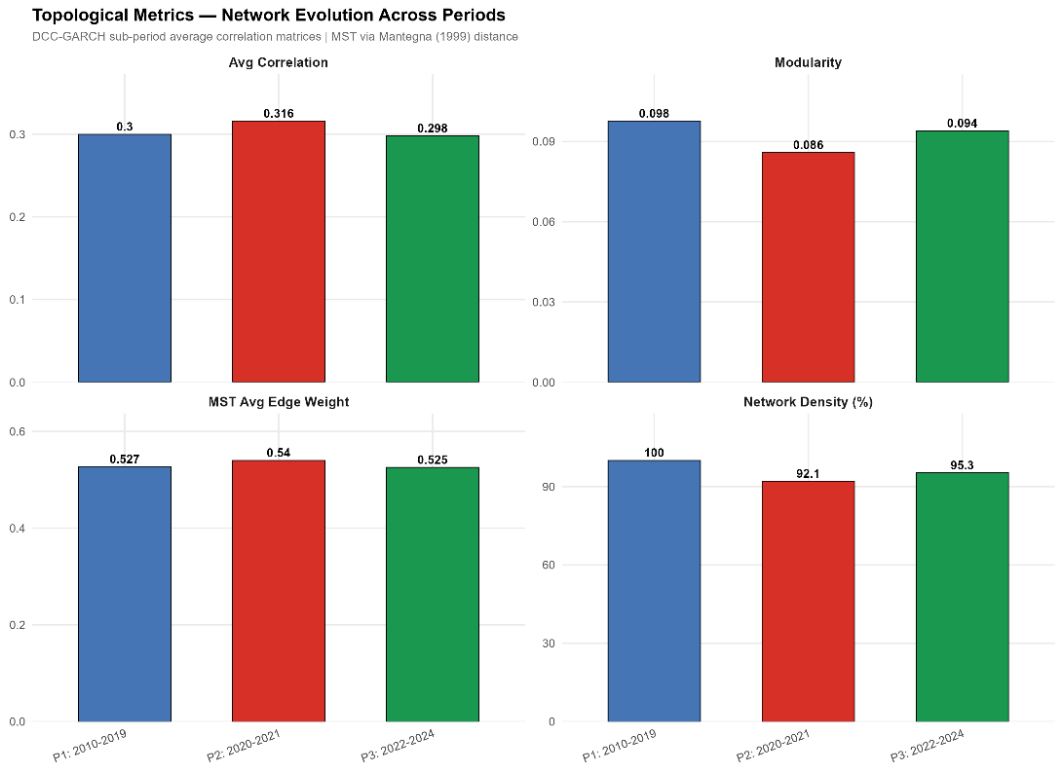

Figure 21: Topological Metrics of Network Evolution.

The four panels compare average DCC correlation, Louvain modularity, average MST edge weight, and network density across three sub-periods: P1 (2010–2019), P2 (2020–2021), and P3 (2022–2024). Bars report the value of each metric for the corresponding period.

The first and most immediate result from Table 16 is the direction of the average DCC correlation across different periods. During the COVID-19 period, the global average correlation increases from 0.300 to 0.316. At first sight, this increase may look small, but it needs to be read together with the network structure described in Chapter 4. In fact, the global average is strongly reduced by the very low cross-border correlations of the APAC group, which lower the overall mean. If we only look at Western markets, the increase during COVID is much stronger, as already shown in the Average Dynamic Correlation analysis in Section 4.2.3. What this 5.4% moderate increase at global level really shows is not a small rise in Western co-movements, but rather that even the APAC region, which is usually quite separated, became more connected to the Western core during the global shock. This result is in line with Forbes and Rigobon (2002), who suggest that diversification benefits between markets that are normally weakly correlated tend to disappear during periods of financial stress.

The Louvain modularity measure supports this interpretation. Modularity captures how much the network is divided into separate groups that are internally strongly connected and weakly connected to other groups. In Period 1, modularity is 0.098, which reflects the stable three-cluster structure. During COVID, modularity drops to 0.086. This means that, although the three groups still exist, they become less separated from each other because links across groups become stronger. In other words, the pandemic period was associated with a reduction in the statistical separation between regions that are usually only weakly

correlated. This pattern is consistent with Kenourgios et al. (2011), who show that cross-market diversification benefits tend to weaken during systemic stress episodes.

The rate hike period (Period 3) displays a partial reversion in network structure. The average DCC correlation decreases to 0.298, slightly below the pre-COVID level of 0.300, while modularity increases to 0.094. At the same time, the MST average edge weight declines to 0.525, below both the COVID peak (0.540) and the pre-COVID level (0.527), suggesting a reduction in overall network connectivity. Taken together, these results indicate a weakening of the global co-movement structure relative to both the pre-pandemic and pandemic periods.

From an economic point of view, this makes sense. As discussed in Section 4.1.1, the impact of the tightening process on the business model of the ECB and the Fed was different (Berends et al., 2013), and therefore the differentiation between life reinsurers, P&C specialists, and conglomerates was even greater. Such differentiation results in reducing common influences that cause co-movements, and as a result, it decreases both correlations and MST influences. In this regard, one can interpret the period of raising interest rates as some kind of diversification, but not in the sense that risks are smaller, but that companies are influenced more by their unique factors and less by the common global factor.

5.3.3 Topological Analysis of the Minimum Spanning Tree (MST)

To filter out the background noise of the dense DCC correlation matrix and isolate the most relevant connections within the correlation-based network, the Minimum Spanning Tree (MST) is constructed for each sub-period following the graph-theoretical framework of Mantegna (1999) and Onnela et al. (2003).

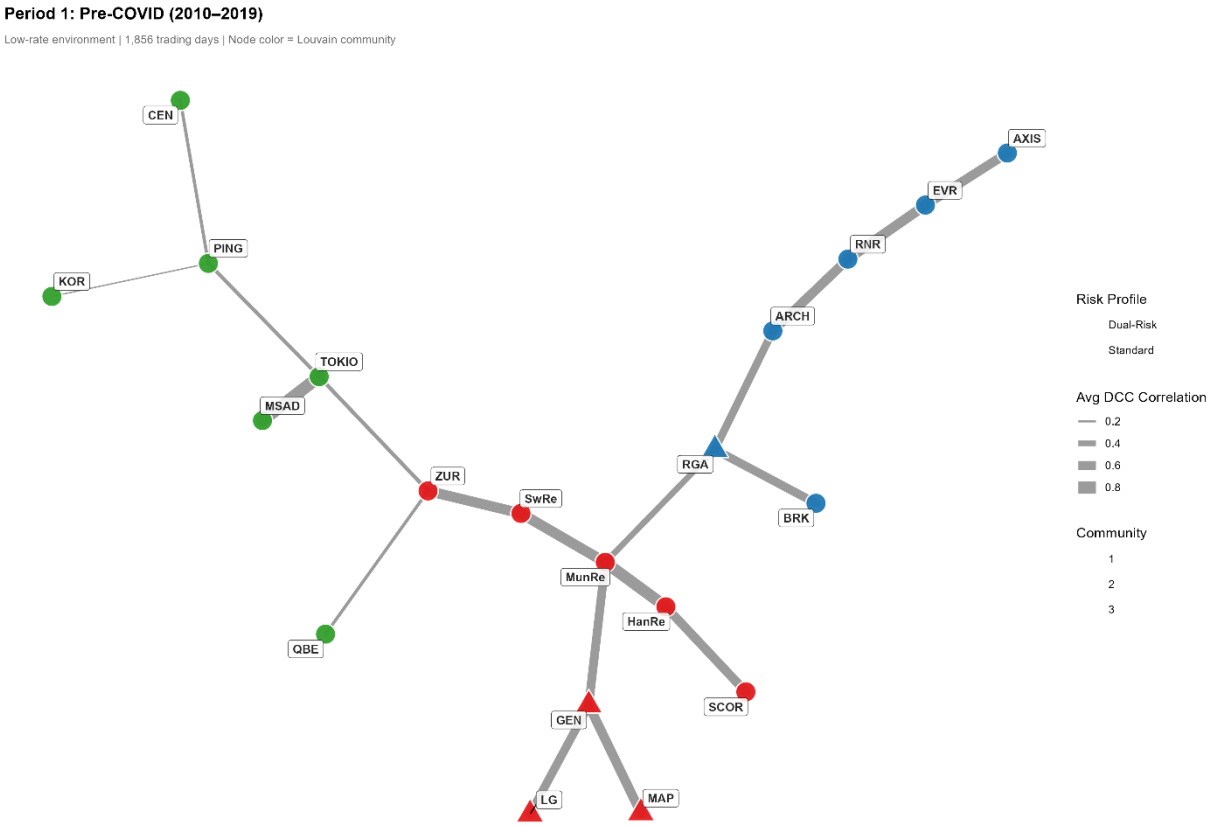

Figure 22: Period 1 MST (Pre-COVID-19).

The MST is constructed from the average DCC correlations estimated over the 2010–2019 sub-period. Edge thickness increases with the period-average DCC correlation. Node colours identify the Louvain communities: red denotes Community 1, blue Community 2, and green Community 3. Triangles identify Dual-Risk institutions, while circles identify Standard-profile institutions. All nodes have the same size.

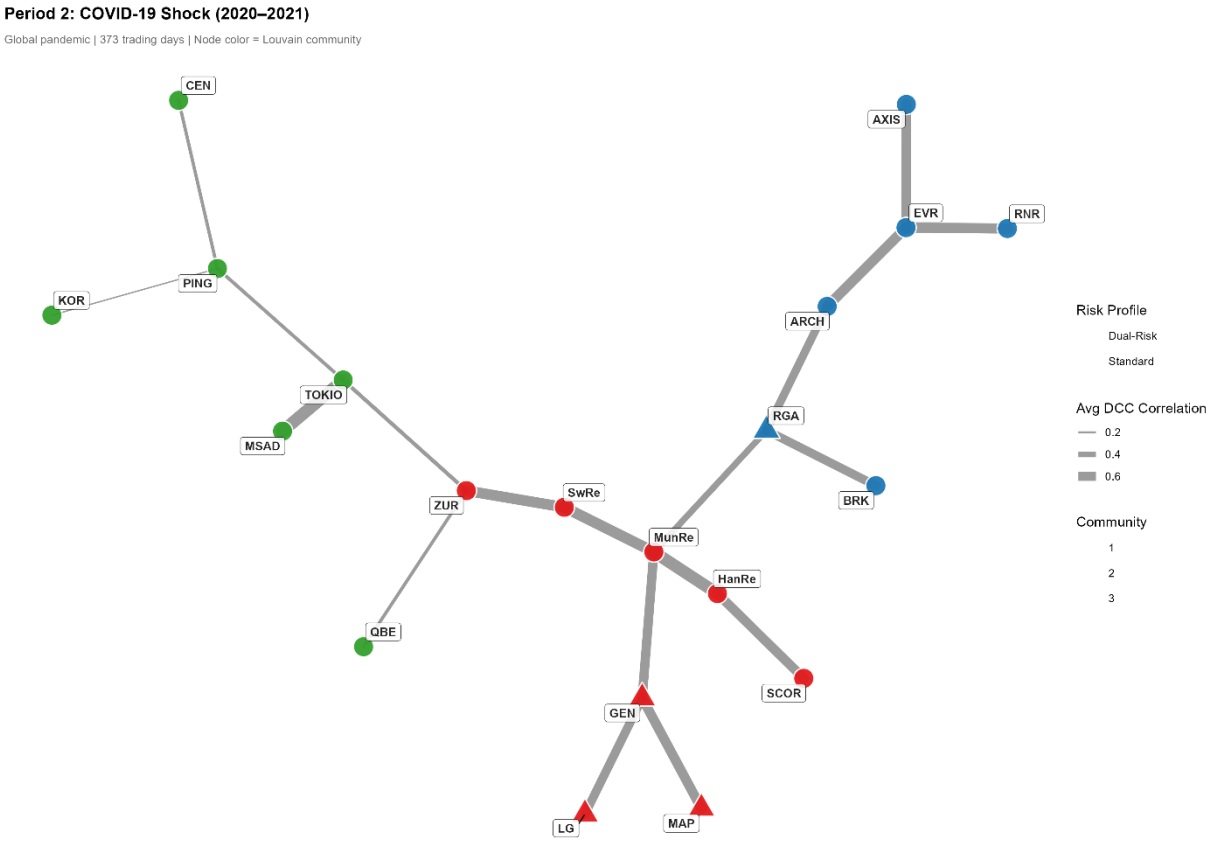

Figure 23: Period 2 MST (COVID-19).

The MST is constructed from the average DCC correlations estimated over the 2020-2021 sub-period. Edge thickness increases with the period-average DCC correlation. Node colours identify the Louvain communities: red denotes Community 1, blue Community 2, and green Community 3. Triangles identify Dual-Risk institutions, while circles identify Standard-profile institutions. All nodes have the same size.

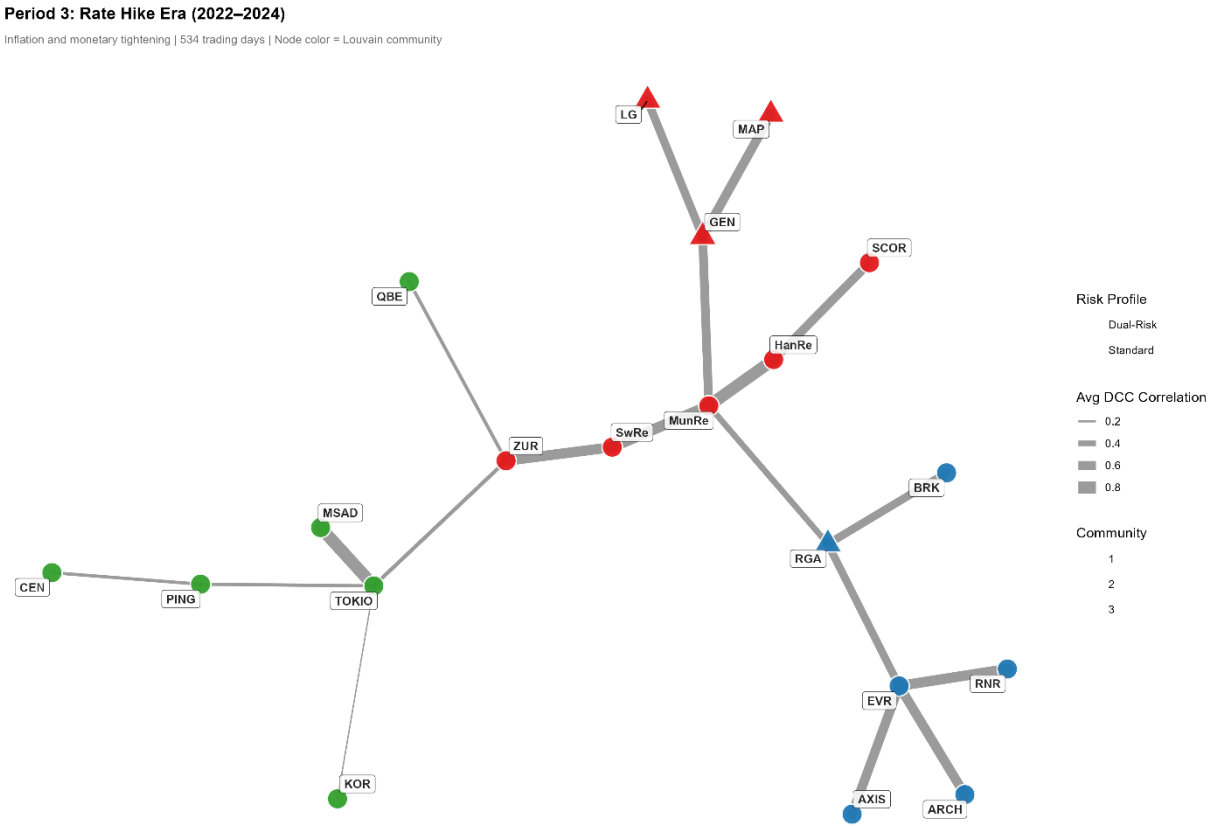

Figure 24: Period 3 MST (Post-COVID-19).

The MST is constructed from the average DCC correlations estimated over the 2022-2024 sub-period. Edge thickness increases with the period-average DCC correlation. Node colours identify the Louvain communities: red denotes Community 1, blue Community 2, and green Community 3. Triangles identify Dual-Risk institutions, while circles identify Standard-profile institutions. All nodes have the same size.

Looking at the three MST plots together with the quantitative results, the main backbone of the correlation-based network appears broadly stable across the three macroeconomic regimes considered. The recurrence of several central nodes and cross-regional links is consistent with a degree of persistence in the estimated network topology across the selected sub-periods. Possible economic explanations include regional regulatory differences, business relationships and common portfolio exposures, although these mechanisms are not tested directly. As highlighted by Billio et al. (2012), a key feature of financial networks is not only their overall level of connectivity, but also the persistence of central nodes, particularly hubs and bridging institutions.

Under this setup, Zurich Insurance appears to have the highest betweenness centrality among the network sample. The centrality measure falls during the COVID era but rises again in the era of interest rate hikes and exceeds the values seen in the pre-COVID era. Zurich's estimated Betweenness therefore varies across sub-periods. This pattern may reflect changes in the relative cross-regional correlation structure, but it should remain descriptive given that the sub-period networks are constructed from period averages

generated by the same full-sample DCC specification. In technical terms, this is consistent with the interpretation of betweenness centrality as a measure of the extent to which a node lies on shortest paths between other nodes (Freeman, 1977).

Munich Re's strength centrality shows a more stable pattern over time. It increases during the COVID period, reflecting the general rise in correlations across firms, and subsequently returns close to its initial level in the final period. This suggests that its central position in the network is relatively robust to changes in macroeconomic conditions and is mainly driven by the underlying structure of the network rather than short-term dynamics, in line with the idea that some institutions occupy persistently central positions in the connectedness structure (Diebold and Yilmaz, 2012).

The consistency of several central nodes across the three sub-periods therefore suggests a degree of topological persistence within the estimated correlation network. This evidence should remain descriptive, since the sub-period networks are constructed from period averages of conditional correlations generated by the same full-sample DCC specification rather than from regime-specific re-estimation or formal structural-break tests.

5.4 Linking ΔCoVaR and Network Centrality

The final stage of the empirical analysis compares the Systemic Contribution and Systemic Vulnerability rankings with the network centrality measures developed in this chapter. The two approaches provide complementary but not independent perspectives on market-based systemic relevance. The systemic-risk measures combine institution–market conditional dependence with tail-risk information, whereas network centrality characterises how each institution is embedded within the multilateral correlation structure of the full sample. Since both approaches ultimately rely on equity-return dependence, some degree of concordance, particularly between Systemic Contribution and Strength centrality, is naturally expected. The main objective of the comparison is therefore not to validate one methodology through the other, but to determine which aspects of institutional importance are common to both and which emerge only from the topology of the network.

Table 17 combines the main ΔCoVaR and network indicators for all 20 institutions. The table reports Systemic Contribution, Systemic Vulnerability, strength centrality, betweenness centrality and Louvain community membership. For each quantitative indicator, the corresponding rank is reported in parentheses, with rank 1 identifying the highest value. For betweenness centrality, only five firms display positive values; all institutions with zero betweenness are therefore reported as tied.

Institution	Region	Contribution (%) [rank]	Vulnerability (%) [rank]	Strength [rank]	Betweenness [rank]	Community
MunRe	Europe	1.198 [1]	1.665 [7]	7.722 [1]	0.000 [tied]	1
ZUR	Europe	1.185 [2]	1.430 [10]	7.508 [3]	0.053 [1]	1
LG	Europe	1.177 [3]	2.160 [1]	6.953 [6]	0.035 [3]	1
GEN	Europe	1.175 [4]	1.946 [3]	7.049 [5]	0.000 [tied]	1

BRK	US/Bermuda	1.126 [5]	1.348 [14]	6.269 [10]	0.000 [tied]	2
MAP	Europe	1.118 [6]	2.001 [2]	6.668 [8]	0.000 [tied]	1
RGA	US/Bermuda	1.093 [7]	1.927 [4]	6.830 [7]	0.047 [2]	2
SwRe	Europe	1.082 [8]	1.663 [8]	7.613 [2]	0.029 [4]	1
HanRe	Europe	1.064 [9]	1.603 [9]	7.376 [4]	0.000 [tied]	1
ARCH	US/Bermuda	0.997 [10]	1.341 [15]	6.070 [12]	0.018 [5]	2
AXIS	US/Bermuda	0.939 [11]	1.402 [11]	6.103 [11]	0.000 [tied]	2
EVR	US/Bermuda	0.897 [12]	1.329 [16]	6.058 [13]	0.000 [tied]	2
SCOR	Europe	0.867 [13]	1.740 [5]	6.489 [9]	0.000 [tied]	1
RNR	US/Bermuda	0.827 [14]	1.146 [17]	5.471 [14]	0.000 [tied]	2
PING	APAC	0.748 [15]	1.667 [6]	3.536 [17]	0.000 [tied]	3
MSAD	APAC	0.719 [16]	1.360 [13]	4.441 [16]	0.000 [tied]	3
TOKIO	APAC	0.691 [17]	1.361 [12]	4.571 [15]	0.000 [tied]	3
QBE	APAC	0.462 [18]	0.945 [18]	3.420 [18]	0.000 [tied]	3
CEN	APAC	0.396 [19]	0.547 [19]	2.686 [19]	0.000 [tied]	3
KOR	APAC	0.290 [20]	0.492 [20]	1.808 [20]	0.000 [tied]	3

Table 17: ΔCoVaR, Network Centrality and Community Membership

The joint table shows substantial overlap between Systemic Contribution and Strength centrality. Munich Re, Zurich, Legal & General, Generali, Swiss Re and Hannover Re all occupy relatively high positions in both rankings. This concordance is consistent with the common dependence component embedded in the two measures: both indicators assign greater relevance to stronger equity-return dependence, although Systemic Contribution is based on institution–market dependence whereas Strength aggregates institution-to-institution correlations. The correspondence is nevertheless far from complete, because the two indicators aggregate dependence differently and Systemic Contribution also incorporates institution-specific tail risk. The deviations between rankings are therefore economically informative rather than simply measurement discrepancies.

Several institutions illustrate this distinction. Swiss Re ranks second in Strength but only eighth in Systemic Contribution, suggesting a highly embedded position in the broad correlation structure that is not matched by an equally high Contribution score. Hannover Re similarly ranks fourth in Strength but ninth in Contribution. Conversely, Ping An ranks sixth in Systemic Vulnerability but only seventeenth in Strength, while SCOR ranks fifth in Vulnerability but ninth in Strength. These cases show that exposure to aggregate market stress and broad network embeddedness need not coincide. Betweenness provides an additional distinction: ARCH ranks only tenth in Contribution and fifteenth in Vulnerability but is fifth among the institutions with positive Betweenness, indicating a structural bridging role that is not apparent from its systemic-risk ranking alone. At the opposite extreme, Munich Re ranks first in both Contribution and Strength but has zero Betweenness, showing that

broad embeddedness and bridging position are conceptually different forms of network importance.

In order to evaluate the relationship between systemic-risk ranking and network centrality measures, Spearman rank correlation coefficients are calculated for the 20 institutions. It is appropriate to use the Spearman correlation coefficient since the goal is to compare rankings, and not to analyze the absolute values of indicators, measured by different scales. A positive coefficient means that institutions ranked higher in one measure are also ranked higher in another.

Ranking pair	**Spearman ρ**	**p-value**
Contribution vs Strength	0.902	< 0.001
Vulnerability vs Strength	0.686	< 0.001
Contribution vs Vulnerability	0.669	0.001
Contribution vs Betweenness	0.478	0.033
Vulnerability vs Betweenness	0.314	0.177
Strength vs Betweenness	0.470	0.036

Table 18: Spearman Rank Correlation

The strongest rank association is observed between Systemic Contribution and Strength centrality, with a Spearman coefficient of 0.902 and a p-value below 0.001. This high concordance indicates that institutions with larger Systemic Contribution scores also tend to occupy more strongly embedded positions in the equity-return correlation network. However, the magnitude of this relationship should not be interpreted as independent validation of the Contribution measure. Both indicators incorporate information on equity-return dependence: Systemic Contribution contains the conditional institution–market covariance, while Strength aggregates institution-to-institution correlation weights. The strong association is therefore economically meaningful but partly expected given their shared dependence component.

The association between Systemic Vulnerability and Strength is also positive and statistically significant, but materially weaker (ρ=0.686). This lower concordance is informative because Vulnerability captures exposure to aggregate market stress, whereas Strength captures broad embeddedness in the institution-to-institution correlation structure. Ping An and SCOR illustrate this distinction: they rank sixth and fifth, respectively, in Vulnerability, but only seventeenth and ninth in Strength. Hence, relatively high market-wide vulnerability does not necessarily imply an equally central position in the correlation network.

Betweenness centrality displays a substantially weaker relationship with the systemic-risk rankings. Its correlation with Contribution is positive but moderate (ρ=0.478), while its association with Vulnerability is weaker and statistically insignificant (ρ=0.314). Rather than indicating a failure of correspondence, this result highlights the incremental information provided by network topology. Betweenness measures whether an institution lies on shortest paths connecting otherwise separated parts of the network, a structural property that is not directly contained in the institution–market covariance underlying the systemic-risk scores (Freeman, 1977; Newman, 2010). Institutions such as Zurich, RGA and ARCH therefore

deserve attention not only because of their Contribution or Vulnerability rankings, but because they occupy potential bridging positions within the correlation structure.

Overall, the comparison provides a nuanced answer to RQ3. Systemic Contribution and Strength centrality display a high degree of rank concordance, which is consistent with their common dependence-based component and indicates that institutions strongly associated with the market factor also tend to be broadly embedded in the firm-level correlation network. This overlap should not be interpreted as independent validation, however. More informative are the deviations across measures. Systemic Vulnerability identifies institutions that are particularly exposed to aggregate market stress even when they are not among the most strongly connected nodes, while Betweenness identifies institutions whose structural relevance derives from their position between different parts of the network rather than from exceptionally high systemic-risk scores. The network analysis therefore adds information on multilateral topology, community structure and bridging positions that cannot be recovered from the institution-to-market systemic-risk measures alone. The two methodologies should consequently be interpreted as complementary views of market-based systemic relevance rather than as independent tests of the same underlying phenomenon.

CHAPTER 6

Risk Management and Macroprudential Implications

This chapter translates the empirical findings of Chapters 4 and 5 into risk-management and macroprudential implications. The interpretation remains deliberately cautious. The DCC-GARCH systemic-risk measures and correlation-network indicators developed in this thesis provide market-based information on conditional dependence, Systemic Contribution, Vulnerability and structural centrality, but they do not measure regulatory capital adequacy, direct contractual exposures or causal contagion. The results are therefore interpreted as complementary indicators that may support internal risk management and macroprudential surveillance when combined with balance-sheet, solvency, liquidity and contractual information. They are not intended to provide a stand-alone basis for firm-specific regulatory interventions or capital-buffer recommendations.

6.1 Summary of Empirical Evidence for Risk Management

The empirical results presented in Chapters 4 and 5 provide several implications for the risk management of internationally active insurance and reinsurance groups. The findings do not identify contractual exposures or causal transmission channels; rather, they provide market-based evidence on the way in which equity-return dependence, tail-risk sensitivity and network position vary across institutions and over time. From a risk-management perspective, their main relevance lies in showing that the risk profile of a reinsurance-related group cannot be evaluated solely through its stand-alone volatility or solvency position. The interaction between an institution and the broader market, the evolution of correlations under stress, and its position within the wider dependence structure provide additional dimensions of information.

The first result concerns the time-varying nature of diversification and dependence. The DCC-GARCH estimates show that correlations are highly persistent but not constant and tend to increase during periods of common market stress. This behaviour is particularly evident during the COVID-19 shock. At the global level, the Average Dynamic Correlation reached approximately 0.37 in March 2020, more than 22% above its long-run mean of approximately 0.302. The increase was considerably stronger within the European and North American/Bermudian samples, where average correlations reached approximately 0.72 and 0.70, respectively. The network-period analysis produces the same general pattern: the average global DCC correlation increased from approximately 0.300 in the pre-COVID period to 0.316 during 2020–2021, before returning to approximately 0.298 in the 2022–2024 period.

For risk management, this implies that diversification benefits inferred from average or unconditional correlations should not be assumed to remain constant during severe market disturbances. A portfolio of exposures that appears relatively diversified under normal

conditions may become substantially more correlated when common shocks dominate idiosyncratic factors. This result is consistent with the broader financial-risk literature showing that dependence structures can change materially during extreme market conditions (Longin and Solnik, 2001; Billio et al., 2012). Consequently, risk monitoring should complement long-run correlation estimates with conditional and stress-sensitive measures capable of identifying changes in co-movement as they occur. This is also consistent with the general principles underlying insurance enterprise risk management. Solvency II Article 44 requires insurance and reinsurance undertakings to identify, measure, monitor and manage risks on both an individual and aggregated basis, explicitly including their interdependencies, while the IAIS framework emphasises an integrated assessment of material risks and their relationships within the enterprise-wide risk profile (Directive 2009/138/EC, Art. 44; IAIS, 2024, ICP 16).

A second result is the presence of substantial regional heterogeneity. European and North American/Bermudian institutions exhibit considerably higher average equity-return co-movement than the APAC group. The European and North American/Bermudian mean ADCs are approximately 0.557, whereas APAC correlations remain for extended periods around 0.15–0.20. Even during COVID-19, when European and North American/Bermudian correlations approached 0.70, the APAC ADC rose only to approximately 0.23. This evidence suggests that geographic diversification may remain relevant from a market-risk perspective, but the lower measured co-movement of the APAC institutions should not be interpreted as a fixed or guaranteed diversification benefit. Cross-regional daily correlations may partly be affected by nonsynchronous market closing times, while international equity correlations can vary across market states and increase under adverse conditions (Longin and Solnik, 2001; Ang and Bekaert, 2002). Geographic diversification should therefore be assessed dynamically and complemented by forward-looking stress and scenario analysis, in line with the ORSA framework (Directive 2009/138/EC, Art. 45).

The third finding concerns the distinction between Systemic Contribution and Systemic Vulnerability. The two measures produce related but clearly non-identical rankings. Systemic Contribution is concentrated primarily among European and large US/Bermudian groups: Munich Re, Zurich, Legal & General and Generali occupy the first four positions, while the six APAC institutions are located at the bottom of the Contribution ranking. Systemic Vulnerability produces a different ordering, with Legal & General, Mapfre, Generali, RGA and SCOR occupying the first five positions and Ping An rising to sixth despite ranking fifteenth in Contribution. Zurich, by contrast, ranks second in Contribution but tenth in Vulnerability, while Berkshire Hathaway moves from fifth to fourteenth.

From a risk-management perspective, this asymmetry is important because it suggests that exposure to aggregate market stress and association with system-wide risk should be monitored as distinct dimensions. A group can display relatively strong market-based Systemic Contribution without being among the most vulnerable institutions when the market itself is under stress, and the opposite pattern can also occur. For example, Munich Re and Zurich rank particularly highly in Contribution but less highly in Vulnerability, whereas SCOR and Ping An display considerably higher Vulnerability rankings than Contribution rankings. An internal risk framework based only on stand-alone VaR, volatility or a single interconnectedness indicator would not capture this directional distinction. A more informative monitoring framework would therefore distinguish between an institution's own

tail-risk sensitivity to aggregate conditions and the degree to which institution-specific tail risk is associated with the broader market.

The same logic underpins the Own Risk and Solvency Assessment (ORSA) under Solvency II. Article 45 requires the assessment of overall solvency needs to reflect the undertaking's specific risk profile, approved risk-tolerance limits and business strategy, and requires ORSA to form an integral part of strategic decision-making. The indicators developed in this thesis should not themselves be interpreted as ORSA or regulatory capital measures; however, the separation between Contribution and Vulnerability illustrates the value of incorporating market-based measures that reveal dimensions of the risk profile that may not be visible from a single stand-alone risk metric. In particular, they could be used as complementary signals when assessing sensitivity to common financial-market stress or when deciding which exposures deserve more detailed internal scenario analysis.

A fourth implication emerges from the network analysis. The network results show that broad connectedness and structural position are related but distinct concepts. Strength centrality is highly correlated with Systemic Contribution ($\rho=0.902$), which is partly expected because both measures incorporate information on equity-return dependence. However, Betweenness shows much weaker associations with Contribution ($\rho=0.478$) and Vulnerability ($\rho=0.314$), indicating that it provides additional information on the structural position of an institution within the correlation network. Zurich, RGA and ARCH, for example, occupy positive bridging positions even though their systemic-risk rankings differ materially. Munich Re provides the opposite example: it ranks first in both Contribution and Strength but has zero Betweenness, demonstrating that a highly embedded institution need not simultaneously function as a bridge between different parts of the network.

For internal risk management, the implication is that a simple ranking of institutions by individual risk or market sensitivity is insufficient to describe the entire dependence structure. Strength can identify institutions that are broadly embedded in market co-movements, whereas Betweenness can identify institutions positioned between otherwise more separated components of the network. Community detection adds a further layer by identifying three broad clusters corresponding closely to Europe, US/Bermuda and APAC. The observed modularity of 0.0953 is significantly higher than that generated by the selected random-network benchmark, with only two of 5,000 randomised networks producing an equal or higher value. Although this should not be interpreted as evidence of contractual reinsurance communities, regional clustering is a discernible feature of the market-based dependence structure

The temporal network analysis reinforces this conclusion. The number of cross-regional links in the MST remains remarkably stable across the three macroeconomic regimes considered: one Europe–US/Bermuda connection, two Europe–APAC connections and no direct US/Bermuda–APAC connection are observed in each period. At the same time, the strength of key nodes changes with market conditions; for example, Munich Re's Strength increases from 7.665 before COVID to 8.090 during the pandemic before returning to 7.664 thereafter. This contrast between a stable topology and time-varying connection intensity matters for risk management. It suggests that risk managers should monitor not only whether peer institutions occupy structurally central positions, but also whether the intensity of their market-based connections is increasing during periods of stress.

Taken together, the evidence suggests that market-based systemic relevance in the global reinsurance ecosystem is multidimensional. Three features appear particularly relevant for risk management: the state-dependence of correlations, the distinction between contribution to and vulnerability from aggregate market stress, and the structural position of institutions within the broader correlation network. These indicators should not replace conventional underwriting, balance-sheet, counterparty, liquidity or solvency analysis. Instead, they can provide a complementary layer of information for internal risk monitoring, stress testing and the identification of changes in the risk profile that may merit further investigation. This interpretation is consistent with both Solvency II and the IAIS ERM framework, which emphasise ongoing, integrated assessment of material risks and their interdependencies rather than reliance on a single risk measure (Directive 2009/138/EC, Arts. 44–45; IAIS, 2024, ICP 16).

6.2 Implications for Macroprudential Monitoring

The empirical evidence developed in this thesis has potential relevance beyond institution-level risk management because it provides information on both the time dimension and the cross-sectional dimension of market-based systemic risk. From a macroprudential perspective, the objective is not only to assess whether individual institutions are financially sound, but also to identify vulnerabilities that may emerge from common exposures, interconnectedness and the simultaneous behaviour of multiple institutions. This distinction is consistent with the macroprudential framework discussed by Borio (2003) and with the current IAIS supervisory framework. In particular, ICP 24 defines macroprudential supervision as the identification, monitoring and assessment of sector-wide vulnerabilities, common exposures and the potential amplification or transmission of shocks through interconnected institutions or collective behaviour (IAIS, 2024, ICP 24).

The first macroprudential implication concerns the usefulness of time-varying interconnectedness as a monitoring signal. The DCC-GARCH analysis shows that dependence between insurance and reinsurance groups is not stable through time and can change materially during episodes of common stress. COVID-19 represents the clearest example in the sample: it produced the strongest cross-regional increase in co-movement, while European and North American/Bermudian correlations rose particularly sharply. The network analysis produces a consistent pattern, with the global average DCC correlation increasing from approximately 0.300 before COVID-19 to 0.316 during 2020–2021. These results suggest that a macroprudential monitoring framework based only on static averages could fail to identify periods in which diversification across institutions becomes temporarily weaker and common market exposures become more important.

This interpretation is closely aligned with ICP 24.2, which requires supervisors to analyse both historical trends and the current risk environment and explicitly identifies interconnectedness and risk concentrations as relevant objects of quantitative macroprudential analysis. The IAIS framework also recognises statistical modelling, trend analysis and horizontal comparisons as legitimate components of this process (IAIS, 2024, ICP 24.2). In this context, the Average Dynamic Correlation and the underlying DCC correlations should not be interpreted as regulatory thresholds, but could serve as complementary indicators of changes in market-wide dependence. A persistent or unusually

large increase in conditional co-movement could therefore motivate closer examination of the exposures generating the observed pattern, rather than automatically triggering a supervisory intervention.

A second implication concerns the distinction between vulnerability to systemic conditions and potential contribution to system-wide stress. This separation matters for macroprudential monitoring because the IAIS framework itself differentiates between inward risks, referring to risks to which insurers or the insurance sector are exposed, and outward risks, referring to situations in which vulnerabilities at insurers may generate externalities that propagate to other markets or the real economy (IAIS, 2024, ICP 24.2.9). The two directional measures adopted in this thesis provide a market-based analogue to this distinction. Systemic Vulnerability identifies institutions whose equity returns are particularly sensitive to aggregate insurance-market stress, whereas Systemic Contribution identifies institutions whose own tail-risk conditions are more strongly associated with deteriorating system-wide market conditions. The ranking asymmetries documented in Section 6.1 are therefore relevant from a supervisory-screening perspective. A monitoring framework that collapsed Contribution and Vulnerability into a single systemic-risk ranking would lose information about the direction of the observed market-based association. Instead, the two measures can help distinguish between institutions that display stronger association with aggregate market risk and those that appear relatively more sensitive to deteriorating sector-wide conditions. These classifications remain descriptive and should not be interpreted as evidence of causal transmission.

The third implication arises from the network structure. Macroprudential supervision is concerned not only with the risk profile of individual institutions but also with concentration and interconnectedness across the system. ICP 24 explicitly identifies interconnectedness, common exposures, and risk concentrations among the characteristics that supervisors should monitor and requires the assessment of potential systemic importance to consider the role of insurers within the broader financial system (IAIS, 2024, ICP 24.3). The network analysis developed in Chapter 5 can contribute to this dimension by distinguishing broad embeddedness from specific structural positions. As shown in Section 6.1, Strength and Systemic Contribution display substantial overlap, whereas Betweenness captures a distinct dimension of structural position. From a macroprudential perspective, the deviations across these measures are particularly informative because they indicate that broad market embeddedness and bridging position need not coincide. Network indicators can therefore complement institution-to-market systemic-risk measures by highlighting structural features that would otherwise remain less visible.

Such information may be useful for supervisory prioritisation, because institutions that appear relatively unremarkable according to one systemic-risk indicator may nevertheless occupy structural positions that justify closer examination. The appropriate implication, however, is not that high betweenness or strength automatically implies systemic importance in a regulatory sense. The network is constructed from equity-return correlations rather than contractual reinsurance exposures, and therefore cannot establish the channels through which losses would actually be transmitted. Instead, network centrality can be interpreted as a screening device for identifying institutions or clusters whose balance-sheet, counterparty and reinsurance relationships may merit further supervisory investigation.

This interpretation is particularly relevant in light of the recent reform of the European Solvency II framework. Directive (EU) 2025/2 introduces an explicit macroprudential dimension into Solvency II. Among other changes, the amended Article 45 requires insurers' ORSA analyses to consider macroeconomic and financial-market conditions and, where requested by supervisors, macroprudential concerns capable of affecting the undertaking's risk profile or arising from its own activities. The amended provisions explicitly mention interconnectedness with other financial-market participants, plausible adverse future scenarios, herd behaviour and excessive sectoral concentrations. These provisions establish a clear conceptual link with the type of information examined in this thesis: time-varying market dependence, cross-sectional differences in vulnerability and contribution, and the concentration of institutions within a broader dependence network.

The reform also moves toward greater aggregation of institution-level macroprudential information. EIOPA's draft Regulatory Technical Standards on macroprudential analysis specify criteria for determining which insurers and reinsurers should incorporate macroprudential considerations into their ORSA and application of the Prudent Person Principle. Under the proposed framework, supervisors would analyse these assessments in aggregate and provide feedback for subsequent assessments. This development is particularly relevant to the empirical approach adopted here because it reinforces the principle that institution-level information should be assessed jointly in order to identify common exposures, concentrations and potential systemic patterns (EIOPA, 2025).

Directive (EU) 2025/2 also introduces dedicated liquidity-risk management requirements, including liquidity risk management plans and liquidity indicators intended to identify, monitor and address potential liquidity stress. The indicators estimated in this thesis do not measure liquidity risk and should not be treated as substitutes for these requirements. Nevertheless, the regulatory development illustrates a broader shift toward combining microprudential information with forward-looking system-wide monitoring.

A practical implication is therefore that the three empirical components developed in the thesis could be viewed as forming a complementary market-based monitoring layer. Dynamic correlations provide information on when common dependence is strengthening; Systemic Contribution and Vulnerability provide information on which listed groups display stronger outward- or inward-oriented market-based risk associations; and network indicators provide information on the multilateral organisation of those dependencies. Used jointly, they could complement institution-level assessments with a system-wide view that considers both common movements and differences in structural position.

This interpretation is consistent with ICP 24, which explicitly recommends combining quantitative and qualitative information and stresses that the assessment of systemic importance should adopt a total balance-sheet approach, consider common exposures and activities, and examine interconnectedness with other financial institutions. Consequently, market-based indicators would be most useful at an initial screening or monitoring stage, after which supervisory authorities could investigate identified signals using more granular information on assets, liabilities, solvency, liquidity, counterparties, intra-group transactions and contractual reinsurance exposures.

The policy implication must therefore remain deliberately limited. The empirical measures in this thesis may help identify institutions, clusters and periods that warrant closer

macroprudential attention, but they are not sufficient on their own to determine whether an institution is systemically important in the regulatory sense. Nor do they provide a basis for calibrating firm-specific capital buffers or other quantitative prudential requirements. Such decisions would require a substantially broader information set and an assessment of actual transmission channels, balance-sheet resilience, substitutability, liquidity conditions and contractual exposures. This cautious interpretation is consistent with the IAIS framework, under which macroprudential analysis informs supervisory judgement but must be integrated with broader prudential and qualitative evidence rather than treated as a stand-alone mechanical classification.

6.3 Limits of Market-Based Indicators

The market-based indicators developed in this thesis provide timely and high-frequency information on conditional dependence, tail-risk sensitivity and network structure. However, their interpretation is subject to several important limitations. These limitations do not invalidate the empirical results, but they define the type of conclusions that can reasonably be drawn from them. In particular, the indicators should be interpreted as complementary signals of market-based systemic relevance rather than as direct measures of regulatory systemic importance, contractual exposure or balance-sheet fragility.

A first limitation derives from the information contained in equity prices. Stock returns aggregate market participants' expectations about the overall listed group and may react rapidly to changes in financial conditions, expected profitability, underwriting losses, interest rates or investor sentiment. This makes market data useful for high-frequency monitoring, but it also implies that the underlying economic source of an observed price movement cannot generally be identified from the return itself. Market-based measures may therefore reveal that two institutions are increasingly moving together without establishing whether this reflects common investment exposures, similar underwriting risks, direct reinsurance relationships or a broader market shock. This limitation is particularly relevant for systemic-risk analysis, since market-based measures are informative about market perceptions and co-movements but do not identify the underlying channels generating those signals. The IMF's systemic-risk monitoring framework similarly notes that market-based measures provide timely and forward-looking information but do not directly identify the linkages through which systemic risk operates (Blancher et al., 2013).

For the present thesis, this limitation is reinforced by the unit of observation. The empirical sample includes both specialised reinsurers and large diversified insurance groups with relevant reinsurance activities. Because the analysis relies on listed equity returns, the observed unit is the publicly traded corporate group rather than the individual reinsurance legal entity or subsidiary. Consequently, a high Systemic Contribution, Systemic Vulnerability or centrality score for a diversified group may reflect not only its reinsurance business, but also primary insurance activities, asset management, investment portfolios and other business lines. The results should therefore not be interpreted as evidence that the reinsurance subsidiary itself is responsible for the measured systemic relevance. This distinction is particularly important for groups such as Zurich, Generali, Legal & General, Mapfre, Ping An or Berkshire Hathaway, whose consolidated market valuations incorporate activities well beyond reinsurance.

A related limitation is sample coverage. Market-based analysis necessarily focuses on institutions for which sufficiently long and liquid market-price series are available. The sample therefore does not represent the complete contractual reinsurance market and may exclude privately held reinsurers, subsidiaries that are not separately listed and other relevant market participants. This means that the estimated network is a network of the sampled listed groups rather than a complete representation of the global reinsurance system. Market-based systemic-risk measures more generally face this constraint because high-frequency indicators can only be computed for institutions with observable market data. For this reason, absence from the empirical sample should not be interpreted as evidence of low systemic relevance.

The second major limitation concerns the distinction between statistical dependence and economic transmission. The DCC correlations, Systemic Contribution and Systemic Vulnerability measures are constructed from equity-return co-movements and conditional second moments. They therefore capture conditional statistical dependence rather than causal relationships. As already emphasised in the methodological framework, the resulting systemic-risk scores should not be interpreted as evidence that distress at one institution mechanically causes losses elsewhere. This point matters in financial markets because stronger co-movement can arise from direct interconnectedness, but also from common exposure to the same macroeconomic or financial shock. Forbes and Rigobon (2002) similarly caution that higher correlations during periods of stress do not automatically establish contagion, since observed dependence can also reflect pre-existing interdependence and changes in volatility.

The same limitation applies to the correlation network. The edges in the network are based on equity-return correlations rather than actual reinsurance contracts, retrocession claims, intra-group transactions or counterparty exposures. The thesis therefore cannot determine whether an observed link corresponds to a direct contractual relationship. Strength centrality identifies broad embeddedness in the statistical dependence structure, and Betweenness identifies positions between different parts of that structure, but neither measure demonstrates the existence or magnitude of a balance-sheet transmission channel. A highly central institution may be exposed to the same macro-financial factors as its peers without being a major contractual counterparty to them. Conversely, an important contractual connection may remain partly invisible in equity correlations if it is not sufficiently reflected in market prices.

This is why market-based network analysis should complement rather than replace supervisory exposure data. EIOPA's own sector-wide monitoring combines market indicators with detailed Solvency II prudential reporting rather than relying exclusively on market prices. Its Insurance Risk Dashboard, for example, draws on financial-stability and prudential reporting from insurance groups and solo undertakings and complements those data with market information (EIOPA, 2026). This combined approach illustrates the informational advantage of integrating rapid market signals with direct information on solvency, assets, liabilities, liquidity and insurance exposures.

A third limitation concerns model dependence. Systemic-risk estimates are not purely observable quantities; they depend on methodological choices regarding the definition of distress, the reference market, the volatility model and the assumed innovation distribution. The robustness analysis mitigates this concern but does not remove it entirely. Changing

the distress threshold from 5% to 1% alters the magnitude of the systemic-risk measures, while replacing the MSCI ACWI Insurance Index with the MSCI World Insurance Index changes some institutional positions even though the broad ranking structure remains relatively stable. The definition of the “system” is therefore economically meaningful: an institution can appear more or less systemically relevant depending on the benchmark against which its dependence is assessed.

The distributional specification also matters. The baseline Student-t model provides a better statistical fit than the Gaussian benchmark, and the resulting rankings are highly stable across the two assumptions. Nevertheless, the robustness exercise does not imply that the operational Student-t construction is analytically exact. As explained in Section 3.3.3, the Student-t conditional scale depends on the realised value of the conditioning variable, while the systemic-risk measure used here retains a covariance-based beta-times-tail-risk representation and estimates tail severity through empirical standardised-residual quantiles. The measures should therefore be interpreted primarily as comparative market-based indicators, rather than exactly calibrated conditional Student-t CoVaR quantities.

More generally, the robustness checks do not cover the full space of possible specifications. The baseline model uses a symmetric GARCH(1,1), while alternative models such as EGARCH or GJR-GARCH could accommodate asymmetric volatility responses. Similarly, symmetric Student-t and Gaussian innovations do not capture all possible forms of skewness in equity-return distributions. These limitations are already recognised in the methodology, where asymmetric volatility models and skewed innovation distributions are identified as possible extensions. Hence, robustness should be interpreted as evidence of stability across the specific alternatives considered, rather than as proof that the rankings are invariant to all plausible modelling choices. This is consistent with the broader systemic-risk literature, which shows that different market-based methodologies can produce materially different assessments and therefore cautions against relying on a single systemic-risk metric in isolation.

A fourth limitation is specific to the international nature of the dataset. The analysis uses daily returns from institutions listed in Europe, North America, Bermuda and APAC. These markets operate in different time zones and close at different times. Matching observations by calendar date therefore ensures that the series refer to common trading dates, but it does not eliminate nonsynchronous trading effects. A shock occurring after the close of an Asian market but before the close of a European or North American market may be reflected in the different return series on different effective information sets. This may attenuate or distort measured contemporaneous cross-regional correlations. The thesis already recognises this issue when interpreting the comparatively low APAC co-movement. Consequently, regional differences in DCC correlations should not be attributed entirely to economic segmentation.

A fifth limitation concerns the temporal interpretation of the network analysis. The sub-period networks are obtained by averaging the daily conditional correlations generated by the same full-sample DCC specification over different macroeconomic periods. The exercise is therefore designed to describe how the estimated dependence structure differs across periods, rather than to estimate independent regime-specific structural models. Accordingly, persistence in network topology should be interpreted as descriptive stability within the estimated DCC framework, not as evidence of a formally identified structural break or an invariant economic network. A future extension could re-estimate the DCC parameters

separately across regimes or implement formal structural-break and rolling-window procedures to assess the stability of the network more directly.

Finally, market-based indicators provide only a partial view of regulatory systemic risk. They do not directly measure solvency capital, reserve adequacy, liquidity needs, collateral requirements, asset-liability mismatches, contractual reinsurance recoverables, concentration of ceded risks or substitutability of individual reinsurers. These variables can be crucial in determining whether market stress would translate into actual losses or disruption of insurance capacity. This is why prudential authorities rely on substantially broader information sets. EIOPA's current sector monitoring, for instance, combines market developments with Solvency II information on capital, liquidity, profitability, credit, insurance and other risk categories. More generally, EIOPA stresses that reliable supervisory reporting is central to both micro- and macroprudential analysis and evidence-based supervision.

These limitations define the appropriate role of the indicators developed in this thesis. Their main advantage lies in their ability to extract timely information from observable market prices and to reveal changes in conditional dependence, relative tail-risk sensitivity and network position. Their main disadvantage is that these signals do not by themselves reveal the underlying economic exposures responsible for the observed market behaviour. The most appropriate use is therefore complementary rather than substitutive: market-based indicators can identify unusual institutions, clusters or periods that warrant closer investigation, while prudential, balance-sheet and contractual information is required to determine whether those signals correspond to economically material systemic vulnerabilities. The regulatory interpretation developed in the next section builds directly on this point.

6.4 Regulatory Interpretation and Caution

The empirical findings of this thesis have potential relevance for financial-stability surveillance, but their regulatory interpretation requires particular caution. The distinction between identifying a market-based signal of systemic relevance and establishing the prudential case for regulatory intervention is fundamental. The DCC-GARCH, Systemic Contribution, Systemic Vulnerability and network indicators provide information on conditional dependence, tail-risk sensitivity and relative structural position within the sampled equity-market network. They do not, however, directly measure regulatory capital adequacy, liquidity resilience, contractual exposure, substitutability or the actual loss-transmission mechanisms that would determine the consequences of institutional distress.

The appropriate regulatory interpretation is therefore one of complementarity rather than prescription. An institution that persistently displays high Systemic Contribution, high Systemic Vulnerability or a central position in the correlation network may warrant closer supervisory attention, particularly when several indicators move simultaneously or deteriorate during periods of market stress. However, such evidence should be regarded as a starting point for further investigation rather than as a regulatory classification in itself. This follows from the market-based nature of the empirical framework. The thesis observes listed corporate groups rather than individual reinsurance legal entities and does not reconstruct contractual retrocession or counterparty exposures. Consequently, the ranking of a

diversified insurance group cannot be translated directly into an assessment of the systemic importance of its reinsurance subsidiary or of a specific regulated legal entity.

This caution is particularly important when interpreting Systemic Contribution. A high Contribution score means that institution-specific tail risk is strongly associated with deterioration in the global insurance-market factor within the estimated DCC-GARCH framework. It does not establish that the institution causes system-wide losses, nor does it identify the channel through which such losses would be transmitted. Similarly, a high Systemic Vulnerability score indicates relatively strong market-based exposure to aggregate insurance-market stress, but it does not establish that the institution lacks sufficient capital or would become insolvent under that stress. The two measures should therefore be interpreted as indicators of conditional market dependence rather than direct prudential measures.

The same principle applies to network centrality. A high Strength score indicates broad embeddedness in the estimated correlation structure, while Betweenness identifies potential bridging positions between different parts of that structure. Yet the network is constructed from equity-return correlations rather than observed reinsurance contracts. A central node may therefore reflect common exposure to macroeconomic factors, investment portfolios or market sentiment rather than a direct contractual transmission channel. The thesis itself distinguishes correlation-based networks from contractual reinsurance networks, noting that the former can identify market co-movement but cannot recover actual exposure relationships. For regulatory purposes, centrality should consequently be interpreted as a reason to investigate an institution's actual exposures, not as evidence that those exposures exist.

The same logic fits the broader international approach to insurance systemic risk. The IAIS Holistic Framework does not rely exclusively on a single firm-level market indicator. Instead, it combines sector-wide monitoring, assessment of activities and exposures, individual-insurer monitoring and supervisory judgement. The framework is designed to detect the possible build-up of systemic risk and then match the supervisory response to the nature of the identified concern rather than mechanically linking one quantitative indicator to a predetermined intervention (IAIS, 2019). This is particularly relevant for the present study: the empirical indicators may contribute to the detection stage, but additional prudential evidence would be required before moving to the intervention stage.

A useful example is the interpretation of capital measures under Solvency II. Article 37 of Directive 2009/138/EC allows supervisory authorities to impose a capital add-on only in exceptional circumstances and under specific prudential conditions, including cases where an undertaking's risk profile deviates significantly from the assumptions underlying its Solvency Capital Requirement or where serious governance deficiencies impair its ability to identify, measure, monitor, manage and report its risks. A high Systemic Contribution score, a high Strength ranking or a bridging position in a correlation network does not by itself establish any of these conditions. In particular, the methodology developed in this thesis does not assess whether the SCR inadequately reflects an undertaking's risk profile and therefore cannot provide a quantitative basis for calibrating a capital add-on (Directive 2009/138/EC, Art. 37; Commission Delegated Regulation (EU) 2015/35).

This point is important because systemic-risk rankings and regulatory capital requirements answer fundamentally different questions. The former identify relative market-based systemic relevance within a specified empirical system, whereas the latter require an assessment of the undertaking's actual risk profile, available own funds, solvency position and the adequacy of the regulatory capital model. Consequently, even a stable ranking across alternative specifications should not be interpreted as evidence that the corresponding institutions require proportionally higher regulatory capital. Robustness of a market-based ranking increases confidence in the empirical pattern being measured; it does not transform that pattern into a prudential capital requirement.

As discussed in Section 6.2, the revised Solvency II framework and EIOPA's implementation work embed quantitative macroprudential indicators within a broader process of institution-specific assessment and supervisory judgement. This reinforces the interpretation of the indicators developed here as complementary monitoring inputs rather than stand-alone triggers for supervisory action (Directive (EU) 2025/2; EIOPA, 2025).

The empirical results of this thesis can be interpreted consistently with this approach. If, for example, an institution experienced a simultaneous increase in Systemic Vulnerability, Strength centrality and conditional correlations during a sector-wide stress episode, the combination could constitute a useful market-based monitoring signal. A supervisor could then examine whether the pattern corresponds to deteriorating solvency, concentrated asset exposures, liquidity pressure, common counterparties, increased reinsurance recoverables or other prudential vulnerabilities. Conversely, if a high centrality score were not accompanied by evidence of weak solvency, liquidity stress or concentrated contractual exposures, the market-based signal alone would provide little justification for supervisory action.

The same reasoning applies to institutions for which the indicators diverge. The finding that an institution can display moderate Systemic Contribution but relatively high Betweenness is economically informative because it identifies a dimension of network position that would otherwise remain invisible. However, the divergence does not establish that the institution constitutes a regulatory transmission channel. Instead, it identifies a question for further investigation: whether the observed bridging position corresponds to meaningful contractual, investment or counterparty relationships. This is precisely where supervisory data can complement public-market information.

The regulatory value of the framework therefore lies mainly in prioritisation and triangulation. Market-based indicators can help supervisors determine where, when and at which institutions a more detailed examination may be useful. They may be particularly valuable because equity-market data are available at relatively high frequency and can react more rapidly than annual or quarterly balance-sheet information. At the same time, supervisory action should depend on whether the observed signal is confirmed by more granular evidence. Relevant information would include solvency and capital positions, asset composition, liquidity profiles, technical provisions, reinsurance recoverables, counterparty concentrations, intra-group transactions, contractual retrocession exposures, business-model characteristics and the substitutability of the institution's activities. This broader information set is also consistent with the IAIS approach, which evaluates systemic risk through multiple dimensions rather than through one market measure alone.

A further reason for regulatory caution is that systemic relevance is context-dependent. The results of Chapter 4 show that rankings depend partly on the definition of the system, as demonstrated by the alternative market-factor robustness test. Similarly, Chapter 5 shows that different network metrics capture different forms of structural importance. Strength and Systemic Contribution display strong rank concordance, partly because both incorporate equity-return dependence, whereas Betweenness provides distinct information about bridging positions. Regulatory assessment should therefore avoid reducing a multidimensional concept such as systemic risk to a single ordinal ranking. An institution may appear important according to one dimension while remaining less relevant according to another.

For the same reason, the empirical framework should not be used to define a mechanical threshold above which a firm becomes “systemically important”. Such a threshold would be difficult to justify economically and statistically, particularly given the sample-specific and model-dependent nature of the measures. A value such as a Contribution score of 1%, a given level of Strength or a particular Betweenness rank has meaning primarily relative to the other institutions and to the model estimated in this thesis. It is not a universal regulatory boundary.

The most defensible regulatory use of the indicators is therefore as part of a multi-stage monitoring process. Market-based measures can first flag unusual changes in dependence or relative systemic-risk positioning. Supervisors can then verify whether these signals persist across methodologies and time. The next stage would involve comparison with confidential prudential and contractual information in order to identify the underlying economic mechanism. Only after that assessment could the supervisor determine whether existing risk-management measures are adequate or whether further supervisory action is justified. This sequencing preserves the informational value of market-based indicators without attributing to them a level of regulatory precision that they do not possess. This sequencing is consistent with the Solvency II supervisory review process and with the IAIS Holistic Framework, which combines sector-wide monitoring, individual-insurer monitoring, data analysis and supervisory judgement before considering an appropriate response (Directive 2009/138/EC, Arts. 36–37; IAIS, 2019).

Overall, the analysis supports a deliberately cautious conclusion. The DCC-GARCH systemic-risk measures and correlation-network indicators developed in this thesis can provide complementary information for macroprudential surveillance, particularly by identifying periods of increasing market dependence, institutions with relatively high Contribution or Vulnerability and structural positions that may deserve further investigation. They are not, however, sufficient on their own to establish regulatory systemic importance, identify actual contagion channels or calibrate firm-specific capital requirements. Any regulatory response would require confirmation through balance-sheet, solvency, liquidity, contractual and supervisory information and would remain subject to the relevant prudential framework and supervisory judgement. The contribution of the empirical framework is therefore not to prescribe regulatory intervention, but to provide an additional market-based layer of evidence that can help make macroprudential monitoring more targeted and informed.

CONCLUSIONS

This thesis investigated the market-based systemic relevance of major listed reinsurers and reinsurance-related insurance groups over the period 2010–2024. The analysis was motivated by the particular role of reinsurance within the financial system. Reinsurance supports risk sharing and diversification by redistributing underwriting exposures across institutions and geographical areas, but this function coexists with common financial exposures, correlated investment behaviour and multiple forms of interdependence. The purpose of the thesis was therefore not to establish that reinsurance is inherently a source of systemic instability, nor to reconstruct the contractual network of the global reinsurance market. Rather, it examined whether the equity-market behaviour of 20 listed institutions reveals identifiable patterns of time-varying interconnectedness, Systemic Contribution, Systemic Vulnerability and network centrality.

To address this objective, the empirical analysis combined three complementary perspectives. First, a GARCH(1,1)-DCC(1,1) framework was used to estimate time-varying conditional volatilities and correlations. Second, the conditional variance-covariance structure generated by the DCC-GARCH model was used to construct two directional systemic-risk indicators: Systemic Contribution, measuring the association between institution-specific tail risk and aggregate insurance-market risk, and Systemic Vulnerability, measuring the association between market-wide tail risk and institution-specific risk. The measures retain the directional intuition of the ΔCoVaR literature, although under the baseline Student-t specification they are interpreted as semi-parametric covariance-based indicators rather than exact analytical conditional Student-t CoVaR measures. Third, a correlation-based network analysis was used to investigate Strength, Betweenness, community structure, and the Minimum Spanning Tree, thereby extending the analysis from institution-to-market dependence to the multilateral structure of equity-return co-movement.

The first research question asked: How does market-based interconnectedness among listed global reinsurers and reinsurance-related insurance groups evolve over time and across regions? The results indicate that interconnectedness is highly persistent but not constant. Moreover, it differs substantially across regions. European and North American/Bermudian institutions display considerably stronger average equity-return co-movement than the APAC group. The time dimension is equally important. Correlations rise during several periods of market stress, although the magnitude and geographical reach of these increases vary across events. The COVID-19 pandemic represents the clearest common shock in the sample. Moreover, the sub-period network analysis provides a consistent result. The answer to RQ1 is therefore that market-based interconnectedness in the global reinsurance ecosystem is dynamic, persistent, and regionally heterogeneous. Dependence strengthens during episodes of common stress, but not all regions respond with the same intensity. This implies that a single static correlation structure would provide an incomplete representation of the system. At the same time, the comparatively low contemporaneous APAC correlations should be interpreted cautiously, particularly because nonsynchronous closing times across international equity markets may contribute to some of the measured regional differences.

The second research question asked: Which institutions display the highest Systemic Contribution and Systemic Vulnerability according to the DCC-GARCH ΔCoVaR framework? The central result is that Systemic Contribution and Systemic Vulnerability produce related but clearly non-identical rankings. These differences demonstrate that systemic relevance is directional. An institution can display a relatively strong association between its own tail risk and aggregate market deterioration without simultaneously being among the institutions most exposed to a market-wide distress state. The reverse can also occur. Consequently, Contribution and Vulnerability should not be collapsed into a single systemic-risk ranking. Their joint interpretation provides a more informative representation of the cross-sectional dimension of systemic risk by distinguishing between different forms of institution–market dependence.

The robustness analysis strengthens this conclusion while also clarifying its limits. Moving from a 5% to a 1% distress threshold substantially increases the magnitude of the systemic-risk indicators but preserves the broad composition of the rankings; in particular, the Vulnerability ranking remains identical at every position, while the Contribution ranking experiences only limited internal reordering. Replacing the MSCI ACWI Insurance Index with the MSCI World Insurance Index similarly preserves the principal structure while producing economically informative changes for some institutions, most notably Ping An. Finally, the Gaussian benchmark produces Spearman rank correlations of 0.985 for Contribution and 0.994 for Vulnerability relative to the Student-t baseline, while the Student-t specification provides the better statistical fit. The main cross-sectional patterns are therefore robust to the specific alternatives considered, although this does not imply invariance to all possible modelling choices.

The third research question asked: To what extent are institutions with higher Systemic Contribution or Vulnerability also more central within the correlation-based network? The answer is one of substantial but incomplete correspondence. Systemic Contribution and Strength centrality display a strong rank association, with a Spearman coefficient of 0.902, while the relationship between Systemic Vulnerability and Strength is positive but weaker, at 0.686. The strong Contribution–Strength association should not, however, be interpreted as independent validation of the systemic-risk measure. Both indicators contain information derived from equity-return dependence: Contribution uses institution–market dependence together with tail-risk information, whereas Strength aggregates institution-to-institution correlation weights. For this reason, the deviations between the indicators are particularly informative. Betweenness provides an additional dimension of structural relevance: its association with Contribution is moderate ($\rho=0.478$), while its relationship with Vulnerability is weaker and statistically insignificant ($\rho=0.314$). The network analysis reinforces this multidimensional interpretation. Strength is concentrated among European institutions. Only five institutions display positive Betweenness. The Louvain algorithm identifies three communities corresponding closely to Europe, US/Bermuda and APAC. Although the observed modularity of $Q=0.0953$ is relatively low in absolute terms, only two of 5,000 randomised networks produce an equal or higher modularity, placing the empirical value at the 99.96th percentile of the selected null distribution. The result supports the presence of non-random organisation within the correlation-based network, but it should not be interpreted as evidence of corresponding contractual reinsurance communities.

The temporal network analysis adds a further distinction between structural position and connection intensity. The pattern of cross-regional MST links remains unchanged across the

three sub-periods considered. At the same time, average correlations and institutional Strength vary across periods, particularly during COVID-19. These results are most appropriately interpreted as evidence of relative topological persistence within the estimated DCC framework, rather than as proof of an invariant economic network or formally identified structural stability.

Taken together, the three research questions lead to the main conclusion of the thesis: market-based systemic relevance in the global reinsurance ecosystem is multidimensional. Its time dimension is reflected in the evolution of conditional correlations and their response to market stress. Its cross-sectional dimension is reflected in the different Contribution and Vulnerability profiles of individual institutions. Its structural dimension is reflected in broad network embeddedness, bridging positions and community organisation. No single measure captures all three dimensions. This multidimensional perspective constitutes the main contribution of the empirical analysis. By integrating dynamic conditional correlations, directional systemic-risk indicators and network methods within a common sample, the thesis makes it possible to examine simultaneously when interconnectedness increases, which institutions display relatively stronger market-based systemic associations and how those institutions are positioned within the wider dependence structure. The comparison between systemic-risk rankings and network centrality also demonstrates that methodological complementarity should not be confused with independent validation. Some correspondence is naturally expected because the measures share equity-return dependence as an underlying input. The additional information comes particularly from their divergences and from structural features, such as bridging positions and community organisation, that cannot be recovered from institution-to-market measures alone.

The findings also provide a cautious basis for risk-management and macroprudential interpretation. Dynamic correlations, directional systemic-risk indicators and network measures can provide complementary market-based signals of changes in dependence and relative systemic relevance. However, they do not directly identify contractual exposures, actual contagion channels, solvency adequacy, liquidity resilience or the substitutability of individual institutions. Their appropriate role is therefore to complement rather than replace prudential, balance-sheet and contractual information. In particular, the results are not sufficient on their own to establish regulatory systemic importance or to justify firm-specific capital requirements.

Several limitations provide natural directions for future research. The use of equity returns restricts the analysis to listed institutions and means that, for diversified groups, measured market risk reflects the consolidated corporate group rather than the reinsurance activity in isolation. Future research could therefore integrate legal-entity or business-line information and extend the sample to non-listed market participants where suitable data become available. More importantly, the correlation network cannot reconstruct actual reinsurance, retrocession or counterparty relationships. Combining market-based dependence measures with contractual exposure data would make it possible to assess whether the structural positions identified in equity markets correspond to economically meaningful risk-transfer channels.

Further extensions could address the international timing and model-specification limitations identified in the analysis. Weekly or lag-adjusted returns could be used to assess the effect of nonsynchronous closing times on cross-regional dependence. The temporal network

analysis could be extended through regime-specific DCC re-estimation, rolling-window procedures or formal structural-break tests rather than relying on sub-period averages generated by the full-sample specification. Alternative volatility models such as EGARCH or GJR-GARCH and skewed or alternative heavy-tailed distributions could provide additional evidence on the sensitivity of the results to asymmetric downside dynamics. Finally, future research could combine the market-based framework with prudential variables related to capital, liquidity, asset concentration, reinsurance recoverables and counterparty exposures, moving toward a more comprehensive assessment of systemic vulnerability.

Overall, the evidence does not support a simple characterisation of reinsurance as either a source of systemic instability or a pure mechanism of diversification. Rather, the empirical results show the coexistence of regional segmentation, time-varying common dependence, heterogeneous sensitivity to aggregate stress and a structured network of market co-movements. The central implication is that systemic risk in the reinsurance ecosystem is better understood not as an isolated characteristic of an individual institution, but as a dynamic and multidimensional property of the relationships between institutions and the broader financial environment. By combining dynamic dependence, directional systemic-risk indicators and network topology, this thesis provides a market-based framework for examining those relationships while recognising that a complete assessment ultimately requires the integration of market evidence with the contractual and prudential information that lies beyond the scope of the present analysis.

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APPENDIX

Appendix A.

Preliminary Diagnostic Tests

Company	ADF Statistics	p-value	ARCH-LM (Chi-Square)	p-value
MunRe	-14.236	<0.01	713.16	<0.01
SwRe	-15.6763	<0.01	604.95	<0.01
HanRe	-15.1002	<0.01	493.08	<0.01
SCOR	-14.8081	<0.01	197.78	<0.01
MAP	-15.8359	<0.01	365.76	<0.01
GEN	-15.7119	<0.01	226.18	<0.01
ZUR	-15.3671	<0.01	608.48	<0.01
LG	-15.5611	<0.01	785.73	<0.01

Table A1: ADF Test & ARCH-LM test -European

Company	ADF Statistics	p-value	ARCH-LM (Chi-Square)	p-value
BRK	-15.932	<0.01	1140.46	<0.01
RGA	-16.331	<0.01	997.51	<0.01
EVR	-16.551	<0.01	965.34	<0.01
RNR	-16.297	<0.01	576.72	<0.01
ARCH	-15.429	<0.01	1316.88	<0.01
AXIS	-15.630	<0.01	910.78	<0.01

Table A2: ADF Test & ARCH-LM test -US & Bermuda

Company	ADF Statistics	p-value	ARCH-LM (Chi-Square)	p-value
PING	-13.2143	<0.01	140.989	<0.01
TOKIO	-14.3669	<0.01	489.5586	<0.01
KOR	-12.4673	<0.01	85.8197	<0.01
QBE	-12.6192	<0.01	99.1513	<0.01
MSAD	-14.1578	<0.01	236.9601	<0.01
CEN	-13.0819	<0.01	513.8673	<0.01

Table A3: ADF Test & ARCH-LM test -APAC

Company	ADF Statistics	p-value	ARCH-LM (Chi-Square)	p-value
MunRe	-14.4824	<0.01	474.4078	<0.01
SwRe	-15.509	<0.01	432.5505	<0.01
HanRe	-14.9241	<0.01	358.6253	<0.01
SCOR	-14.3908	<0.01	120.5444	<0.01
MAP	-14.9373	<0.01	243.9047	<0.01
GEN	-14.8892	<0.01	198.7744	<0.01
ZUR	-15.0832	<0.01	397.4392	<0.01
LG	-14.8068	<0.01	479.3715	<0.01
BRK	-14.765	<0.01	457.0711	<0.01
RGA	-15.3982	<0.01	580.9257	<0.01
EVR	-15.5225	<0.01	533.8909	<0.01
RNR	-15.0236	<0.01	225.9549	<0.01
ARCH	-14.7362	<0.01	985.0842	<0.01
AXIS	-15.1584	<0.01	514.5491	<0.01
PING	-13.5052	<0.01	285.4914	<0.01
TOKIO	-15.292	<0.01	413.2839	<0.01
KOR	-14.2167	<0.01	184.4754	<0.01
QBE	-14.1104	<0.01	11.7984	0,2988
MSAD	-14.2277	<0.01	111.7065	<0.01
CEN	-14.6289	<0.01	287.6542	<0.01

Table A4: ADF Test & ARCH-LM test -Global