WORKING paper

BANQUE DE FRANCE
EUROSYSTÈME

The Rising Interconnectedness of the Insurance Sector

January 2022, WP #857

Tristan Jourde[1]

ABSTRACT

This paper examines the long-term evolution of the linkages of the insurance sector with financial and non-financial companies. We develop a measure of connectedness using a multifactor model of weekly equity returns. The empirical analysis is conducted from 1973 to 2018, for 16 developed countries, at both the sectoral and institution levels. The results indicate that, unlike other sectors, the connectedness level of the insurance industry has strengthened over time. We also find that the linkages of the largest insurance companies with financial and non-financial firms are structurally different but as high as those of the largest banks.

Keywords: Comovements, Insurance Sector, Interconnectedness, Macroprudential Regulation, Systemic Risk

JEL classification: G22, G15

[1] Banque de France and Université Paris-Dauphine, tristan.jourde@banque-france.fr

This article benefited greatly from helpful comments and discussions of Sanvi Avouyi-Dovi, Sylvain Benoit, Maxime Bonelli, Sébastien Cabrol, Bertrand Candelon, Martine Carré-Tallon, Olivier Darné, Florence Legros, Marie Missioux, Arthur Stalla-Bourdillon, and Bertrand Villeneuve. I am indebted to the Banque de France for granting me access to Securities Holdings Statistics and I thank Floris Van Dijk for his assistance in using this dataset. Finally, I am grateful to the organizers and participants of the Dauphine Economics Ph.D. Workshop, the EconWorld Conference, the Dauphine Finance Ph.D. Workshop, and an internal seminar of the Banque de France (Atelier DGSO). This manuscript is a revised version of the third chapter of my 2020 Ph.D. thesis. I alone am responsible for the views expressed in this article and for any errors that may remain.

NON-TECHNICAL SUMMARY

The interconnectedness of the insurance sector represents the linkages with other parts of the financial system and the real economy, which can serve as a channel for shock propagation and amplification. Regulatory authorities consider that the interconnectedness of the insurance sector contributed to the spread of the 2007–2009 global financial crisis. As a result, in the aftermath of the crisis, the authorities decided to strengthen the regulation of the insurance sector by introducing new macroprudential measures primarily based on the interconnectedness of insurers.

Recognizing the critical need to better monitor the interconnectedness of the insurance sector, regulators have undertaken considerable work to collect detailed accounting data on bilateral linkages (G20 Data Gap Initiative). However, to date, these proprietary datasets are mostly available over the short term, at relatively low frequency, and cover a limited scope of institutions and potential linkages. In this context, this paper introduces a new measure of interconnectedness for insurance companies based on public stock market data, which cover an extended timeframe and reflect information more rapidly than accounting data. Unlike other market-based indicators that focus on the linkages of insurers within the financial sector, the proposed measure can capture the linkages of insurers with both financial and non-financial companies. We argue that measuring the interconnectedness of the insurance sector with the real economy is essential to assess the likelihood of future insurance crises.

The main goal of this paper is to investigate whether the level of interconnectedness of the insurance sector has increased over the past decades. A better understanding of the evolution of interconnectedness can help determine whether the probability of a crisis in the insurance sector has risen over time. Even though insurers played a central role during the global financial crisis, their status as systemically important financial institutions remains questioned, considering that, historically, insurance crises have been rare and have had limited consequences (Baluch et al., 2011). To our knowledge, this article is the first to test for a long-term rise in the level of connectedness of the insurance sector.

Our empirical analysis is conducted from 1973 to 2018, for 16 developed countries, at both the sectoral and institution levels. We show that the level of connectedness of the entire insurance sector with financial and non-financial companies has significantly increased over the last decades (see Figure 1). On the other hand, the linkages of non-financial firms (with the financial sector and the real economy) have not experienced the same phenomenon. Besides, while the interconnectedness of the insurance sector remains lower on average than that of the banking sector, the largest insurance companies appear as interconnected as the largest banks.

These results shed light on the rise in the interconnectedness of the insurance sector, which supports the ongoing development of macroprudential regulation. Specifically, our results suggest that there is a case for the current shift toward regulation that targets the entire sector rather than a small number of large insurers. In addition to this new framework, our findings call for continued annual identification of global systemically important insurers, as the level of interconnectedness of some major insurers stands out well above the rest of the sector.

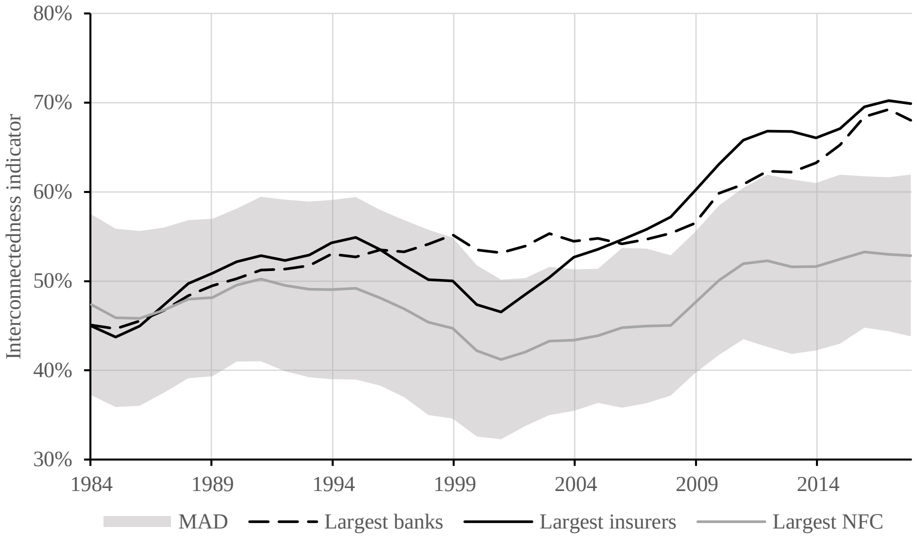

Figure 1. Interconnectedness of the largest insurers, banks, and non-financial firms

This figure compares the evolution (1974–2018, ten-year moving averages) of the interconnectedness of the largest insurers, banks, and non-financial firms based on individual stocks from developed countries (unweighted cross-sectional averages). The grey area represents the median absolute deviation (MAD) between the levels of interconnectedness of non-financial sectors.

Les interconnexions croissantes du secteur de l'assurance

RÉSUMÉ

Ce document examine l'évolution à long terme des liens du secteur de l'assurance avec les sociétés financières et non financières. Nous développons une mesure d'interconnexion en utilisant un modèle multifactoriel basé sur les performances hebdomadaires des marchés actions. L'analyse empirique est menée de 1973 à 2018, pour 16 pays développés, à la fois au niveau sectoriel et des institutions. Les résultats indiquent que, contrairement aux autres secteurs, le niveau d'interconnexion du secteur de l'assurance s'est renforcé au fil du temps. Nous constatons également que les liens des plus grandes compagnies d'assurance avec les entreprises financières et non financières sont structurellement différents mais aussi importants que ceux des plus grandes banques.

Mots-clés : co-mouvements, secteur de l'assurance, interconnexion, réglementation macroprudentielle, risque systémique.

1. Introduction

Interconnectedness represents the linkages with other parts of the financial system and the real economy, which can serve as a channel for shock propagation and amplification (IAIS, 2018). After the 2007–2009 global financial crisis (GFC), interconnectedness has become a key component of the macroprudential supervision of the insurance sector. Historically, economists and policymakers have paid little attention to the risk associated with the linkages of the insurance sector and considered systemic risks[1] to be mostly confined to the banking sector. However, the GFC highlighted the vulnerability of the insurance sector to external shocks and its potential to spread disturbances to the rest of the economy. At the peak of the crisis, the US government had to bail out the American International Group (AIG), which threatened to collapse and disrupt the entire financial system. Similarly, two other US insurers, Hartford and Lincoln National, as well as Aegon in the Netherlands and Ethias in Belgium, asked for government support.

In the aftermath of the crisis, the authorities decided to strengthen the regulation of the insurance sector by introducing macroprudential measures. Developed by the Financial Stability Board (FSB) in consultation with the International Association of Insurance Supervisors (IAIS), macroprudential regulation attaches great importance to interconnectedness and defines new regulatory measures for "systemically relevant institutions." In 2013, the FSB published a list of nine global systemically important insurers (G-SIIs)[2] that must comply with enhanced group supervision, higher loss absorbency requirements, as well as group-wide recovery and resolution planning. While this entity-based framework focuses only on a limited number of firms, macroprudential regulation is now moving toward a sector-wide approach based on activities

[1] The 2009 report to the G20 from the BIS, FSB and IMF defines systemic risk as "a risk of disruption to financial services that is (i) caused by an impairment of all or parts of the financial system and (ii) has the potential to have serious negative consequences for the real economy." The Systemic Risk Center emphasizes the importance of interconnectedness: "Systemic risk […] captures the risk of a cascading failure in the financial sector, caused by interlinkages within the financial system, resulting in a severe economic downturn."

[2] The list consists of Aegon (added into the list in 2015), AIG, Allianz, Assicurazioni Generali (excluded from the list in 2015), Aviva, AXA, MetLife, Ping An Insurance Company of China, Prudential (UK), and Prudential Financial (US).

(IAIS, 2018). The FSB will assess this new holistic framework and review the need for the annual identification of G-SIIs in November 2022.

The main goal of this paper is to study whether the level of interconnectedness of the insurance sector has increased over the past decades. A better understanding of the evolution of interconnectedness can help assess whether insurers have become structurally more exposed to systemic risk. Even though insurers played a central role during the GFC, their status as systemically important financial institutions remains questioned, considering that, historically, insurance crises have been rare and have had limited consequences (Baluch et al., 2011). To our knowledge, our article is the first to test for a long-term rise in the level of connectedness of the insurance sector. By contrast, previous studies focus on crisis periods or use systemic risk measures that are not designed to detect a structural rise in interconnectedness (e.g., Dungey et al., 2014; Gehrig and Iannino, 2018; Kaserer and Klein, 2019; Malik and Xu, 2017).

Second, we address the question of the parallel treatment of the banking and insurance sectors in the entity-based macroprudential regulation. Both criteria for identifying systemically important institutions and policy measures applied to these entities share common features. Thimann (2015) challenges this framework by providing a descriptive and theoretical comparison of the business model and balance sheet structures of banks and insurers. He argues that, while both banks and insurers can be significantly exposed to non-financial companies, banks are likely to have stronger linkages with other financial institutions, notably through the interbank market. Some empirical papers support the latter assumption, showing that banks tend to be more systemically relevant than insurance companies within the financial system (Chen et al., 2014; Elyasiani et al., 2015; Geraci and Gnabo, 2018). However, as far as we know, the linkages between insurers and non-financial companies remain unexplored. We complement the literature by testing the previous hypotheses in a multifactor framework that aims to disentangle the exposures of banks and insurers to financial and non-financial companies. This approach allows us to better understand the structure of the interconnectedness of banks and insurers.

Third, the upcoming review of the annual identification of G-SIIs raises the need to determine whether the largest insurance companies (including G-SIIs) are more interconnected than the rest of the insurance industry. Previous studies find mixed results with regard to this question. Billio et al. (2012) and Chen et al. (2014) show that insurance companies are, in general, a non-negligible source of systemic risk. By contrast, Weiß and Mühlnickel (2014) underline that the size of insurance companies helps determine their exposure and contribution to the risk of the financial system. Finally, Chen and Sun (2020) highlight that G-SIIs are more systemically relevant than non-G-SIIs overall, but a small number of non-G-SIIs outweigh G-SIIs during periods of market turbulence. We revisit this issue using a novel measure of interconnectedness, which captures exposures to both financial and non-financial shocks.

In practice, there are two ways of measuring interconnectedness among firms. The first one is based on information from accounting data, such as common risk exposures or counterparty risk. Regulatory authorities have undertaken extensive work to collect detailed data on bilateral links to better monitor the interconnectedness of the insurance sector (G20 Data Gaps Initiative). However, to date, these proprietary datasets are mostly available over the short term, at relatively low frequency, and cover a limited scope of institutions and potential linkages. Given the large number of potential connections, existing papers tend to focus on one type of linkages, such as common portfolio exposures (e.g., Greenwood et al., 2015).

The second approach is based on market data. The main assumption underlying all market-based measures of interconnectedness is that prices reflect firms' risks and expected returns, which are affected by the degree of intricacy among financial institutions and with the rest of the economy. From a theoretical perspective, the economic rationale for using this type of indicator is that interconnectedness depends on the level of comovements among the securities holdings of financial institutions and common exposures to variations in market prices and economic conditions (Billio et al., 2012). Finally, our emphasis on public stock market data is motivated by the desire to investigate the long-term evolution of interconnectedness. Indeed, market returns cover many sectors over an extended period and reflect information more rapidly than accounting variables.

The hypothesis that equity prices reflect fundamental information on linkages between companies has been tested at the country level by several empirical studies showing that market comovements are related to the degree of trade and financial globalization (e.g., Barrot et al., 2019; Boeckelmann and Stalla-Bourdillon, 2021; Eiling and Gerard, 2015; Forbes and Chinn, 2004; Jourde, 2021; Quinn and Voth, 2008). Brooks and Del Negro (2006) also report firm-based evidence that international activities positively influence international factor loadings and negatively impact local factor loadings.

We complement these results by conducting three tests to examine the relationship between our interconnectedness measure and available accounting data on insurers' holdings and activities. The first test examines the ability of our interconnectedness measure to identify the list of G-SIIs. The second one checks whether the proposed measure is related to the structure of insurers' securities holdings (based on Securities Holdings Statistics, a unique proprietary dataset of the Eurosystem). Finally, our third test specifically investigates whether the exposure of insurance stocks to local and global shocks is related to the percentage of foreign sales made by insurance companies. All these tests are detailed in Section 2 and indicate that our market-based metric accurately estimates the level and the structure of interconnectedness of the insurance sector with financial and non-financial companies.

Our interconnectedness measure is based on a multifactor model of weekly equity returns, with time-varying loadings and time-varying factor variance, derived from the literature on market integration. Our framework nests several capital asset pricing models, with country, regional, world and industry portfolios as benchmark assets. It estimates the part of the variation in insurance stock returns that is common with the stocks issued by other financial and non-financial companies, respectively. Our approach differs from spillover measures, such as Granger-causality networks (Billio et al., 2012), networks based on the forecast error variance decomposition of a VAR model (e.g., Diebold and Yilmaz, 2014), state-dependent sensitivity Value-at-Risk models (Adams et al., 2014), and multivariate GARCH frameworks (Elyasiani et al., 2015 for an application). These measures allow one to examine the direction of the shocks among financial institutions. However, due to dimensionality issues, these approaches can only be applied to a small subset of institutions, overlooking the linkages between financial and non-financial firms. Factor models, on the other hand, do not face the same limitation. Provided that the factors are chosen adequately, factor models can fit comovements across companies satisfactorily (Bekaert et al., 2009; see Section 4). Another important property of factor models is their ability to disentangle the interconnectedness of insurers with the rest of the financial sector and non-financial companies. This breakdown of insurers' interconnections between financial counterparties and common economic exposures is consistent with the approach developed by the regulator to identify G-SIIs (IAIS, 2016). We argue that measuring the linkages of the insurance sector with the real economy is essential to assess the likelihood of future insurance crises.

Our indicator of interconnectedness is also complementary to recently developed measures of systemic risk, which are based on extreme dependence and losses in asset prices. Some indicators, such as the marginal expected shortfall (MES; Acharya et al., 2017), assess the vulnerability of financial institutions to external shocks in distressed periods. Others, such as the Delta-conditional value at risk (ΔCoVaR; Adrian and Brunnermeier, 2016) and the systemic risk index/capital shortfall (SRISK; Brownlees and Engle, 2017), measure the contribution of each financial institution to the risk of the financial system. In terms of directionality, the nature of the risk captured by the proposed measure of interconnectedness falls into the first category, as we regress insurers' returns on a set of risk factors. Note that many indicators exist beyond these popular measures, such as models based on dynamic copula (Oh and Patton, 2018).

Existing systemic risk indicators are not designed for the same purpose as our interconnectedness measure. While the former seek to assess the magnitude of losses due to connectedness during periods of distress, the proposed measure can detect the emergence of new connections between firms that have not yet resulted in simultaneous losses. Therefore, our approach is more forward-looking in nature: it helps explain why some companies experienced greater distress during the GFC and assists in determining whether the likelihood of an insurance crisis has increased over time. For example, Berger and Pukthuanthong (2012) note that the probability of market crashes is linked to the overall level of interconnectedness. Moreover, Bierth et al. (2015) show that the level of interconnections of insurers is one of the main determinants of the vulnerability of the insurance sector in distressed periods. Finally, systemic risk indicators depend on more stringent assumptions than our measure of connectedness: (i) the ability of investors to price extreme risk, which might not be well represented in historical data, and (ii) the fact that the risk premium of stock returns might also incorporate bailout probabilities (Gandhi and Lustig, 2015).

Our empirical analysis is conducted from 1973 to 2018, for 16 developed countries, both at the industry and institution levels. The results shed new light on the evolution of the interconnectedness of the insurance sector. We show that the level of connectedness of the entire insurance sector with financial and non-financial companies has significantly increased over the last decades. On the other hand, the linkages of non-financial firms (with the financial sector and the real economy) have not experienced the same phenomenon. Besides, while the interconnectedness of the insurance sector remains lower on average than that of the banking sector, the largest insurance companies are as interconnected as the largest banks. These findings suggest that the conjunction of the entity-based macroprudential regulation and the new holistic framework may be relevant to deal with (i) the growing linkages of the entire insurance sector and (ii) the existence of a small group of large and highly interconnected insurers. Finally, banks seem more exposed to the rest of the financial sector, while insurance companies are more connected with non-financial sectors. We thus stress that distinct regulatory measures may be needed to handle the respective features of the interconnections of banks and insurers.

The rest of the study is structured as follows: Section 2 introduces the methodology and describes the data; Section 3 details the results of our empirical analysis; Section 4 presents the robustness tests; Section 5 concludes.

2. Methodology

2.1. Interconnectedness measure

Insurance companies can theoretically have connections with any other financial or non-financial firms in the world through direct linkages or common exposures. One might capture such interconnections by estimating the covariance matrix among the stocks issued by these companies. However, there are tens of thousands of stocks across the world and a relatively small number of data points, so the resulting matrix would contain a lot of estimation errors (e.g., Ledoit and Wolf, 2004). In addition, the existence of common risk factors makes the assessment of bilateral linkages a difficult task. We therefore estimate interconnectedness using a factor model, which provides a useful tool to capture the structure of comovements among stock returns. Specifically, factor models reduce dimensionality to make estimation possible and can identify the main causes that drive pairwise correlations.

Our measure of interconnectedness represents the percentage of the variance of insurance stock returns explained by a set of factors. We obtain a dynamic measure by allowing both factor loadings and variance to vary over time, based on a rolling window estimation procedure (see Appendix A). The following equation governs our linear multifactor model:

$$y_{i,t} = \alpha_{i,t} + \sum_{j=1}^{5} \beta_{i,j,t} f^{\perp}{}_{i,j,t} + \varepsilon_{i,t} \tag{1}$$

in which y_i represents the weekly returns of the local industry index (or the firm) i; $f^{\perp}_{i,j}$ is a matrix containing five orthogonalized factors; $\beta_{i,j}$ are the factor loadings and ε_i represents the residuals of the estimation. Our selection of factors is guided both by a statistical perspective and the need to preserve the interpretability of the results, in particular the ability of the model to distinguish the exposures of insurers to financial and non-financial companies.

While hundreds of factors based on firm characteristics have been proposed in the literature (Harvey et al., 2016), we restrict ourselves to the construction of five factor-mimicking equity portfolios based on industrials and geographic characteristics. Previous studies on financial market integration motivate the use of country, regional, global, and industry factors to fit the comovements between firms (e.g., Bekaert et al., 2014; Bekaert et al., 2009; Eiling and Gerard, 2015; Roll, 1992). In addition, many factors identified in the asset pricing literature seek to capture risk premia and explain the cross-section of returns rather than fit the covariance matrix of returns (Pukthuanthong et al., 2019). The inclusion of several geographic factors is important, as firms have become increasingly integrated at the regional and global scales over the past decades. Chaieb et al. (2018) also show that including country factors still helps to capture the structure of stock returns. Moreover, the investment portfolios of insurance companies are usually home-biased, and insurance activities might be less globalized than other financial activities due to strong national specificities (Thimann, 2014). By the same token, Eiling et al. (2012) show that industry factors have become increasingly relevant to explain stock returns. Our emphasis on industry factors also aims to match the IAIS (2016) framework, which distinguishes between financial and common macroeconomic exposures.

All factors are derived from value-weighted (long-only) equity portfolios that cover more than 75% of the stocks of a given industry or market at a specific scale. Our method differs from the principal component approach suggested by Billio et al. (2012) for two main reasons. First, statistical factors based on principal components are difficult to interpret. Second, while the authors estimate the loadings of a group of insurers to a common set of factors—fitting the comovement matrix among insurance companies—we investigate the exposures of each insurer to a specific set of local, regional, and global factors. Therefore, our approach can capture the interconnections of insurers with both financial and non-financial companies and is not limited to common exposures.

Multifactor models seek a compromise between estimating the sample covariance matrix or using a highly structured estimator, such as a single factor model. In applied work, idiosyncratic terms tend to be weakly mutually correlated $(\mathrm{E}(\varepsilon_i \varepsilon_j) \neq 0)$. We test the significance of the factors and control for the presence of omitted variables in Section 4. We show that residual correlation is equal to 0 on average and 3% in absolute terms (Table VI). We also compare the performances of our factor model with alternative specifications, by adding the size and value factors proposed by Fama and French (1992). We find that adding additional factors only results in minimal improvement in the performance of the model to capture the comovements among stocks.

To alleviate the concern of endogeneity, we build specific sets of non-overlapping factors that exclude the returns of the left-hand-side variable. Since dependent variables represent local industry indices (or firms), we only include regional and global industry effects in our set of explanatory factors. Nevertheless, it should be noted that systemically important institutions can generate spillover effects on the rest of the system, potentially affecting the explanatory variables. We stress that our factor model seeks to fit correlations among stock returns rather than capturing contagion effects, which mitigates this problem. Shocks originating from a single institution but having a global impact are thus treated as global shocks. Also note that when we estimate the level of interconnectedness of non-financial sectors, each dependent variable is regressed on its own industry factors. Finally, to obtain an intuitive interpretation of the factor loadings and facilitate the variance decomposition process (Equation 2), we construct "pure" industry and geographic portfolios by pre-orthogonalizing factors (see details in Appendix A) for each regression window.

Beta estimates obtained in Equation (1) do not allow for aggregation and comparison of insurance linkages. To deal with this limitation, we use a variance decomposition process (Equation 2). Factors and residuals are uncorrelated due to the estimation procedure $(\mathrm{E}(f^{\perp}{}_{i,j}\varepsilon_i) = 0)$. Moreover, the covariances between factors are null because of the pre-orthogonalization process, such as $E(f^{\perp}{}_{j} f^{\perp}{}_{j+1}) = 0$ (see Appendix A). Therefore, the variance of the returns can be expressed as

$$\sigma^2_{y_{i,t}} = \sum_{j=1}^{5} \beta^2_{i,j,t} \sigma^2_{f^{\perp}{}_{i,j,t}} + \sigma^2_{\varepsilon_{i,t}} \tag{2}$$

where $\sigma^2_{y_i}$, $\sigma^2_{f^{\perp}{}_{i,j}}$, and $\sigma^2_{\varepsilon_i}$ represent the historical variances of the index (or firm) i, factor j, and the regression residuals, respectively.

Our main measure of interconnectedness is based on a variance ratio (VR). We divide each component of Equation (2) by the variance of the dependent variable. For each domestic sector (or firm) *i*, the interconnectedness measure represents the percentage of the variations in the local industry (or firm) returns that is common with other financial and non-financial firms in the same country, region, or in the rest of the world (see Equation 3). The indicator is bounded between 0 and 1. Small values characterize poorly interconnected sectors or firms, while high values indicate that insurers are strongly exposed to financial and non-financial shocks. As a robustness test, we also use a logit transformation of this measure to ensure that the limits of 0 and 1 do not bias our linear trend tests (see Section 4).

$$VR_{i,t} = \sum_{j=1}^{5} \frac{\beta_{i,j,t}^2 \sigma_{f^{\perp}{}_{i,j,t}}^2}{\sigma_{y_{i,t}}^2} \tag{3}$$

VR provides a consistent summary of the exposure to multiple risk factors. It also enables us to examine the evolution of interconnectedness over time. However, this indicator can be affected by relative shifts in the variance of the factors with respect to the dependent variables (Forbes and Rigobon, 2002). We thus perform a robustness test by examining the evolution of VR when setting either the betas or the variances to their sample mean. The test confirms that our results are driven by the evolution of beta estimates (see Table V). We also directly examine the value and the dynamics of each factor loading in Section 4.

Besides, VR may not be adequate for cross-sectional comparison across countries and sectors, as the level of idiosyncratic variance of a portfolio partly depends on the number of assets and the benefits of portfolio diversification. To control for this potential bias, we also construct a measure of interconnectedness based on the absolute level of systematic variance (VL; see Equation 4), which does not consider the level of idiosyncratic variance ($\sigma_{\varepsilon_{i,t}}^2$).

$$VL_{i,t} = \sum_{j=1}^{5} \beta_{i,j,t}^2 \sigma_{f^{\perp}{}_{i,j,t}}^2 \tag{4}$$

Note that although portfolio construction does not affect VL, the measure is not superior to VR, as it depends heavily on the underlying level of market volatility. In short, the two measures of interconnectedness are complementary, with VR being more relevant for time series analysis and VL being useful for cross-sectional studies, mainly in the case of industry indices.

Unlike accounting-based indicators, our market-based measure of interconnectedness is available over the long term, allowing us to examine whether the level of interconnectedness in the insurance industry has increased over the past few decades. To control the validity of the proposed measure, we check in the short term whether it is consistent with existing accounting data on interconnections. Our first test is based on the list of G-SIIs published by the FSB. As detailed in Section 3.2, most of the institutions designed as systemically relevant are also identified as the most interconnected insurance companies by our measure. Second, we investigate whether the share of the variance explained by each factor is related to the securities holdings of insurance companies (as a percentage of total asset holdings) in the same area and industry (financial or non-financial sectors). This test is based on the ECB's Securities Holding Statistics (SHS-S) dataset. We can match data for 14 euro area member countries from 2014 to 2020 at a quarterly frequency. Our results, presented in Table VII, show that all factor exposures are positively linked to the percentage of securities holdings in the same area and sector. Three out of five of these links are statistically significant. Finally, our third test explores whether the foreign sales (Refinitiv WorldScope) of insurance companies help explain stock exposures to local and global factors. The test is based on 51 insurance companies from 2000 to 2020 at an annual frequency. Unsurprisingly, we find a positive (negative) relationship between the degree of exposure to the global (local) factor and foreign sales. The coefficients, shown in Table VII, are both significant at the 1% level.

2.2. Data

Our dataset includes the shares issued by companies from the following sectors: insurance, banking, basic materials, consumer goods, consumer services, health care, industrials, oil and gas, technology, telecommunications, and utilities. As we want our sample to be relatively homogeneous and available over the long term, we use daily prices from 16 developed markets (Australia, Austria, Belgium, Canada, Denmark, France, Germany, Ireland, Italy, Japan, the Netherlands, Norway, Spain, Switzerland, the United Kingdom, and the United States) between 1973 and 2018 (see Table I1, online Appendix).

We use Level 2 and Level 3[3] total return sectoral indices from Datastream Global Equity Indices, which are built according to the FTSE-Dow Jones Industry Classification Benchmark. These indices are market-value weighted and include dividends. Local industry indices from

[3] Insurers and banks are categorized as super-sectors, while basic materials, consumer goods, etc., are categorized as industries. We describe the components of each domestic insurance index in Table I2 (see Internet Appendix).

Refinitiv Datastream are interesting for sectoral studies, as each index represents more than 75% of the market value of the related domestic sector at any period. We use Datastream indices instead of those provided by local stock exchanges because they are constructed according to a unique methodology. There is no overlap between indices, as foreign listings are excluded from each index.

In 1996, our market selection represented more than 98% of all listed insurance assets and sales across the world (see Table I1). Unsurprisingly, this proportion fell to 80–85% in 2017 due to the emergence of large insurance companies in emerging markets. The relative size of each local insurance sector has also changed over time, which may be due to significant waves of mergers and acquisitions within the insurance industry, suggesting a need to examine the insurance sector globally rather than locally.

For each sector, we also select the ten major companies available since 1973 (in terms of assets and sales[4]; see Table I3 in Internet Appendix). Regarding the insurance sector, we ensure that our selection is made up of the five largest life and non-life insurers (including reinsurers). In 1978, our group of major insurers represented 22% of the market capitalization of our selection of 16 local insurance sectors. This proportion has increased only moderately over time (23% in 2018). Consequently, the concentration process seems to have remained limited within the insurance sector (see Section 4). It is worth noting that the dataset is limited to the publicly traded portion of the insurance sector. In the United States, for instance, stock insurers held about 78% of the total cash and invested assets owned by US insurers in 2013, according to the National Association of Insurance Commissioners. Therefore, one of the limitations of our approach is that we cannot assess the interconnectedness of some potentially large mutual insurers.

Three challenges emerge when dealing with international stock return comovements: missing data, non-alignment of time zones, and differences of currencies. The existence of missing data, which stems from non-synchronized public holidays between countries, can bias the estimation of comovements among markets. Financial markets also have different opening and closing hours, implying partial (or the absence of) overlapping trading hours. We fix these issues by calculating weekly returns, even though doing so induces a loss of observations and information compared

[4] For insurance companies, total assets represent the sum of cash, total investments, premium balance receivables, investments in unconsolidated subsidiaries, net property, plant and equipment, and other assets.

to daily return calculations. All the series are denominated in US dollars (including currency risk) to preserve data consistency and for realism purposes.

We compute the main descriptive statistics and diagnostic tests for domestic indices and firms from 1973 to 2018 (2,345 weekly returns). The results indicate the existence of extreme returns that could impact the regressions. This finding leads us to winsorize all return series at the 1% and 99% percentiles. In Section 4, we discuss alternative methods to tackle potential outliers. We also find evidence of serial correlation and heteroscedasticity in the return series, which is accounted for in our estimation method (Newey and West, 1987). The estimation method to compute our interconnectedness measure dynamically is explained in Appendix A.

3. Empirical results

This section presents the empirical results. We first apply our methodology to each domestic insurance index, which gives us an overall picture of the level of connectedness of the insurance sector with financial and non-financial companies. Special attention is then paid to the interconnectedness of the largest insurance companies. In both cases, we estimate connectedness according to the previously discussed methodology (VR and VL) and treat the resulting time series as observable.

3.1. The interconnectedness of the entire insurance sector

We first focus on the interconnectedness of 16 domestic insurance sectors from 1974 to 2018. As we are mostly interested in the existence of common dynamics, we calculate the unweighted cross-sectional average of the domestic interconnectedness measures at each period. We do not employ capitalization-weighted averages, as such would strongly bias the results toward the largest domestic insurance sectors, such as the US, UK, or Japanese insurance industries. However, the results are overall robust to the use of value-weighted average indices. More details on the connectedness of each local insurance sector are provided in Section 3.1.2.

3.1.1. Global Perspective

We first compare the total level of interconnectedness (VR & VL) of insurers, banks, and non-financial firms. We investigate whether the interconnectedness of the insurance sector exhibits some specificities based on paired t-tests (see Table II). More specifically, we compare the mean of each interconnectedness series from 1974 to 2018. The connectedness measure (VR) of the insurance sector reaches 63% on average. We highlight that the insurance sector is significantly less interconnected than the banking sector (−3.8 and −3.2 percentage points for VR and VL, respectively). On the other hand, VR and VL lead to mixed results when comparing the interconnectedness of the insurance sector with that of non-financial sectors (+0.6 and +10.4 points, respectively).

Our results also suggest that the insurance sector has grown more interconnected than non-financial sectors over time. We test for a structural break (Bai and Perron, 2003) in the spread between the interconnectedness measures of insurers and non-financial firms. This test indicates that a structural break occurred in 1995. We perform additional paired t-tests on the two resulting sub-periods. Based on VR, we find that the insurance sector used to be significantly less interconnected than non-financial sectors (−2.4 points) from 1974 to 1995. By contrast, it became more connected than non-financial firms (+7.0 points) during the second sub-period (1996–2018). The VL measure also captures this increasing gap (+2.7 and +23.6 points over the periods 1974–1995 and 1996–2018, respectively).

Table I tests for deterministic trends in the interconnectedness series (VR). As the assumptions of autocorrelation and unit-roots are not rejected, we run several trend tests that are robust to strong serial correlation as well as stationary and nonstationary errors (Bunzel and Vogelsang, 2005; Harvey et al., 2007). We report the statistics associated with the one-tailed tests, as the most likely alternative hypothesis is that interconnectedness has grown over time. Moreover, we control for the presence of structural breaks in level and trend using the test of Harvey et al. (2009). Since VR is bounded between 0 and 1, we also perform a logit transformation on the interconnectedness indicators and check whether the results of the trend tests are consistent (see Section 4).

Our findings indicate that the connectedness level of the insurance and banking sectors follow significant upward deterministic trends (+0.3% annually). By contrast, there is no such evidence for the average interconnections of non-financial sectors. In addition, the findings suggest that the risk exposures of the insurance sector have changed considerably over time. The influence of the local factor decreased, especially between 1974 and 2001, while the importance of the global factor sharply rose during the 2000s. We also detect a significant increase in the linkages of the entire insurance sector with the rest of the financial industry.

There are several possible explanations for the structural rise in the level of interconnectedness of the insurance sector, related to changes in the business model of the insurance industry. We review the potential causes of this trend here but rely on future research to provide formal evidence due to limited data availability. First, insurance companies have expanded their activities across borders. While insurance premium volumes grew at about the same pace as the economy, the weight of insurance and financial services in commercial service exports almost doubled between 1983 and 2019 (from 4.6% to 8.4%).[5]

Second, the insurance sector has become one of the major institutional investors, holding about 12% of financial assets worldwide, and an essential source of funding for banks (IMF, 2016). Moreover, regulatory developments in the 1990s initiated a trend towards a "bancassurance" system. In 2016, the Joint Committee of European Supervisory Authorities identified 83 financial conglomerates in Europe, up from 75 in 2009. It is worth noting that most of the G-SIIs are insurer-led conglomerates.

Third, insurers have engaged in non-traditional and non-insurance (NTNI) activities (i.e., investment banking activities, direct lending, investments via hedge funds, and third-party asset management). NTNI activities are more cyclical and harder to diversify than traditional insurance businesses. They increased from 3% of total assets in 2004 to 8% in 2014 for non-life US insurers, and from 2.5% to 4.5% for life insurers (IMF, 2016).

Finally, life insurers that sell financial products with minimal return guarantees (variable annuities) are under pressure from the low-interest-rate environment, a common risk exposure that might lead them to take additional risks. In the US, for example, variable annuities grew from $875 billion in 2003 to $1.5 trillion in 2015, which represents 35% of U.S. life insurer liabilities (Koijen and Yogo, 2020). By the same token, property and casualty insurers have to deal with increased climate risk.

3.1.2. Local specificities

We check whether the previous results conceal some local-specific features. We reexamine the interconnectedness of each domestic insurance sector compared to the relative local banking and

[5] Based on the Sigma reports (Swiss Re) and the IMF Balance of Payments Statistics Yearbook.

non-financial sectors using paired t-tests. The results are globally in line with our aggregate findings. On average, most of the domestic insurance sectors are significantly less interconnected than the domestic banking sectors, especially the Spanish, Australian, and Belgian insurance sectors based on VR (-12.3, -9.5, and -9.0 points, respectively) and the Irish, German, and US insurance sectors based on VL (-12.3, -11.1, and -10.2 points, respectively).

We also confirm that most of the domestic insurance sectors have become more interconnected than non-financial firms over time. Based on VR, our findings indicate that, while 7 out of 16 domestic insurance sectors were significantly less interconnected than the respective non-financial industries between 1974 and 1995, only 1 out of 16 remained significantly less connected from 1996 to 2018.

Besides, we examine the trends in the level of connectedness of each local insurance index. The results indicate that the interconnectedness of the insurance sector has increased in all countries except Japan. The linear deterministic upward trends are significant for Australia, Belgium, Canada, France, Germany, the Netherlands, Norway, and Spain. We also control that the rise in connectedness remains significant when we exclude some of the local insurance indices from the aggregate measure. To this end, we recompute the trend tests by successively excluding one of the domestic insurance indices from the global measure of interconnectedness. The results show evidence of positive and significant deterministic trends for all the resulting series (unreported results).

Finally, we provide further details on the dynamics of the interconnectedness of the non-financial sectors (see Table I). We note that, apart from the insurance and banking sectors, only the technology and telecommunications sectors have experienced a permanent rise in connectedness. Therefore, even though the global measure conceals some heterogeneity, our detailed analysis globally confirms the robustness of the main results.

3.2. The interconnectedness of the largest companies

The interconnectedness of the largest insurers could be lower than that of the whole insurance sector due to a greater ability to pool and diversify risks. On the other hand, the largest insurers are more likely to have closer links with other financial and non-financial firms than smaller insurance companies. Moreover, some of the largest insurers have massively engaged in NTNI activities, thus increasing their exposure to external shocks (Berdin and Sottocornola, 2015). For example, Harrington (2009) shows that the near default of AIG during the financial crisis resulted from the issuance of credit default swaps.

3.2.1. Global Perspective

We study the interconnectedness of the largest insurers, banks, and non-financial firms. First, we find that the largest insurance companies are significantly more interconnected than the largest non-financial firms (+8.0 and +20.4 points for the VR and VL measures, respectively; see Table II). This difference appears to be both statistically and economically significant. The interconnectedness (VR) of the largest insurers is 16.8% higher than that of the largest non-financial companies over the whole period. On the other hand, there is no significant difference between the interconnectedness of the largest insurers and banks (+0.3 and +1.4 points for VR and VL, respectively). This finding is in line with Kaserer and Klein (2019) who show that some multi-line and life insurers are as systemically important as the riskiest banks. Therefore, contrary to the assumption that insurance companies need to be large to efficiently pool and diversify risks, it seems that the major insurers are more vulnerable to external shocks than smaller ones.

We compare the level of interconnectedness of the largest insurers and the domestic insurance indices using VL. Based on Table I, we observe that the largest insurers are 21.8% more interconnected than the rest of the insurance industry (+12.6 points). Interestingly, the difference between the level of interconnectedness of the major non-financial firms and their respective sectors is only equal to +2.6 points (+8.0 points for banks). This result is important because it underscores that the level of interconnectedness of large insurance companies should be monitored very carefully, contrasting with the ongoing regulatory evolution toward a holistic framework.

We also examine the primary sources of systematic risk (VR) for the largest insurers and banks (see Table II). Our findings indicate that insurers are more exposed than banks to common macroeconomic and market shocks and less interconnected with other financial institutions (counterparty exposures). Specifically, the largest insurance companies are significantly more exposed than banks to the global, regional, and local factors (+2.6, +0.4, and +1.2 points, respectively). Conversely, insurers are significantly less exposed to global and regional *industry* shocks (−2.0 points). In other words, the major insurers are, on average, 15.1% more exposed to non-financial companies and 32.9% less interconnected with other financial institutions than the largest banks. These results are in line with those based on the VL indicator. They are consistent with the findings of Thimann (2015) based on a descriptive and theoretical comparison of the balance sheets of banks and insurers. The sensitivity of insurers to non-financial firms and global market fluctuation is likely to be enhanced by their investor status. By contrast, banks are more dependent on short-term funding from the interbank market, which seems to increase their exposure to other financial institutions and, in turn, the risk of a domino effect in the banking sector.

In addition, we test for linear deterministic trends in the connectedness series (VR) of the largest companies (see Table I and Figure 1). While the degree of connectedness of the largest insurers and banks follow significant upward deterministic trends (+0.3 and +0.4% annually, respectively), there is no such evidence for the largest non-financial firms. In Table I, we also test for trends in the connectedness series of each non-financial industry and highlight that, apart from the oil and gas sector, none of them have structurally increased over time. Consequently, the difference between the interconnectedness of the largest insurers and non-financial firms has widened over the past decades. For example, the level of interconnectedness of the largest insurers was 33.3% higher than that of the largest non-financial firms in 2018. As a robustness test, we control whether this trend is driven by a concentration process in Section 4.

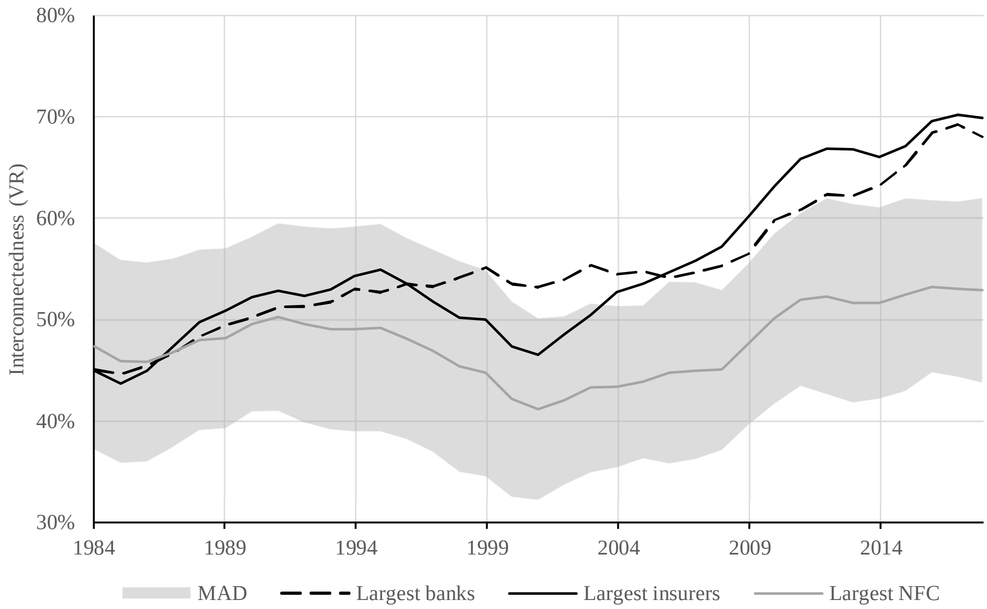

Figure 1. Interconnectedness (VR) of the largest insurers, banks, and non-financial firms

This figure compares the evolution (1974–2018, ten-year moving averages) of the interconnectedness of the largest insurers, banks, and non-financial firms based on individual stocks from developed countries (unweighted cross-sectional averages). The grey area represents the median absolute deviation (MAD) between the levels of interconnectedness of non-financial sectors.

3.2.2. Categories of insurance and G-SIIs

Insurance companies can be classified as falling into one of three categories: life insurers, non-life insurers, and reinsurers. To investigate the specificities of each type of insurer, we select the ten largest firms in each group from our sample of developed markets (details in Table I3, online Appendix).[6]

Non-life insurers are likely to be less exposed to financial and non-financial companies than life insurers. Indeed, demand for non-life insurance products is relatively inelastic because few substitutes for insurance exist, and some major lines (such as motor) are mandatory. By contrast, demand for life insurance contracts is more dependent on economic and market shocks, as these products are often used as investment vehicles. Moreover, Harrington (2009) underlines that life insurers have higher leverage and are more exposed to policyholder withdrawal than non-life insurers. We also analyze reinsurance companies whose transactions connect insurers through bilateral exposures, which might increase the systemic risk of the entire insurance sector.

Using paired t-tests (see Table III), we first compare the average level of interconnectedness (VR & VL) of life and non-life insurers over the sample period. Interestingly, the results indicate that non-life insurers are significantly more interconnected than life insurers (+4.0 and +4.6 points for the VR and VL indicators, respectively). However, we also show that the interconnectedness of life insurers has increased more substantially than that of non-life insurers (Table IV and Figure 3). We find evidence of a structural break in the spread between the level of connectedness of life and non-life insurers in 2000. We thus compare the interconnectedness of life and non-life insurers over the sub-periods 1974–2000 and 2001–2018. Our analysis reveals that life insurers became more interconnected than non-life insurers from the first (−8.4 and −11.0 points for VR and VL, respectively) to the second (+2.5 and +5.2 points) sub-period. This result is consistent with EIOPA (2018), which reports that the GFC led to a substantial increase in the number of failures in the life insurance segment, while the non-life sector was relatively unaffected. Moreover, Cummins and Weiss (2014) argue that the most systemically relevant activities are the non-core activities conducted by life insurers. Finally, the low-interest-rate

[6] We rely on the Industry Classification Benchmark, which categorizes each company according to its principal business activity. Hence, some companies, such as AXA, may be classified as non-life insurers while still being involved, to a certain extent, in life insurance activities. Non-life insurance includes full line insurance, insurance brokers, and property and casualty insurance. We consider reinsurers as a special case.

environment, which has significantly impacted life insurers' profits, may partly explain this trend. For example, Koijen and Yogo (2020) show that the exposure of the US life insurance sector to 10-year Treasury bond returns has increased over time. By contrast, non-life insurers have suffered less damage, as they can reprice existing contracts and have a shorter investment horizon (IMF, 2016).

Table III and Figure 3 also indicate that reinsurers are significantly less interconnected than life and non-life insurers (−11.3 and −15.4 points for VR; –25.6 and −30.0 points for VL, respectively). This finding is in line with Chen et al. (2020), who show that the reinsurance business is not systemically relevant by building a network among US property-casualty insurers based on bilateral reinsurance liabilities. Nevertheless, the interconnectedness level of reinsurers has significantly increased over time (+0.3% per year from 1974 to 2018; see Table IV). This result calls for caution and may indicate that the insurance industry offers more products with non-diversifiable risks. It is consistent with the analysis of Cummins and Weiss (2014), which points out that, despite historical facts, a reinsurance crisis could severely impact the insurance sector.

Finally, we plot the average level of interconnectedness (VR & VL) of each insurance company (see Figure 2). The analysis is conducted from 2003 to 2018, the longest time frame for which data are available for all entities. We first check whether some outliers impact the previous results. With a few exceptions, such as Progressive, which is classified as a non-life insurer but is less interconnected than most of the reinsurers, the general results presented above are in line with the firm-level analysis.

Figure 2 also highlights that our interconnectedness measure can identify most of the companies designated as G-SIIs by the FSB. Aegon, Allianz, Assicurazioni Generali (excluded from the 2015 list), Aviva, AXA, Prudential, and Prudential Financial all appear among the most interconnected insurers. One notable exception is AIG, which is significantly less interconnected than the other G-SIIs. This finding can be explained by the fact that we winsorize all return series at the 1% and 99% percentiles. Indeed, the study aims to examine the long-term evolution in connectedness rather than extreme connectivity in times of crisis. Without winsorizing the returns, AIG becomes the most interconnected institution based on the absolute level of systematic volatility (VL). By contrast, the variance ratio (VR) remains approximately the same, indicating that the stress experienced by AIG during the GFC was also due to idiosyncratic shocks. Interestingly, we note that some insurance companies are as interconnected as the G-SIIs, such as Lincoln National—which required government support during the GFC—and Legal & General. Although our results suggest that some insurers might be added to the list of G-SIIs, it should be noted that interconnectedness represents no more than 50% of the indicator developed by the IAIS (2016) to identify systemic institutions.

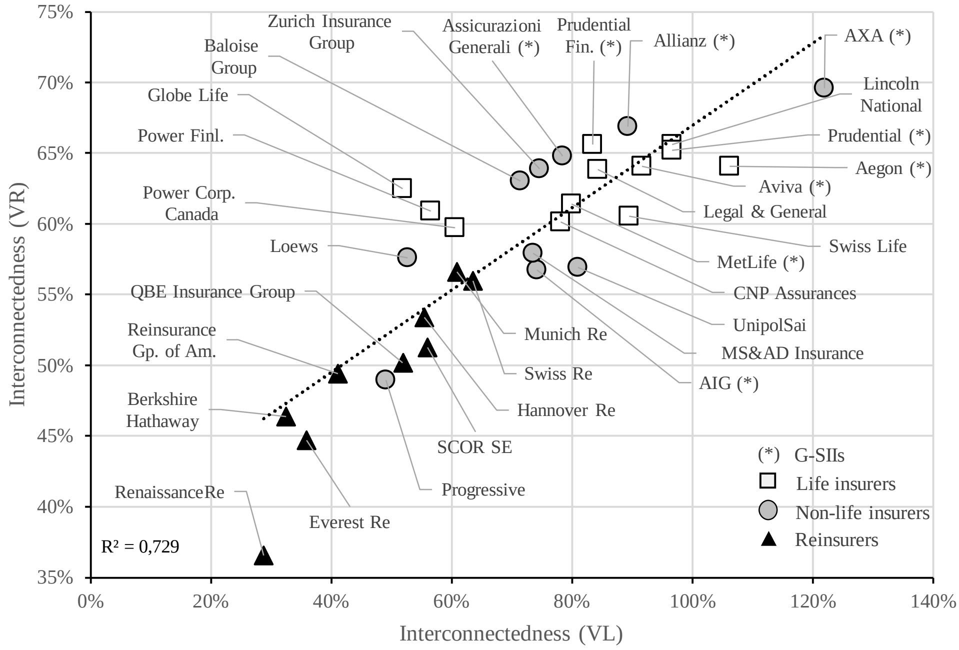

Figure 2. Mapping insurers based on interconnectedness measures (VR & VL)

This figure illustrates the average level of interconnectedness of life insurers (squares), non-life insurers (circle), and reinsurers (triangle) from 2003 to 2018 (the longest period for which data from all companies are available). We add data for MetLife and Prudential Financial, which are not included in our selection (of the largest insurers) but are part of the list of G-SIIs.

4. Robustness tests

4.1. Estimation procedure

To limit the impact of extreme returns on the interconnectedness measure, we winsorize all series at the 1% and 99% percentiles. As an alternative, we can use a robust regression framework based on iteratively reweighted least squares. The results, presented in Table I4 (Internet Appendix), confirm our main findings both at the sectoral and institution levels. Furthermore, the findings are robust to ordinary least squares regressions based on non-winsorized returns.

We also investigate the impact of the shrinkage method (described in Appendix A) on the results. To this end, we reestimate our interconnectedness measure without shrinking the parameters (see Table I4, online Appendix). Overall, the shrinkage approach does not significantly impact our main results. It is worth noting that the impact of the shrinkage approach was stronger at the beginning of the period, which may be related to the low explanatory power of industry factors at that time.

Finally, we control the robustness of the results to alternative specifications of the size of the rolling window. We reexamine the dynamics of interconnectedness based on two-year and six-month windows (see Table I4 in Internet Appendix). We globally confirm our main results even if the test of Harvey et al. (2007) is not significant based on six-month windows.

4.2. Variance ratio

Variance ratios are affected by relative shifts in the variance of the factors with respect to the dependent variables (see Equation 3). We argue that an increase in factor loadings better reflects the rising interconnections of insurers than a change in the variance of the returns. We thus test whether the increase in the interconnectedness level of the insurance sector (VR) is due to changes in the variance of the series or the factor loadings. To this end, we recalculate VR by setting either betas or variances to their sample mean. We examine the trends of these constrained measures of interconnectedness. We find significant upward trends in the interconnectedness series when keeping the variances constant. By contrast, there is no such evidence when betas are fixed. Therefore, our results confirm that shifts in the factor loadings drive the rise in the interconnections of the insurance sector, both at the institution and industry level (see Table V in Appendix C).

Then, we investigate the dynamics of each factor exposure. The analysis reveals that betas have significantly increased over time for all factors (except the local one) and sectors. Interestingly, the slopes of the trends are steeper for the insurance and banking sectors than for non-financial sectors. Finally, as previously done for the VR and VL indicators, we compare the value of betas for insurers, banks, and non-financial firms based on paired t-tests (unreported results). Again, we confirm our main findings.

Another potential limitation is that the VR measure is bounded between 0 and 1, which can be a concern for linear trend tests. As a result, we map the original indicator (VR) to the real line using a logit transformation, such as $VR_{adj,i} = \ln(\frac{VR_i}{1-VR_i})$. We confirm that the interconnections of insurers have significantly increased over time (see Table I4, online Appendix).

4.3. Factor model

The accuracy of the interconnectedness measure depends on the ability of the factor model to capture the plurality of the linkages between firms. We first control the significance of the coefficients associated with the risk factors. The measures are based on the unweighted average of the t-values. We compute these measures for the entire sample period (1974–2018) and analyze its evolution by dividing the sample into two equal sub-periods. The results indicate that while the geographic factors are significant over the whole time frame, the industry factors are only significant during the second sub-period.

Then, we check the ability of our five-factor model to fit the comovements within our sample (see Table VI in Appendix C). Strong residual cross-correlations would be the sign of a missing factor in our model. The analysis is based on several measures. We assess the degree of residual comovements using the average of the absolute value of pairwise correlations across the residuals and the 25% and 75% percentile pairwise correlation coefficients. We compute these measures from our initial samples and based on the residuals of the factor model.

Initially, the average absolute pairwise correlations across industry and firm returns are equal to 41.4% and 26.7%, respectively. We show that our baseline factor model can capture most of the common risk exposures, as the average absolute pairwise correlation across residuals decreases to 3.1% and 3.5%. Moreover, the average standard pairwise correlation tends towards zero. Although our five-factor model appears to satisfactorily capture the comovements among returns, we still compare its performances with other specifications.

We consider including the size (SMB) and value (HML) factors in our baseline specification (Fama and French, 1992). Our analysis shows that the seven-factor model does not lead to a substantial improvement in the previously defined metrics. Whereas we note a small rise in the adjusted R-squared, the average absolute correlations across the residuals remain equal to 3.1% and 3.5% for industry and firms, respectively. We decide not to include the size and value factors in our baseline specification to preserve its ability to distinguish between financial and non-financial loadings. Finally, we compare our five-factor model with a three-factor model and find that adding regional factors leads to a substantial improvement of the model performances based on all the previously defined metrics.

4.4. Concentration

We examine whether the rise in connectedness could be driven by a process of industry concentration. In theory, a few large international firms are more likely to share bilateral linkages or common exposures than many small or medium companies. Such a concentration process could strengthen linkages both within and between industries, affecting our measure of interconnectedness. We first look at the concentration level in each sector by examining the share that the ten major companies represent in terms of market capitalization over time. In contrast with banks, we find that the insurance sector has not experienced a significant concentration process. The ten major insurance companies represented 22% in 1978 (against 18% for banks) and this proportion has remained approximately equal over the past decades (23% for insurers against 32% for banks in 2018). In parallel, even if there is a large heterogeneity across sectors, the ratio has decreased from 27 to 23% on average for non-financial firms. In the same vein, we study the growth rate of the size of the different industries and show that the market capitalization of the insurance and banking sectors has expanded at a similar pace as the average of non-financial sectors.

Next, we run an exercise that focuses on the concentration level within the ten largest companies in each sector. The Herfindahl-Hirschman Index (HHI), an indicator of concentration, is calculated from 1995 to 2018 for comparison purposes. We find that the HHI for the largest insurers slightly increased from 0.18 in 1995 to 0.23 in 2018 compared to a small decrease in the level of concentration of the largest banks (from 0.19 to 0.16) and non-financial firms (from 0.19 to 0.17). We also divide the insurance sector into several groups and note that the concentration within life insurers has remained approximately the same between 1995 and 2018 (about 0.14). For non-life insurers, the concentration has decreased from 0.21 to 0.15. Finally, for reinsurers, the results depend largely on the inclusion of Berkshire Hathaway, with the HHI rising from 0.36 in 1995 to 0.42 in 2018 in one case, or falling from 0.37 to 0.18 in the other. Based on these results, we conclude that the concentration process has remained limited within the insurance sector and is unlikely to drive the strengthening in insurers' linkages observed over the past decades. Other factors detailed in Section 3.1.1 and 3.2.2 might be more relevant.

5. Conclusion

This article studies the evolution of the interconnectedness level of the insurance sector over the past four decades. We estimate the level of connectedness based on a multifactor model of weekly equity returns with time-varying factor loadings and time-varying factor variance. Our indicator is complementary to recently developed measures of systemic risk and spillover and helps determine whether the probability of an insurance crisis has increased over time.

The results indicate that the connectedness of the whole insurance sector has experienced a significant increase over the past four decades. By contrast, the interconnectedness of non-financial firms has remained more stable. This upward trend may result from changes in the business models and balance sheets of insurers due to large waves of mergers and acquisitions, the development of global and NTNI activities, and the low-interest-rate environment. This finding supports the recent proposal of the IAIS to implement new macroprudential supervision based on a holistic framework.

Second, the major insurance companies are more connected than both the rest of the insurance sector and the largest non-financial firms. Therefore, major insurance companies pose a higher threat to financial stability due to their size and strong connections with financial and non-financial companies. This result underscores the relevance of the entity-based macroprudential regulation initially implemented by the FSB. Therefore, despite the transition to sector-wide macroprudential regulation, our findings suggest that the FSB should continue the annual identification of G-SIIs. Our conclusions are also of interest to investors, as we show that the stocks issued by the largest insurers should not be included in equity portfolios for diversification purposes due to high systematic risk.

Finally, insurers and banks are exposed to different sources of risk. While insurers are more vulnerable to shocks stemming from non-financial sectors, banks have stronger links with the rest of the financial industry. This result is consistent with theoretical models showing that banks are institutionally connected with the rest of the financial sector through large direct balance sheet exposures. It also suggests that distinct regulatory measures may be needed to handle the specific structures of the interconnectedness of insurers and banks.

References

[1] Acharya, V. V., Pedersen, L. H., Philippon, T., & Richardson, M. (2017). Measuring Systemic Risk. *Review of Financial Studies*, *30*(1). https://doi.org/10.1093/rfs/hhw088

[2] Adams, Z., Füss, R., & Gropp, R. (2014). Spillover Effects among Financial Institutions: A State-Dependent Sensitivity Value-at-Risk Approach. In *Journal of Financial and Quantitative Analysis*. https://doi.org/10.1017/S0022109014000325

[3] Adrian, T., & Brunnermeier, M. K. (2016). CoVaR. *American Economic Review*, *106*(7), 1705–1741. https://doi.org/10.1257/aer.20120555

[4] Bai, J., & Perron, P. (2003). Computation and Analysis of Multiple Structural Change Models. *Journal of Applied Econometrics*, *18*(1), 1–22. https://doi.org/10.1002/jae.659

[5] Baluch, F., Mutenga, S., & Parsons, C. (2011). Insurance, Systemic Risk and the Financial Crisis. *The Geneva Papers on Risk and Insurance - Issues and Practice*, *36*(1), 126–163. https://doi.org/10.1057/gpp.2010.40

[6] Barrot, J. N., Loualiche, E., & Sauvagnat, J. (2019). The Globalization Risk Premium. *The Journal of Finance*, *74*(5), 2391–2439. https://doi.org/10.1111/jofi.12780

[7] Bekaert, G., Ehrmann, M., Fratzscher, M., & Mehl, A. (2014). The Global Crisis and Equity Market Contagion. *The Journal of Finance*, *69*(6), 2597–2649. https://doi.org/10.1111/jofi.12203

[8] Bekaert, G., Hodrick, R. J., & Zhang, X. (2009). International Stock Return Comovements. *The Journal of Finance*, 64(6), 2591–2626. https://doi.org/10.1111/j.1540-6261.2009.01512.x

[9] Berdin, E., & Sottocornola, M. (2015). Insurance Activities and Systemic Risk. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2701821

[10] Berger, D., & Pukthuanthong, K. (2012). Market Fragility and International Market Crashes. *Journal of Financial Economics*, *105*(3), 565–580. https://doi.org/10.1016/j.jfineco.2012.03.009

[11] Bierth, C., Irresberger, F., & Weiß, G. N. F. (2015). Systemic Risk of Insurers around the Globe. *Journal of Banking & Finance*, *55*, 232–245. https://doi.org/10.1016/j.jbankfin.2015.02.014

[12] Billio, M., Getmansky, M., Lo, A. W., & Pelizzon, L. (2012). Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors. *Journal of Financial Economics*, *104*(3), 535–559. https://doi.org/10.1016/j.jfineco.2011.12.010

[13] Boeckelmann, L., & Stalla-Bourdillon, A. (2020). Structural Estimation of Time-Varying Spillovers: an Application to International Credit Risk Transmission. *SSRN Electronic Journal*. http://dx.doi.org/10.2139/ssrn.3827913

[14] Brooks, R., & Negro, M. Del. (2006). Firm-Level Evidence on International Stock Market Comovement. *Review of Finance*, *10*(1), 69–98. https://doi.org/10.1007/s10679-006-6979-1

[15] Brownlees, C., & Engle, R. F. (2017). SRISK: A Conditional Capital Shortfall Measure of Systemic Risk. *Review of Financial Studies*, *30*(1), 48–79. https://doi.org/10.1093/rfs/hhw060

[16] Bunzel, H., & Vogelsang, T. J. (2005). Powerful Trend Function Tests That Are Robust to Strong Serial Correlation, With an Application to the Prebisch–Singer Hypothesis. *Journal of Business & Economic Statistics*, *23*(4), 381–394. https://doi.org/10.1198/073500104000000631

[17] Chaieb, I., Langlois, H., & Scaillet, O. (2018). Time-Varying Risk Premia in Large International Equity Markets. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3103752

[18] Chen, H., Cummins, J. D., Sun, T., & Weiss, M. A. (2020). The Reinsurance Network Among U.S. Property–Casualty Insurers: Microstructure, Insolvency Risk, and Contagion. *Journal of Risk and Insurance*, *87*(2), 253–284. https://doi.org/10.1111/jori.12269

[19] Chen, H., Cummins, J. D., Viswanathan, K. S., & Weiss, M. A. (2014). Systemic Risk and the Interconnectedness Between Banks and Insurers: An Econometric Analysis. *Journal of Risk and Insurance*, *81*(3), 623–652. https://doi.org/10.1111/j.1539-6975.2012.01503.x

[20] Chen, H., & Sun, T. (2020). Tail Risk Networks of Insurers Around the Globe: An Empirical Examination of Systemic Risk for G-SIIs vs Non-G-SIIs. *Journal of Risk and Insurance*, *87*(2), 285–318. https://doi.org/10.1111/jori.12296

[21] Cummins, J. D., & Weiss, M. A. (2014). Systemic Risk and The U.S. Insurance Sector. *Journal of Risk and Insurance*, *81*(3), 489–528. https://doi.org/10.1111/jori.12039

[22] Diebold, F. X., & Yılmaz, K. (2014). On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms. *Journal of Econometrics*, *182*(1), 119–134. https://doi.org/10.1016/j.jeconom.2014.04.012

[23] Dungey, M. H., Luciani, M., & Veredas, D. (2014). The Emergence of Systemically Important Insurers. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2494030

[24] Eiling, E., & Gerard, B. (2015). Emerging Equity Market Comovements: Trends and Macroeconomic Fundamentals. *Review of Finance*, *19*(4), 1543–1585. https://doi.org/10.1093/rof/rfu036

[25] Eiling, E., Gerard, B., & De Roon, F. A. (2012). Euro-Zone Equity Returns: Country versus Industry Effects. *Review of Finance*, *16*(3), 755–798. https://doi.org/10.1093/rof/rfq034

[26] Elliott, G., & Müller, U. K. (2006). Efficient Tests for General Persistent Time Variation in Regression Coefficients. *Review of Economic Studies*, *73*(4), 907–940. https://doi.org/10.1111/j.1467-937X.2006.00402.x

[27] Elyasiani, E., Kalotychou, E., Staikouras, S. K., & Zhao, G. (2015). Return and Volatility Spillover among Banks and Insurers: Evidence from Pre-Crisis and Crisis Periods. *Journal of Financial Services Research*, *48*(1), 21–52. https://doi.org/10.1007/s10693-014-0200-z

[28] European Insurance and Occupational Pensions Authority (2018). *Failures and Near Misses in Insurance: Overview of the Causes and Early Identification*. Luxembourg. Retrieved from https://eiopa.europa.eu/Publications/Reports/EIOPA_Failures_and_near_misses_FINAL%20(1).pdf

[29] Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. The Journal of Finance, 47(2), 427–465. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

[30] Forbes, K. J., & Chinn, M. D. (2004). A Decomposition of Global Linkages in Financial Markets over Time. *Review of Economics and Statistics*, *86*(3), 705–722. https://doi.org/10.1162/0034653041811743

[31] Forbes, K. J., & Rigobon, R. (2002). No Contagion, Only Interdependence: Measuring Stock Market Comovements. *The Journal of Finance*, *57*(5), 2223–2261. https://doi.org/10.1111/0022-1082.00494

[32] Gandhi, P., & Lustig, H. (2015). Size Anomalies in U.S. Bank Stock Returns. *The Journal of Finance*, *70*(2), 733–768. https://doi.org/10.1111/jofi.12235

[33] Geraci, M. V., & Gnabo, J. Y. (2018). Measuring Interconnectedness between Financial Institutions with Bayesian Time-Varying Vector Autoregressions. In *Journal of Financial and Quantitative Analysis*. https://doi.org/10.1017/S0022109018000108

[34] Gehrig, T., & Iannino, M. C. (2018). Capital Regulation and Systemic Risk in the Insurance Sector. *Journal of Financial Economic Policy*, *10*(2), 237–263. https://doi.org/10.1108/JFEP-11-2017-0105

[35] Greenwood, R., Landier, A., & Thesmar, D. (2015). Vulnerable Banks. *Journal of Financial Economics*, *115*(3), 471–485. https://doi.org/10.1016/j.jfineco.2014.11.006

[36] Harrington, S. E. (2009). The Financial Crisis, Systemic Risk, and the Future of Insurance Regulation. *Journal of Risk and Insurance*, *76*(4), 785–819. https://doi.org/10.1111/j.1539-6975.2009.01330.x

[37] Harvey, C. R., Liu, Y., & Zhu, H. (2016). … and the Cross-Section of Expected Returns. *Review of Financial Studies*, *29*(1), 5–68. https://doi.org/10.1093/rfs/hhv059

[38] Harvey, D. I., Leybourne, S. J., & Taylor, A. M. R. (2007). A Simple, Robust and Powerful Test of the Trend Hypothesis. *Journal of Econometrics*. https://doi.org/10.1016/j.jeconom.2007.02.005

[39] Harvey, D. I., Leybourne, S. J., & Taylor, A. M. R. (2009). Simple, Robust, and Powerful Tests of the Breaking Trend Hypothesis. *Econometric Theory*, *25*(4), 995–1029. https://doi.org/10.1017/S0266466608090385

[40] Hollstein, F., & Prokopczuk, M. (2016). Estimating Beta. *Journal of Financial and Quantitative Analysis*, *51*(4), 1437–1466. https://doi.org/10.1017/S0022109016000508

[41] International Association of Insurance Supervisors (2016). *Global Systemically Important Insurers: Updated Assessment Methodology*. Basel. Retrieved from https://www.iaisweb.org/page/supervisory-material/financial-stability/archive/file/61179/updated-g-sii-assessment-methodology-16-june-2016

[42] International Association of Insurance Supervisors (2018). *Holistic Framework for Systemic Risk in the Insurance Sector*. Basel. Retrieved from https://www.iaisweb.org/file/77862/holistic-framework-for-systemic-risk-consultation-document

[43] International Monetary Fund (2016). The Insurance Sector-Trends and Systemic Risk Implications. *Global Financial Stability Report* (April). http://dx.doi.org/10.2139/ssrn.2795694

[44] Jourde, T. (2021). The Long-Term Effect of Globalization on International Stock Return Comovements. *SSRN Electronic Journal*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3916844

[45] Karolyi, G. A. (1992). Predicting Risk: Some New Generalizations. *Management Science*, *38*(1), 57–74. https://doi.org/10.1287/mnsc.38.1.57

[46] Kaserer, C., & Klein, C. (2019). Systemic Risk in Financial Markets: How Systemically Important Are Insurers? *Journal of Risk and Insurance*, *86*, 729–759. https://doi.org/10.1111/jori.12236

[47] Klein, R. F., & Chow, V. K. (2013). Orthogonalized Factors and Systematic Risk Decomposition. *The Quarterly Review of Economics and Finance*, *53*(2), 175–187. https://doi.org/10.1016/j.qref.2013.02.003

[48] Koijen, R. S. J., & Yogo, M. (2020). The Fragility of Market Risk Insurance. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2972295

[49] Ledoit, O., & Wolf, M. (2004). Honey, I Shrunk the Sample Covariance Matrix. In *Journal of Portfolio Management* (Vol. 30, Issue 4). https://doi.org/10.3905/jpm.2004.110

[50] Lewellen, J., & Nagel, S. (2006). The Conditional CAPM Does Not Explain Asset-Pricing Anomalies. *Journal of Financial Economics*, *82*(2), 289–314. https://doi.org/10.1016/j.jfineco.2005.05.012

[51] Malik, S., & Xu, T. (2017). Interconnectedness of Global Systemically-Important Banks and Insurers. *IMF Working Papers*, *17*(210), 1. https://doi.org/10.5089/9781484320716.001

[52] Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, *55*(3), 703. https://doi.org/10.2307/1913610

[53] Oh, D. H., & Patton, A. J. (2018). Time-Varying Systemic Risk: Evidence From a Dynamic Copula Model of CDS Spreads. *Journal of Business & Economic Statistics*, *36*(2), 181–195. https://doi.org/10.1080/07350015.2016.1177535

[54] Pukthuanthong, K., Roll, R., & Subrahmanyam, A. (2019). A Protocol for Factor Identification. *The Review of Financial Studies*, *32*(4), 1573–1607. https://doi.org/10.1093/rfs/hhy093

[55] Quinn, D. P., & Voth, H.-J. (2008). A Century of Global Equity Market Correlations. *American Economic Review*, *98*(2), 535–540. https://doi.org/10.1257/aer.98.2.535

[56] Roll, R. (1992). Industrial Structure and the Comparative Behavior of International Stock Market Indices. *The Journal of Finance*, *47*(1), 3–41. https://doi.org/10.1111/j.1540-6261.1992.tb03977.x

[57] Thimann, C. (2014). Regulating the Global Insurance Industry: A Compendium of Motivations and Challenges. In *CESifo Forum* (Vol. 15, No. 3, pp. 72–78). München: ifo Institut–Leibniz-Institut für Wirtschaftsforschung an der Universität München. Retrieved from http://cesifo-group.info/DocDL/forum3-14-special3.pdf

[58] Thimann, C. (2015). Systemic Features of Insurance and Banking, and the Role of Leverage, Capital and Loss absorption. *The Geneva Papers on Risk and Insurance - Issues and Practice*, *40*(3), 359–384. https://doi.org/10.1057/gpp.2015.13

[59] Vasicek, O. A. (1973). A Note on Using Cross-Sectional Information in Bayesian Estimation of Security Betas. *The Journal of Finance*, *28*(5), 1233–1239. https://doi.org/10.1111/j.1540-6261.1973.tb01452.x

[60] Weiß, G. N. F., & Mühlnickel, J. (2014). Why Do Some Insurers Become Systemically Relevant? *Journal of Financial Stability*, *13*, 95–117. https://doi.org/10.1016/j.jfs.2014.05.001

Appendices

Appendix A. Methodology

a. Factor processing

We use factor-mimicking portfolios based on the weekly returns of Datastream equity indices. The factors are reprocessed to improve the interpretation of the coefficients and prevent endogeneity issues. As the world portfolio aggregates the stocks included in regional and local indices, we generate, for each local industry index, a specific set of non-overlapping factors that exclude the regional returns from the world factor and the local returns from the regional factor.

Second, we use an orthogonalization process to decorrelate each set of non-overlapping factors. Factors must be independent to ensure that regressions capture the specific risk exposures of each local industry index (or firm). We use a combination of the hierarchical and symmetric orthogonalization methods. First, the Gram–Schmidt method enables us to build an orthonormal matrix from a free set of factors. It is a hierarchical procedure based on the assumption that there is a top-down causal relationship between factors.

By contrast, the symmetric method, first implemented in the finance literature by Klein and Chow (2013), does not impose any hierarchical choice between factors, as it is not sensitive to the order in which the series are orthogonalized. All explanatory variables are thus simultaneously adjusted against each other. Therefore, it can generate the least distinct set of decorrelated factors from the original matrix. This procedure is especially helpful when we can hardly make reliable ranking hypotheses.

Except for a few cases, we use the Gram–Schmidt method, as we can reasonably assume that shock transmission goes from global to local factors. We thus consider that a shock originating from a small country with global impacts is, by definition, a global shock. Since we cannot make reliable assumptions on the direction of shocks between some factors, we then use the symmetric procedure. The Gram–Schmidt orthogonalization procedure is first applied using successive regressions, as follows

$$f_{i,RE,t} = \alpha_{i,RE} + \beta_{i,RE} f_{i,GE,t} + \varepsilon_{f_{i,RE,t}}$$

$$f_{i,LE,t} = \alpha_{i,LE} + \beta_{i,1,LE} f_{i,GE,t} + \beta_{i,2,LE} \varepsilon_{f_{i,RE,t}} + \varepsilon_{f_{i,LE,t}}$$

$$f_{i,GI,t} = \alpha_{i,GI} + \beta_{i,GI} f_{i,GE,t} + \varepsilon_{f_{i,GI,t}}$$

$$f_{i,RI,t} = \alpha_{i,RI} + \beta_{i,1,RI} f_{i,GE,t} + \beta_{i,2,RI} \varepsilon_{f_{i,RE,t}} + \beta_{i,3,RI} \varepsilon_{f_{i,GI,t}} + \varepsilon_{f_{i,RI,t}}$$

for each industry index i, $f_{i,GE}$, $f_{i,RE}$, $f_{i,LE}$, $f_{i,GI}$, and $f_{i,RI}$ represent the global, regional, and local *geographic* factors, as well as the global and regional *industry* factors. The residuals of the regressions $\varepsilon_{f_{i,RE}}$, $\varepsilon_{f_{i,LE}}$, $\varepsilon_{f_{i,GI}}$, and $\varepsilon_{f_{i,RI}}$ are the orthogonalized factors. We deal with residual correlation using the symmetric orthogonalization method (see Klein and Chow, 2013 for a description of the procedure). Note that the orthogonalization process is important to disentangle the relative risk exposures to financial and non-financial companies but does not impact the aggregate interconnectedness measure.

b. Estimation procedure

The assumption of constant parameters is rarely verified in asset pricing models. We test the null hypothesis that factor loadings are fixed over the sample period using the test suggested by Elliott and Müller (2006). This test is valid for a wide range of possible departures from the stable model (i.e., many or few breaks, clustered breaks, regular breaks, or smooth variations in the parameters). We check the stability of the coefficients for every local insurance index. We first perform the test for each factor separately and then for all regressors simultaneously (see Equation 1). The assumption that all coefficients are fixed is always rejected at the 1% level (unreported results). Therefore, we estimate the factor model using rolling window linear regressions, without overlapping data.

This method is easily implementable since assumptions regarding the dynamics of the coefficients are not required. However, it is difficult to determine the appropriate length of the rolling window, which must be wide enough to estimate precise parameters and short enough to avoid smoothing out important evolutions. Lewellen and Nagel (2006) argue that short windows provide conditional parameters without the need to specify conditioning information, as long as the coefficients are relatively stable within the window. Note that other dynamic estimators based on structural assumptions exist, but standard historical betas yield lower out-of-sample estimation errors (Hollstein and Prokopczuk, 2016). We arbitrarily fix a one-year window (52 observations) and test the robustness of the results based on two-year (104 observations) and six-month (26 observations) windows. Since the data shows evidence of serial correlation and heteroscedasticity, we estimate the model based on Newey and West (1987).

Estimating parameters using relatively short time windows might lead to estimation errors. We follow Vasicek (1973), who suggests shrinking each historical estimate toward a prior, depending on the relative precision of the historical coefficient ($\beta_{i,j}^{hist}$) and prior ($b_{sect,j}$). As the value of each coefficient might depend on the variance of the underlying series, we directly apply the shrinkage approach to each component ($VR_{i,j}^{hist}$) of our interconnectedness measure. To obtain a posterior belief of the estimator ($VR_{i,j}^{Shr}$), we combine the historical ratio with the prior ($VR_{sect,j}$), following Equation (5):

$$VR_{i,j}^{Shr} = \frac{\sigma_{b_{sect,j}}^2}{\sigma_{\beta_{i,j}^{hist}}^2 + \sigma_{b_{sect,j}}^2} VR_{i,j}^{hist} + \frac{\sigma_{\beta_{i,j}^{hist}}^2}{\sigma_{\beta_{i,j}^{hist}}^2 + \sigma_{b_{sect,j}}^2} VR_{sect,j} \tag{5}$$

where $\sigma_{\beta_{i,j}^{hist}}^2$ and $\sigma_{b_{sect,j}}^2$ are the variances of the coefficients $\beta_{i,j}^{hist}$ and $b_{sect,j}$, respectively. Following Karolyi (1992), we use a specific (informative) prior for each sector-factor pair. Each prior ($b_{sect,j}$ and $VR_{sect,j}$) are computed as the cross-sectional average of all estimates associated with a given sector and risk factor. Consequently, when the variance of the estimator is high compared to that of the respective prior, the interconnectedness measure is strongly adjusted toward $VR_{sect,j}$. We apply the same shrinkage method for the absolute level of systematic variance (VL). Since we focus primarily on aggregate measures, the shrinkage approach allows us to calculate an outlier-robust average of individual interconnectedness indicators. Our main results remain valid without using the shrinkage approach.

Appendix B. Main results

Table I. Interconnectedness—Levels & Trends

Sector	Average measure		Robust trend test			Structural break test
	VR (%)	VL $\times 10^3$ (%)	Trend VR (%)	$\mathcal{Z}_\lambda$	*Dan-J*	t_λ
Panel A: Industry indices						
Insurers	63	58	0.3	(1.7)**	(1.6)*	(1.4)
Banks	67	61	0.3	(1.8)**	(2.2)**	(1.1)
Basic Materials	71	57	0.0	(0.0)	(0.2)	(1.2)
Consumer Goods	58	45	0.1	(0.1)	(0.4)	(2.1)
Consumer Services	69	44	0.1	(0.3)	(0.7)	(1.8)
Healthcare	66	34	-0.3	(-1.2)	(-1.8)*	(1.5)
Industrials	71	50	0.3	(0.6)	(1.0)	(1.5)
Oil & Gas	64	59	0.0	(0.1)	(0.5)	(1.4)
Technology	55	59	0.4	(1.4)*	(2.7)**	(1.1)
Telecommunications	54	48	0.2	(2.5)***	(2.1)**	(1.4)
Utilities	54	32	0.1	(0.3)	(0.5)	(1.5)
Panel B: Largest firms						
Insurers	56	70	0.3	(1.3)*	(2.5)**	(1.3)
Banks	56	69	0.4	(2.4)***	(3.2)**	(1.7)
Basic Materials	58	66	0.1	(0.1)	(0.2)	(1.1)
Consumer Goods	47	49	0.0	(0.1)	(0.5)	(1.5)
Consumer Services	42	43	-0.5	(-1.1)	(-0.8)	(1.7)
Healthcare	47	35	-0.3	(-0.6)	(-0.7)	(2.3)
Industrials	56	62	-0.0	(-0.3)	(-0.1)	(1.9)
Oil & Gas	50	47	0.4	(0.6)	(1.6)*	(1.6)
Technology	41	68	0.0	(0.1)	(0.0)	(1.5)
Telecommunications	47	50	-0.4	(0.9)	(0.4)	(4.1)***
Utilities	41	30	-0.1	(0.5)	(0.3)	(1.4)

Notes: This table compares the average interconnectedness measures (VR & VL) across industries (1974–2018) for both industry indices and the largest firms. We report the annualized trends (%) and test statistics (*Dan-J* and $\mathcal{Z}_\lambda$) based on the linear deterministic trend tests of Bunzel and Vogelsang (2005) and Harvey et al. (2007), respectively. The null hypothesis is that there is no trend in the series. The *Dan-J* statistics are different at the 1%, 5%, and 10% levels because of the scaling to achieve optimal size in a finite sample. We also control for the existence of a structural break in level and trend following Harvey et al. (2009). The signs *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table II. Comparing interconnectedness levels—Insurers, banks, and non-financial firms

	Local industries				Largest firms			
	Diff (VR)	t-stat	Diff (VL)	t-stat	Diff (VR)	t-stat	Diff (VL)	t-stat
Insurance vs. Non-financial sectors								
Total connectedness	0.6	(0.8)	10.4	(2.8)***	8.0	(7.1)***	20.4	(3.6)***
Global factor	-1.0	(-1.7)	4.5	(1.7)*	4.7	(5.0)***	12.4	(2.6)**
Global industry factor	-1.0	(-3.6)***	-0.7	(-2.0)**	-0.5	(-1.3)	-0.2	(-0.4)
Regional factor	0.4	(0.9)	2.3	(3.0)***	2.0	(3.2)***	3.2	(3.2)***
Regional industry factor	2.2	(6.4)***	1.8	(5.9)***	3.1	(7.6)***	3.8	(5.6)***
Local factor	-0.0	(-0,1)	2.5	(3.0)***	-1.3	(-3.3)***	1.2	(1.2)
Insurance vs. Banking sector								
Total connectedness	-3.8	(-5.1)***	-3.2	(-1.5)	0.3	(0.2)	1.4	(0.5)
Global factor	-0.6	(-1.1)	-1.2	(-1.3)	2.6	(2.8)***	6.7	(2.9)***
Global industry factor	-1.2	(-3.3)***	-1.7	(-2.7)***	-2.0	(-4.7)***	-2.9	(-3.3)***
Regional factor	-1.5	(-4.1)***	-0.7	(-1.4)	0.4	(0.7)	0.3	(0.4)
Regional industry factor	-1.6	(-4.5)***	-1.6	(-3.4)***	-2.0	(-3.9)***	-3.6	(-4.3)***
Local factor	1.0	(2.1)**	2.1	(2.4)**	1.2	(2.3)**	0.9	(0.6)

Notes: This table compares the level of interconnectedness of insurers, banks, and non-financial sectors using paired t-tests. We report the average spread (Diff) between the interconnectedness series (VR or VL). Based on VR, Diff is expressed in percentage points, while based on VL, it is measured as the absolute level of variance multiplied by 10^3. Test statistics are in parentheses. The signs *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table III. Comparing interconnectedness levels—Details by insurer types

Interconnectedness measure	Life vs. Non-life insurers		Life vs. Reinsurers		Non-life vs. Reinsurers	
	Diff (%)	t-stat	Diff (%)	t-stat	Diff (%)	t-stat
VR	-4.0	(-3.0)***	11.3	(7.7)***	15.4	(12.8)***
VL	-4.6	(-1.1)	25.6	(4.0)***	30.0	(8.4)***
VR (1974–2000)	-8.4	(-5.3)***	9.5	(4.2)***	17.9	(11.2)***
VL (1974–2000)	-11.0	(-2.1)**	19.0	(3.1)***	30.0	(10.0)***
VR (2001–2018)	2.5	(1.9)*	11.7	(7.9)***	14.2	(10.0)***
VL (2001–2018)	5.2	(0.9)	30.3	(3.9)***	35.5	(2.8)**

Notes: This table compares the level of interconnectedness of life insurers, non-life insurers, and reinsurers using paired t-tests. We report the average spread (Diff) between the interconnectedness series over a given period. The periods are defined based on a structural break test. Test statistics are in parentheses. The signs *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table IV. Interconnectedness—Details by firms

Largest firms	Average measure (2000-2018)		Robust trend test			Structural break test
	VR (%)	VL $\times 10^3$ (%)	Trend VR (%)	$\mathcal{Z}_\lambda$	*Dan-J*	t_λ
Panel A: Life insurers						
Aegon (*)	64	106	0.4	(1.3)	(2.2)**	(1.2)
Aviva (*)	64	92	0.1	(0.2)	(1.0)	(1.8)
CNP Assurances	60	78	1.8	(1.1)	(1.1)	(2.8)
Legal & General	64	84	0.0	(0.1)	(0.5)	(2.4)
Lincoln National	66	97	0.3	(0.8)	(1.9)**	(1.7)
Power Corp. Canada	60	61	0.5	(1.3)*	(1.9)*	(1.4)
Power Financial	61	56	1.0	(2.2)**	(2.2)**	(2.1)
Prudential (*)	65	97	0.1	(0.1)	(0.5)	(1.9)
Swiss Life	61	89	0.7	(3.0)***	(2.1)**	(1.4)
Globe Life	62	52	0.6	(2.0)**	(3.5)**	(1.4)
Panel B: Non-life insurers						
Allianz (*)	67	89	0.4	(3.8)***	(2.0)*	(1.0)
American Intl. Gp. (*)	57	74	0.1	(0.5)	(0.6)	(1.6)
Assicur. Generali (*)	65	78	-0.1	(-0.1)	(-0.5)	(1.8)
AXA (*)	70	122	0.1	(0.2)	(2.0)**	(2.0)
Baloise Group	63	71	0.1	(0.2)	(1.3)	(1.3)
Loews Corporation	60	53	-0.1	(-0.2)	(0.2)	(1.6)
MS&AD Insurance	58	73	-0.7	(-0.7)	(-0.4)	(2.5)
Progressive	49	49	0.1	(0.7)	(1.0)	(1.3)
UnipolSai	57	81	-0.1	(-0.3)	(-0.1)	(1.6)
Zurich Insurance Gp.	64	75	0.3	(1.5)*	(0.5)	(1.9)
Panel C: Reinsurers						
Berkshire Hathaway	46	32	1.0	(1.6)*	(1.6)*	(1.6)
Everest Re	45	36	0.1	(0.1)	(0.2)	(2.9)*
Hannover Re	53	55	1.5	(1.4)*	(1.6)	(2.1)
Munich Re	57	61	0.5	(3.0)***	(2.3)**	(1.3)
QBE Insurance Gp.	50	52	0.7	(3.7)***	(3.8)**	(2.0)
Reinsur. Gp. of Am.	49	41	0.9	(2.0)**	(3.1)**	(2.2)
RenaissanceRe	37	29	0.7	(0.9)	(1.6)*	(2.2)
SCOR SE	51	56	1.0	(1.8)**	(1.8)*	(2.2)
Swiss Re	56	63	0.1	(0.3)	(0.4)	(1.2)

Notes: This table compares the average interconnectedness measures (VR & VL) of life insurers, non-life insurers, and reinsurers (from 2000 to 2018, the largest period for which all data are available). We report the annualized trends (%) and test statistics (*Dan-J* and $\mathcal{Z}_\lambda$) based on the linear deterministic trend tests of Bunzel and Vogelsang (2005) and Harvey et al. (2007), respectively. The null hypothesis is that there is no trend in the series. The *Dan-J* statistics are different at the 1%, 5%, and 10% levels because of the scaling to achieve optimal size in a finite sample. We also control for the existence of a structural break in level and trend following Harvey et al. (2009). The signs *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. (*) indicates that the insurer belongs to the list of G-SIIs.

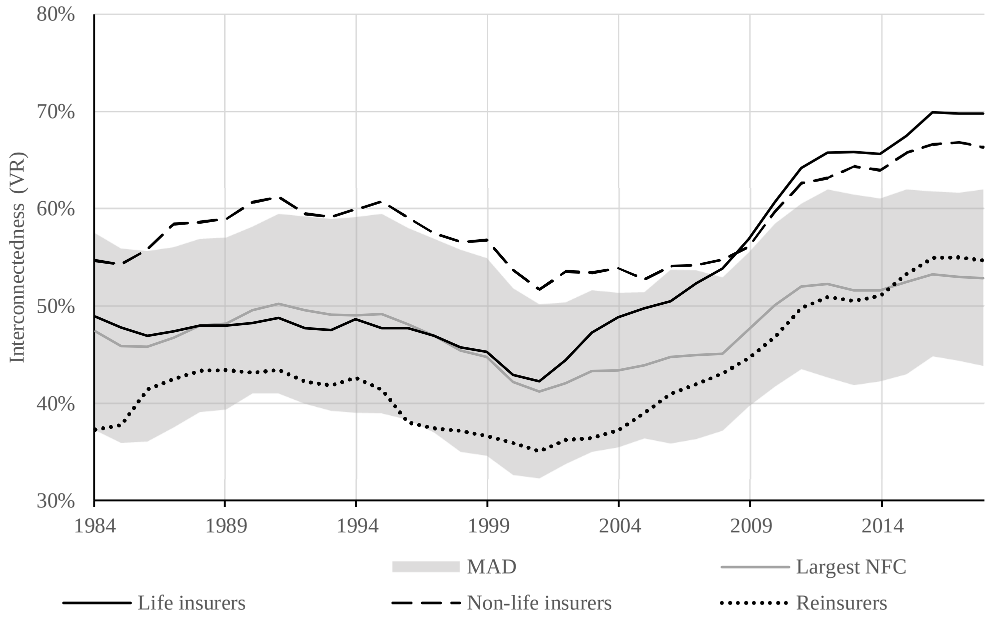

Figure 3. Interconnectedness (VR) of the largest insurers by category

This figure compares the evolution (1974–2018, ten-year moving averages) of the interconnectedness of the largest life insurers, non-life insurers, reinsurers, and non-financial firms based on individual stocks from developed countries (unweighted cross-sectional averages). The grey area represents the median absolute deviation (MAD) between the level of interconnectedness of non-financial sectors.

Appendix C. Robustness tests

Table V. Factor loadings

Interconnectedness measures		Fixed betas/ Time-varying variances			Fixed variances/ Time-varying betas		
		Trend (%)	$\mathcal{Z}_\lambda$	*Dan-J*	Trend (%)	$\mathcal{Z}_\lambda$	*Dan-J*
Industry indices	Insurers	-0.2	(-0.1)	(-0.8)	1.5	(2.5)***	(2.2)*
	Banks	-1.0	(-1.1)	(-1.2)	2.0	(2.0)**	(2.2)**
	Average sector	0.8	(2.4)***	(2.0)**	0.9	(2.1)**	(3.1)**
Largest firms	Insurers	0.2	(0.1)	(-0.0)	1.5	(3.2)***	(2.8)***
	Banks	-0.3	(-0.4)	(-0.3)	1.6	(4.1)***	(4.1)***
	Average sector	0.5	(1.0)	(1.5)*	0.6	(3.6)***	(5.0)***

Notes: This table tests whether the increase in the interconnectedness measures (VR) is due to changes (i) in the variance of the series or (ii) in the factor loadings (see Equation 3). To this end, we recalculate VR by setting either betas or variances to their sample mean. The trend test statistics (*Dan-J* and $\mathcal{Z}_\lambda$) are based on Bunzel and Vogelsang (2005) and Harvey et al. (2007), respectively. The signs *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table VI. Model comparison

Data/Residuals		Avg adj R^2 (%)	Avg abs(corr) (%)	Quant 25% (corr)	Quant 75% (corr)
Local industry indices	Initial sample	n/a	41.4	22.9	35.7
	Three-factor model	57.7	3.7	-1.5	2.4
	Five-factor model	60.1	3.1	-1.5	1.9
	Seven-factor model	60.3	3.1	-1.6	1.9
Largest firms	Initial sample	n/a	26.7	13.4	23.5
	Three-factor model	39.8	4.0	-1.7	2.4
	Five-factor model	41.9	3.5	-1.5	2.0
	Seven-factor model	42.7	3.5	-1.6	1.9

Notes: This table tests the ability of various time-varying factor models to capture the degree of comovements across our sample. We compare the model performances based on several measures: (i) the average adjusted R-squared, (ii) the average of the absolute value of the pairwise correlations, and (iii) the 25 and 75% percentile pairwise correlation coefficients. Since the global Fama–French factors are only available since 1990, the model comparison is limited to the period 1990–2018.

Table VII. Accounting data

	(1) LM factor	(2) RI factor	(3) RM factor	(4) GI factor	(5) GM factor	(6) LM factor	(7) GM factor
LM holding	2.47***						
	(3.90)						
RI holdings		0.07					
		(0.67)					
RM holdings			0.28*				
			(1.91)				
GI holdings				0.23*			
				(1.78)			
GM holdings					0.17		
					(0.54)		
World sales						-0.06***	0.09***
						(-5.92)	(4.60)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	No	No
N	392	392	392	392	392	914	914
T	28	28	28	28	28	21	21
n	14	14	14	14	14	51	51

Notes: This table tests the extent to which our interconnectedness measure is related to recent accounting data on (i) insurers' securities holdings (models 1–5) for a sample of 14 domestic insurance sectors in the euro area (2014–2020) and (ii) insurers' world sales (as a percentage of total sales; models 6 and 7) for a sample of 51 insurers (2000–2020). The signs *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. We use robust standard errors based on the White method. LM, RI, RM, GI, and GM stand for the exposures to the "local", "regional industry", "regional", "global industry", and "global" factors, respectively.

Table I1. Description of the selected domestic insurance indices

Countries	Starting point	Total assets (as a % of the world)		Total sales (as a % of the world)	
		As of 1996	As of 2017	As of 1996	As of 2017
United States	1973	31.8	20.8	31.1	22.9
Japan	1973	1.1	18.7	1.9	11.9
United Kingdom	1973	13.8	9.8	12.5	9.0
Canada	1976	3.6	7.9	3.5	5.6
Germany	1973	14.0	6.7	18.0	7.6
France	1977	9.1	6.5	6.9	6.5
Italy	1973	4.3	4.7	6.5	5.4
Switzerland	1973	6.9	3.9	7.7	4.5
Netherland	1973	4.5	3.3	3.5	2.1
Australia	1973	0.1	0.8	0.2	1.4
Belgium	1973	7.9	0.5	4.7	0.4
Austria	1973	0.3	0.4	0.4	0.5
Spain	1987	0.2	0.4	0.5	0.9
Norway	1980	0.7	0.4	0.6	0.3
Denmark	1973	0.1	0.1	0.2	0.2
Ireland	1989	0.03	0.01	0.04	0.01
All (above countries)		98.6	84.7	98.2	79.4
World		100	100	100	100

Notes: For each country, we compare the insurance total assets and sales (as a % of the world) as of 1996 and 2017, the first and last year for which data are available.

Table I2. Component list of the domestic insurance indices

Country	Insurance company	Country	Insurance company
Australia	Insurance Australia Group	United Kingdom	Prudential (*)
	QBE Insurance Group		Aviva (*)
	AMP		Legal & General
	Challenger		Old Mutual Limited
	Medibank Private		RSA Insurance Group
	Steadfast Group		Admiral Group
Austria	Vienna Insurance Group		St. James's Place
	Uniqa Insurance Group		Direct Line Insurance Group
Belgium	Ageas		Beazley
Canada	Manulife Financial		Phoenix Group
	Great-West Lifeco		Hastings Group
	Sun Life Financial		Hiscox
	Power Financial		Jardine Lloyd Thompson
	Fairfax Financial Holdings		Esure Group
	Intact Financial		Just Group
	Power Corp. Canada		Chesnara
	Industrial Alliance Insurance & Finl. Svs.		Lancashire Group
	E-L Financial		Sabre Insurance Group
Denmark	Tryg	United States	Berkshire Hathaway
	Topdanmark		Chubb
	Alm Brand		American International Group (*)
France	AXA (*)		MetLife (*)
	CNP Assurances		Prudential Financial (*)
	SCOR SE		Marsh & McLennan
	Coface		Aflac
	April		Allstate
Germany	Allianz (*)		Aon
	Munich Re		Travelers
	Hannover Re		Progressive
	Talanx		The Hartford
	Nüernberger		Willis Towers Watson
Ireland	FBD Holdings		Loews Corporation
Italy	Assicurazioni Generali (*)		CNA Financial
	Poste Italiane		Principal Financial Group
	Banca Mediolanum		XL Group
	UnipolSai		Lincoln National
	Unipol Gruppo Finanziario		Markel
	Cattolica Assicurazioni		Arch Capital Group
	Vittoria Assicurazioni		Arthur J. Gallagher
Japan	Japan Post Holdings		Cincinnati Financial
	Tokio Marine Holdings		Globe Life
	Dai-Ichi Life Holdings		American Financial Group
	MS&AD Insurance Group		Everest Re
	Sompo Holdings		Unum
	Japan Post Insurance		Alleghany Corporation
	T&D Holdings		Assurant
	Sony Financial Holdings		Brown & Brown
	Anicom Holdings		Reinsurance Group of America
Netherlands	Aegon (*)		W. R. Berkley
	NN Group		Assured Guaranty
	ASR Nederland		AXIS Capital
Norway	Gjensidige Forsikring		Brighthouse Financial
	Storebrand		Erie Indemnity
	Protector Forsikring		First American
Spain	MAPFRE		Hanover Insurance Group
	Grupo Catalana Occidente		Old Republic International
Switzerland	Zurich Insurance Group		Primerica
	Swiss Re		RenaissanceRe
	Swiss Life		Validus Holdings
	Baloise Group		
	Helvetia Group		
	Vaudoise		

Notes: The list includes 121 insurance companies as of 2018. The sign (*) indicates that the insurance firm belongs to the list of G-SIIs published by the FSB.

Table I3. List of the largest companies of each sector

Sector	Company	Country	Sector	Company	Country
Bank	Bank of America	US	Life Insurance	Aegon (*)	Netherlands
	Barclays	UK		Aviva (*)	UK
	Deutsche Bank	Germany		CNP Assurances	France
	HSBC	UK		Legal & General	UK
	JP Morgan Chase & Co.	US		Lincoln National	US
	Royal Bank of Canada	Canada		Power Corp. Canada	Canada
	Sumitomo Mitsui Financial	Japan		Power Financial	Canada
	Toronto-Dominion Bank	Canada		Prudential (*)	UK
	UniCredit	Italy		Swiss Life	Switzerland
	Wells Fargo	US		Globe Life	US
Basic Materials	Air Liquide	France	Non-Life Insurance	Allianz (*)	Germany
	Anglo American	UK		American Intl. Gp. (*)	US
	BASF	Germany		Assicurazioni Generali (*)	Italy
	Freeport-McMoRan	US		AXA (*)	France
	International Paper	US		Baloise Group	Switzerland
	Linde plc	Germany		Loews Corporation	US
	Nippon Steel	Japan		MS&AD Insurance Gp.	Japan
	Rio Tinto	UK		Progressive	US
	Sumitomo Chemical	Japan		UnipolSai	Italy
	Toray Industries	Japan		Zurich Insurance Group	Switzerland
Consumer Goods	BMW	Germany	Reinsurance	Berkshire Hathaway	US
	Fiat Chrysler Automobiles	UK		Everest Re	US
	Ford Motor	US		Hannover Re	Germany
	Honda Motor	Japan		Munich Re	Germany
	Nestlé	Switzerland		QBE Insurance Group	Australia
	Nissan Motor	Japan		Reinsurance Gp. of Am	US
	Procter & Gamble	US		RenaissanceRe	US
	Sony	Japan		SCOR SE	France
	Toyota Motor	Japan		Swiss Re	Switzerland
	Volkswagen	Germany		Talanx	Germany
Consumer Services	Carrefour	France	Oil & Gas	BP	UK
	Comcast	US		Chevron	US
	CVS Health	US		ConocoPhillips	US
	Ahold	Netherlands		Enbridge	Canada
	Kroger	US		ExxonMobil	US
	Target	US		Repsol	Spain
	Tesco	UK		Schlumberger	US
	Walgreens Boots	US		Suncor Energy	Canada
	Walmart	US		Total	France
	Walt Disney	US		Valero Energy	US
Health Care	Abbott Laboratories	US	Technology	Apple	US
	Bayer	Germany		Canon	Japan
	GlaxoSmithKline	UK		Fujifilm	Japan
	Humana	US		Fujitsu	Japan
	Johnson & Johnson	US		Hewlett-Packard	US
	Medtronic	US		Intel	US
	Merck & Co.	US		IBM	US
	Novartis	Switzerland		Micron Technology	US
	Pfizer	US		Microsoft	US
	Hoffmann-La Roche	Switzerland		Western Digital	US
Industry	Boeing	US	Telecom	AT&T	US
	Caterpillar	US		BCE	Canada
	General Electric	US		BT Group	UK
	Hitachi	Japan		CenturyLink	US
	Itochu	Japan		KDDI	Japan
	Marubeni	Japan		NTT	Japan
	Mitsubishi Motors	Japan		Telecom Italia	Italy
	Mitsui	Japan		Telefónica	Spain
	Siemens	Germany		Verizon Communications	US
	United Technologies	US		Vodafone	UK
Insurance	Allianz (*)	Germany	Utilities	Duke Energy	US
	AXA (*)	France		E.ON	Germany
	Berkshire Hathaway	US		Exelon	US
	MS&AD Insurance Group	Japan		Kansai Electric Power	Japan
	Munich Re	Germany		NextEra Energy	US
	Aegon (*)	Netherlands		PG&E	US
	Aviva (*)	UK		RWE	Germany
	Lincoln National	US		Enel	Italy
	Power Corp. Canada	Canada		Southern Company	US
	Prudential (*)	UK		TEPCO	Japan

Notes: This table presents the largest companies in each sector. Our selection is based on (i) a ranking of the firms in terms of assets and sales (as of 2018) and (ii) data availability. (*) indicates that the insurer belongs to the list of G-SIIs.

Table I4. Alternative specifications

Measure			Average value (%)	Trend (%)	$\mathcal{Z}_{\lambda}$	*Dan-J*
Without shrinkage	Industry indices	Insurers	60	0.4	(2.2)**	(1.9)*
		Banks	65	0.3	(2.1)*	(2.7)**
		Average sector	60	0.1	(0.2)	(0.7)
	Largest firms	Insurers	54	0.4	(1.6)*	(2.4)**
		Banks	54	0.4	(2.2)**	(2.8)***
		Average sector	46	0.1	(0.2)	(0.3)
Logit transformation	Industry indices	Insurers	56	1.5	(1.5)*	(1.4)*
		Banks	73	1.3	(1.5)*	(2.3)**
		Average sector	52	0.4	(0.3)	(0.8)
	Largest firms	Insurers	25	1.3	(1.3)*	(2.1)**
		Banks	23	1.5	(2.3)**	(3.2)**
		Average sector	-9.2	-0.4	(-0.5)	(-0.1)
Robust regressions	Industry indices	Insurers	62	0.4	(2.5)***	(1.9)**
		Banks	66	0.4	(2.5)***	(2.5)**
		Average sector	61	0.2	(0.5)	(1.0)
	Largest firms	Insurers	55	0.5	(1.8)**	(2.4)**
		Banks	55	0.4	(3.0)***	(3.3)**
		Average sector	48	-0.1	(-0.3)	(0.2)
Two-year rolling window	Industry indices	Insurers	61	0.4	(1.7)**	(1.3)
		Banks	65	0.5	(3.6)***	(1.7)*
		Average sector	60	0.2	(0.8)	(0.7)
	Largest firms	Insurers	54	0.4	(1.5)*	(2.5)*
		Banks	53	0.4	(3.8)***	(3.8)***
		Average sector	44	-0.1	(-0.1)	(0.2)
Six-month rolling window	Industry indices	Insurers	67	0.1	(0.1)	(2.6)**
		Banks	70	0.2	(1.1)	(2.5)***
		Average sector	66	-0.1	(-0.2)	(1.7)*
	Largest firms	Insurers	61	0.2	(0.6)	(3.2)**
		Banks	60	0.3	(1.6)*	(3.8)***
		Average sector	54	-0.1	(-0.3)	(0.5)

Notes: This table controls the robustness of our main results to alternative specifications. We report the value and the trend of VR estimated (i) without shrinkage (see Section 3), (ii) based on a logit transformation of the series, (iii) using robust regressions instead of return winsorization, and (iv) based on two-year or six-month rolling windows. The trend tests are based on Bunzel and Vogelsang, 2005 (*Dan-J*) and Harvey et al., 2007 ($\mathcal{Z}_{\lambda}$). The signs *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.