Systemic risk monitoring in Europe: Mapping financial contagion with Block-Level Dynamics *

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Abstract

How do financial shocks ripple through an economy - globally, regionally, or idiosyncratically? We propose a novel decomposition of connectedness across European sovereigns, financial institutions, and non-financial firms by separating global shocks, block-level shocks (within economic or sectoral groups), and purely idiosyncratic spillovers. Using credit default swaps (CDS) spreads as a forward-looking measure of credit risk, we show that ignoring block-level dynamics can misattribute sector-wide or regional movements to firm-specific contagion. Our heatmap visualizations reveal clear shifts in transmission patterns when these block factors are included, shedding light on where financial contagion originates and how it spreads, offering a more nuanced view of systemic risk and its underlying structure. This layered approach not only improves our understanding of systemic risk, but also provides a valuable tool for macrofinancial surveillance, offering insight into where vulnerabilities lie.

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1 Introduction

The roots of the most recent global financial crisis can be traced back to the lending conditions and financial environment that emerged in the early 2000s. In response to the bursting of the dot-com bubble, the brief recession in 2001, and the aftermath of the 9/11 terrorist attacks, central banks aggressively lowered interest rates from 6.5% in 2001 to approximately 1% by mid-2003. This prolonged period of monetary easing significantly altered lending conditions, fostering an unprecedented expansion in consumer, mortgage, and corporate credit markets. Looser lending standards, historically low borrowing costs, and increasingly relaxed regulatory oversight encouraged rapid and extensive credit growth, particularly within the housing sector. Although these conditions initially facilitated economic recovery, they simultaneously led to increased financial vulnerabilities, ultimately amplifying systemic risks. These vulnerabilities became starkly evident with the collapse of the subprime mortgage market, which triggered severe financial contagion and widespread economic distress.

In a lending process, credit acquisition gives purchasing power and creates debt for the borrower, and it also assigns risk exposure to the lender. The latter can be distinguished into liquidity risk, associated with financing long-term loans and readily withdrawable deposits, interest rate risk, due to loans maturing at a different time than deposits, and credit risk, related to the credit quality characteristics of the borrower. To isolate risk exposures from the lending process, modern banking has increasingly relied on credit derivatives. Examples of credit derivatives include credit default swaps (CDS) and total return swaps (TRS), while broader risk transfer tools include securitization, syndicated lending, and investments in nontraditional assets such as hedge funds. In particular, the national amount of outstanding over-the-counter CDS alone was $13.9 trillion in December 2005, $28.8 trillion in December 2006 and more than $60 trillion in 2008 (Dalio (2022)). Credit default swaps (CDS), first developed by JPMorgan Chase in the 1990s, are financial contracts between a buyer and a seller of credit protection that function similarly to insurance. The protection buyer pays periodic premiums to the seller, who agrees to compensate the buyer if a predefined credit event (such as default or bankruptcy) occurs on a reference entity. Although they share similarities with insurance, CDSs are traded over-the-counter and are used by a wide range of financial institutions, including banks, hedge funds, and insurers, to hedge or speculate on credit risk. Therefore, CDS can be used to hedge credit risk exposures specifically, without directly transferring interest rate risk, unlike total return swaps, which expose the holder to both credit and interest rate fluctuations (Ashraf, Altunbas, and Goddard (2007); Jarrow (2011); Zhang, Zhou, and Zhu (2009)).

The bankruptcy of Lehman Brothers and the near-collapse of AIG were not random events, but rather the result of concentrated risk exposures in structured credit markets. AIG, in particular, was a major seller of CDS on mortgage-backed securities and lacked the capital reserves to honor those contracts when defaults surged. Lehman Brothers, while involved in CDS markets, was more broadly exposed to losses on mortgage-linked assets and faced acute funding pressures. The widespread issuance of loans to subprime borrowers, whose repayments depended on rising home prices and refinancing, led to a breakdown in repayment capacity once housing markets declined. As defaults mounted, CDS payouts were triggered, transferring credit risk to protection sellers and amplifying systemic stress. The resulting chain reaction of institutional distress exemplifies financial contagion, where shocks propagate across institutions through complex interconnections and concentrated exposures.

The absence of a straightforward European policy framework on how to tackle a banking crisis led several European sovereigns to act in favor of banks in trouble during the 2008 financial crisis and provide the funding needed for their rescue. Inevitably, this increased sovereign risk and debt accumulation, contributing to the European sovereign debt crisis of 2010. Gerlach, Schulz, and Wolff (2010) find that countries with a large financial sector have a higher credit risk due to the higher probability of stepping up and rescuing banks. In response to changes in the creditworthiness of sovereign institutions, the corporate sector becomes vulnerable and exposed to measures such as higher corporate taxes leading to lower profitability. This created a "transfer risk" channel where the risk is transferred from sovereigns to corporate banks. In parallel, banks in distress struggle to reduce their risk exposure. As large banks hold sovereign debt of different countries, sovereign risk is exchanged among international banks, feeding systemic risk mechanisms.

This chronicle is an example of how contagion and amplification effects can pose a threat to the stability of the entire economy. Thus, it is crucial for idiosyncratic spillovers to be carefully monitored to determine their ability to activate systemic risk. In particular, estimating idiosyncratic spillover effects among economic institutions can reveal critical information about the magnitude and speed of propagation of shocks in one or a group of institutions. We use CDS spreads as a measure of perceived credit risk to study potential transmission channels among European banks, sovereigns, and non-financial firms. Zingales and Hart (2010), emphasizes that CDS spreads can be seen as a bet on the strength of an institution, and hence their price or spread depicts the probability that the debt will not be paid back in full. Annaert et al. (2013), also highlights that increases in CDS spreads can be viewed as warnings to regulators to check the financial health of an institution.

This paper makes two contributions to this literature. First, following the methodological tools of Diebold and Yilmaz (2014) we provide a measure of systemic risk by estimating measures of connectedness that are quantitative and directional. This allows us to represent connectedness in a heatmap matrix. Secondly, we contribute to the previous measures by adding block factors to the estimation, where the blocks are naturally suggested by our data: four blocks for the non-financial sectors (Automobiles, Consumers, Energy and Telecommunications), one block for financial firms and one block for sovereign countries. By extending the connectedness measure of Diebold and Yilmaz (2014) to incorporate block-specific common factors in addition to the global factor, we isolate pure idiosyncratic spillovers that are not driven by shared sectoral or regional dynamics. This refinement demonstrates that estimated spillover effects can differ substantially depending on whether only a global factor or both global and block-level factors are considered. Furthermore, by explicitly modeling block factors, we can distinguish between spillovers caused by shocks to an entire block and those arising from purely idiosyncratic sources, providing a more nuanced view of systemic risk.

The paper is organized as follows. Section 2 provides the literature review. The methodology and modeling approach are described in Section 3. In Section 4, we discuss the empirical application, while Section 5 offers concluding remarks. A detailed data description, along with tables and robustness checks, is provided in the Appendix.

2 Literature Review

The 2008 financial crisis and the subsequent European sovereign debt crisis ignited widespread interest in the transmission of risk across financial institutions and sovereigns. A central theme in this literature is the mutual reinforcement of bank and sovereign vulnerabilities. For example, Acharya, Drechsler, and Schnabl (2012) develop a structural framework linking sovereign credit risk to bank fragility, showing how government bond holdings create channels for risk to flow between sovereigns and domestic banks. Building on this, Acharya, Drechsler, and Schnabl (2014) employ a Vector Autoregression (VAR) approach to quantify the so-called "doom loop" in which declining sovereign creditworthiness weakens bank balance sheets, leading to tighter credit conditions amplifying economic downturns. Alter and Beyer (2014) extend this analysis with a network-based perspective, using CDS data to capture market-perceived risk spillovers between banks and sovereigns, especially during crises. Finally, De Bruyckere et al. (2013) apply panel data regressions to analyze the impact of sovereign creditworthiness on the probabilities of bank default. Their results indicate that sovereign downgrades increase the risk of bank credit, both through direct exposure to debt and broader macroeconomic deterioration. This effect is particularly pronounced in financially fragile economies, where sovereign distress more severely weakens bank stability.

A related line of work explores how sovereign risk transmits to corporate entities, constraining lending, and raising borrowing costs. Bedendo and Colla (2015) analyze firm-level CDS data to demonstrate how sovereign risk affects corporate credit spreads, particularly for firms tied to government spending. Henry et al. (2013) incorporate macroeconomic shock scenarios into a stress testing framework to evaluate how sovereign distress is transmitted to corporate sectors. Broadening the scope, Gross and Siklos (2020) apply a TVP-VAR framework to examine the interconnectedness between banks, corporations, and sovereigns, underscoring how interconnectedness intensifies during crises.

Beyond sector-specific or sovereign-focused studies, a rich literature investigates general measures of financial connectedness. Barigozzi and Hallin (2017) use a high-dimensional factor model to assess interconnectedness in financial markets. Using principal component analysis (PCA), they extract the primary risk factors driving financial contagion. Their findings reveal that systemic risk clusters around key financial institutions and sovereigns, reinforcing the importance of monitoring these entities in crisis periods. Demirer et al. (2018) take a network analysis approach, employing dynamic connectedness measures based on generalized variance decompositions. Their study shows that financial interconnectedness fluctuates over time, intensifying during crises, and highlights the role of non-financial firms in facilitating risk transmission. In particular, Diebold and Yilmaz (2014) and Diebold and Yilmaz (2009) introduce a widely used connectedness index derived from VAR forecast error variance decompositions estimated from VARs. Their findings reveal that financial links strengthen sharply in times of crisis, emphasizing the need for real-time systemic risk monitoring.

Our contribution is built directly on this foundation. We extend the connectedness framework of Diebold and Yilmaz (2014) by explicitly modeling block-specific common factors representing sectoral or regional economic groups, alongside the global factor. This innovation allows us to disentangle truly idiosyncratic spillovers from those driven by shared sector or regional dynamics. Our application of block factors within the Diebold-Yilmaz connectedness framework is novel in the literature. Our methodology is different from Moench, Ng, and Potter (2013)'s which highlights the economic importance of block factors in a hierarchical dynamic factor model. Using our approach, we estimate and visualize connectedness among banks, sovereigns, and corporates, comparing results with and without block factors that provide insight for macrofinancial surveillance and systemic risk monitoring.

3 Measures of Connectedness

In recent literature, h-step forecast error variance decompositions (see Pesaran and Shin (1998)) have been used to provide estimates of spillovers. Most articles calculating variance decompositions debate directly or indirectly between choosing generalized (see Diebold and Yilmaz (2014), Demirer et al. (2018)) or structural variance decompositions (Barigozzi and Hallin (2017), Yang, Tong, and Yu (2021), Diebold and Yilmaz (2009)). In this paper, we are using generalized variance decompositions (GVD), due to the high dimensionality of our model and because we are interested in a general measure of connectedness not related to one specific structural shock.[1] Following Diebold and Yilmaz (2014), we use generalized variance decomposition to estimate how much of the institution i's h-step forecast error variance is attributable to shocks originating from institution j. Because we are interested in a large number of institutions, we are assuming sparsity in the VAR coefficient matrix and use elastic net shrinkage to tackle high-dimensionality. Unlike traditional directional network measures, this approach allows us to capture not only the direction of spillovers but also their magnitude, providing a richer metric of connectedness across institutions. Because we are specifically interested in spillovers driven by idiosyncratic shocks, it is common practice in this literature to control for global common factors, typically by including one or two global factors in the analysis. Our contribution to this literature is to control not only for global factors, but also for blocks (or groups) specific factors.[2] Block-specific factors are predefined by the user and are often dictated by the data. In our case, we will have six blocks corresponding to 4 sectors within the non-financial firms (Auto and Industrials, Consumers, Energy, and Telecommunications) in addition to one factor specific to financial firms and one factor for sovereign countries (see Table 2 in Appendix A to see which firms belong to each group).

3.1 Connectedness in a Static form of a Dynamic Factor Model

To review how our measure of connectedness is computed, let us first describe how to estimate it when only global factors are assumed. The next section will generalize the measure to allow for block factors. Consider a static dynamic factor model (see Stock and Watson

[1] While outside the scope of this paper, it could be possible to also include a factor normalization identification similar to Stock and Watson(2016) to study connectedness due to a specific normalized factor.

[2] In the multi layers network language the blocks would correspond to layers.

(2016)):

$$X_t = \Lambda F_t + \varepsilon_t \tag{1}$$
$$F_t = \Phi(L)F_{t-1} + G\eta_t \tag{2}$$
$$\varepsilon_t = \Theta\left(L\right)\varepsilon_{t-1} + v_t \tag{3}$$

In this model, where our dependent variable X_t is $N \times 1$, there are r global common factors, so F_t is $r \times 1$, Λ is $N \times r$, $\Phi(L)$ is $r \times r$, η_t is an $r \times 1$ vector of factors' shocks, ε_t is a $N \times 1$ vector of idiosyncratic shocks which are allowed to be serially correlated, and $\Theta(L)$ is $N \times N$ and v_t are the innovations to the idiosyncratic shocks. Following the literature, we assume that the factor shocks and the idiosyncratic shocks are orthogonal, therefore uncorrelated at all leads and lags, which implies that v_t and η_t are uncorrelated. The MA representation of the model is given by

$$X_t = \Lambda D\left(L\right)\eta_t + C\left(L\right)v_t \tag{4}$$

where [3]

$$\begin{aligned} D\left(L\right) &= (1-\Phi(L)L)^{-1}G \\ C\left(L\right) &= \left(1-\Theta\left(L\right)L\right)^{-1} \end{aligned}$$

and, by assumption,

$$E\left(\eta_t' v_{t-k}\right) = 0 \quad \text{for all } k \geq 0.$$

The total variance of each X_{it} can then be decomposed into two parts:

$$\text{VAR}\left(X_{it}\right) = \sum_{h=0}^{H}\left(e_i'\Lambda D_h \Sigma D_h' \Lambda' e_i\right) + \sum_{h=0}^{H}\left(e_i' C_h \Omega C_h' e_i\right) \tag{5}$$

where e_i is a $N \times 1$ selection vector with 1 on the i^{th} element and zeros everywhere else. We have two types of shocks in this model: The first component is due to shocks to the common factor (elements of $D(L)$ and, Σ the variance covariance of η_t) while the second is due to shocks to the idiosyncratic components (elements of $C(L)$ and the variance covariance matrix of v_t denoted as Ω). Following Diebold and Yilmaz (2014), we now construct measures of generalized variance decomposition (GVD) in response to the two sets of shocks. Define $\Sigma = E\left(\eta_t'\eta_t\right)$ and assume normality as in Pesaran and Shin (1998) to define the GIRF as the

[3] While we leave the matrix G in model (4) unrestricted for generality, we will later assume that the number of shocks is equal to the number of factors and impose the restriction $G = I$. See **?** for a discussion on the role of G .

difference of two expectations. Suppose, for example, that we are interested in a shock to the first global factor; then

$$GIRF_{X,1} = E\left[X_{t+h}|\eta_{1t} = \delta_1, \Omega_{t-1}\right] - E\left[X_{t+h}|\Omega_{t-1}\right],$$

which implies

$$\begin{aligned}
GIRF_{X,1} &= \Lambda E\left[\sum_{i=0}^{\infty} D_i \eta_{t+h-i}|\eta_{1t} = \delta_1, \Omega_{t-1}\right] \\
&= \Lambda D_h E\left[\eta_t|\eta_{1t} = \delta_1, \Omega_{t-1}\right] \\
&= \Lambda D_h E\left[\begin{array}{c} \eta_{1t} \\ \eta_{2t} \end{array} |\eta_{1t} = \delta_1, \Omega_{t-1}\right] \\
&= \Lambda D_h \left[\begin{array}{c} \delta_1 \\ E(\eta_{2t}|\eta_{1t} = \delta_1, \Omega_{t-1} \end{array}\right] \\
&= \Lambda D_h \left[\begin{array}{c} \delta_1 \\ \Sigma_{21}\sigma_{11}^{-1}\delta_1 \end{array}\right] \\
&= \Lambda D_h \left[\begin{array}{c} \sigma_{11} \\ \Sigma_{21} \end{array}\right] \sigma_{11}^{-1}\delta_1 \\
&= \Lambda D_h \Sigma e_1 \sigma_{11}^{-1}\delta_1
\end{aligned}$$

In general, the GIRF of the vector X to the j factor is

$$GIRF_{X,j} = \Lambda D_h \Sigma e_j \sigma_{jj}^{-1}\delta_j,$$

and the scaled (the GIRF for a shock of one standard deviation size) is

$$GIRF_{X,j} = \Lambda D_h \Sigma e_j \sigma_{jj}^{-1/2}, \tag{6}$$

where e_j is a $r \times 1$ selection vector with one on the j^{th} element and zeros everywhere else. Equation (6) measures the effect of a shock of one standard deviation on the j^{th} global common factor at time $t+h$ on all N variables. The response of variable i will be given by

$$GIRF_{X_i,j} = e_i' \Lambda D_h \Sigma e_j \sigma_{jj}^{-1/2}$$

where now e_i is a $N \times 1$ selection vector with 1 on the i^{th} element and zero everywhere else. The factor j's contribution to the firm i's H-step ahead generalized forecast error variance, where $H = 0, 1, \ldots$, is then

$$\phi_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H}\left(e_i'\Lambda D_h \Sigma e_j\right)^2}{\sum_{h=0}^{H}\left(e_i'\Lambda D_h \Sigma D_h' \Lambda' e_i\right) + \sum_{h=0}^{H}\left(e_i' C_h \Omega C_h' e_i\right)}. \tag{7}$$

Similarly, the GIRF from a shock in idiosyncratic component is

$$GIRF_{X_i,j} = e_i' C_h \Omega e_j \omega_{jj}^{-1/2} \tag{8}$$

where Ω is the variance covariance of v_t. The firm's j contribution to the firm i's H-step ahead generalized forecast error variance is

$$\theta_{ij}^g(H) = \frac{\omega_{jj}^{-1} \sum_{h=0}^{H} \left(e_i' C_h \Omega e_j\right)^2}{\sum_{h=0}^{H} \left(e_i' \Lambda D_h \Sigma D_h' \Lambda' e_i\right) + \sum_{h=0}^{H} \left(e_i' C_h \Omega C_h' e_i\right)}. \tag{9}$$

Because we work in the generalized VAR framework, variance shares do not necessarily add up to 1; that is, in general, $\sum_{j=1}^{N} \xi_{ij}^g(H) \neq 1$, $\xi \in \{\phi, \theta\}$. Hence we normalize each entry of the generalized variance decomposition matrix by the row sum to obtain pairwise directional connectedness from factor j to firm i (see also Diebold and Yilmaz (2014)) :

$$\xi_{ij}^g(H) = \frac{\xi_{ij}^g(H)}{\sum_{j=1}^{r} \xi_{ij}^g(H)}. \tag{10}$$

3.2 Connectedness in a Static form of a Dynamic Factor Model with Blocks

Now consider a dynamic factor model in which, in addition to the r global factors, there are s block factors specific to each sector (e.g. financial, sovereigns, and non-financial), one factor for each block. Following the notation from the previous section, the model becomes:

$$X_t = \Lambda F_t + \Gamma R_t + \varepsilon_t \tag{11}$$

$$F_t = \Phi(L) F_{t-1} + G\eta_t \tag{12}$$

$$R_t = \Psi(L) R_{t-1} + H w_t \tag{13}$$

$$\varepsilon_t = \Theta(L) \varepsilon_{t-1} + v_t \tag{14}$$

where F_t is an $r \times 1$ vector of global factors, R_t is a $s \times 1$ vector of block or group factors. Λ is the $N \times r$ loading matrix for the global common factors F_t. Γ is the $N \times s$ loading matrix for the block common factors R_t, so only the block factor R_{jt}, where $j = \{1, 2, \ldots, s\}$, enters the equation for the variables in the block j. All factors and idiosyncratic shocks are assumed to be dynamic, ε_{it} is assumed to be cross-sectionally uncorrelated, and η_t, w_t, and v_t are assumed to be orthogonal to each other. We will define $W = E(w_t w_t')$ and assume that it is diagonal, so the block factors are assumed to be uncorrelated.

The moving average representation of the model with block factors is:

$$
\begin{aligned}
X_t =& \Lambda \left(I - \Phi\left(L\right) L\right)^{-1} G\eta_t + \Gamma \left(I - \Psi\left(L\right) L\right)^{-1} H w_t + \left(1 - \Theta\left(L\right) L\right)^{-1} v_t \\
=& \Lambda D\left(L\right)\eta_t + B\left(L\right) w_t + C\left(L\right) v_t.
\end{aligned}
$$

where $D(L) = \left(I - \Phi\left(L\right) L\right)^{-1} G,\ B(L) = \Gamma\left(I - \Psi\left(L\right) L\right)^{-1} H$, and $C(L)$ is as defined before. We assume that H and G are equal to I so that the number of shocks is equal to the number of factors.

We can now define the response of X at time $t+h$ to a shock to the first block factor as

$$
\begin{aligned}
GIRF_{X,1} &= E\left[X_{t+h} | w_{1t} = \delta_1, \Omega_{t-1}\right] \\
&= \Gamma E\left[\sum_{i=0}^{\infty} B_i w_{t+h-i} | w_{1t} = \delta_1, \Omega_{t-1}\right] \\
&= \Gamma B_h E\left[w_t | w_{1t} = \delta_1, \Omega_{t-1}\right] \\
&= \Gamma B_h E\left[\begin{array}{c} w_{1t} \\ w_{2t} \end{array} | w_{1t} = \delta_1, \Omega_{t-1}\right] \\
&= \Gamma B_h \left[\begin{array}{c} \delta_1 \\ W_{21}\sigma_{11}^{-1}\delta_1 \end{array}\right] \\
&= \Gamma B_h W e_1 w_{11}^{-1}\delta_1.
\end{aligned}
$$

Notice that because $B_{s\times s}$ is a full matrix, a shock to the block factor in group j will still affect the variables in group j'. This is true even if we allow the shocks to the group factors to be contemporaneously uncorrelated. The contribution of the group factor j' to the firm i"s H-step ahead generalized forecast error variance is

$$
\psi_{ij}^g(H) = \frac{w_{jj}^{-1} \sum_{h=0}^{H} \left(e_i' \Gamma B_h W e_j\right)^2}{\sum_{h=0}^{H} \left(e_i' \Lambda D_h \Sigma D_h' \Lambda' e_i\right) + \sum_{h=0}^{H} \left(e_i' \Gamma B_h W B_h' \Gamma' e_i\right) + \sum_{h=0}^{H} \left(e_i' C_h \Omega C_h' e_i\right)}, \tag{15}
$$

For normalization purposes we can compute the pairwise directional connectedness from block factor j to firm i, as follows,

$$
\psi_{ij}^g(H) = \frac{\psi_{ij}^g(H)}{\sum_{j=1}^{r} \psi_{ij}^g(H)}. \tag{16}
$$

4 Empirical Results

To study risk transmission channels among European institutions, we use data from the CDS spreads from DataStream. The data consists of 152 institutions categorized into 3 sectors, namely, the Non-Financial sector, the Financial sector, and Sovereigns. The Non-Financial sector can be further categorized into the following four subsectors: Automobile, Consumer, Energy, and Telecommunication Industries. Data are daily spreads from October 23, 2006, to May 19, 2022, and are standardized by logarithmic units.[4]

Our goal is to analyze the contribution of including block factors in our measure of connectedness and systemic risk contagion. To achieve this, we estimate a Dynamic Factor Model, as outlined in the previous section, using either one global common factor or a combination of one global common factor and six block-specific factors (one for each subsector). In both cases, we examine the spillovers among industries and from block and global factors to industries. The decision to retain a single global factor is supported by its explanatory power: It accounts for 46.57% of the total variance. In comparison, the second global factor contributes only 3.7%, providing minimal additional information. Due to the high dimensionality inherent in our setting, we estimate the VAR coefficients and residuals for the idiosyncratic component (Equations (1-3)) using elastic net regularization with 10-fold cross-validation. When block factors are introduced, we include one per group, allowing us to capture region- or sector-specific comovements. Specifically in our dataset, we have 6 natural blocks[5]; 4 blocks within non-financial firms (Automobiles, Consumers, Energy and Telecommunications), plus one block for all financial firms and one block for sovereign countries. Both global and block factors are modeled as AR(1) processes, as suggested by the BIC criterion (see Table 1).

Comparing connectedness estimates with and without block factors helps disentangle the sources of spillovers, revealing the extent to which they are driven by global shocks, group-specific (block-level) dynamics, or truly idiosyncratic firm-level factors. This distinction is crucial for identifying the source of financial contagion and for designing policies that target systemic versus localized vulnerabilities.

4.1 Variance decomposition of a shock in the global factor

Figure 7 shows the share of each institution's 10-day forecast error variance explained by a shock to the global factor, both without (panel a) and with (panel b) the inclusion of block factors. The colors in the heatmaps represent the relative strength of the connections: darker blue shades indicate stronger links between the global factor and the institutions,

[4]The transformed data is confirmed to be stationary via standard Augmented Dickey-Fuller unit root test.

[5]Appendix B includes connectedness estimates for a model with one global factor and only three block factors corresponding to non-financial, financial, and sovereign.

while lighter shades reflect relatively weaker connections.

A careful comparison of the two panels reveals that the overall structure and ranking of variance contributions are largely unchanged. This is consistent with the model design: since global and block-level factors are assumed to be orthogonal, introducing block factors should not affect the estimated impact of global shocks. Instead, the block factors mostly influence the idiosyncratic variance decomposition examined in later figures.

The figure highlights several important patterns. First, global shocks account for a substantial share of variability among non-financial institutions (indices 0–108). Some firms are especially sensitive, including Volvo (1), Akzo Nobel (2), BAE Systems (7), Saint-Gobain (13), Daimler (16), Vinci (37), Kering (56), E.ON (74), Deutsche Telekom (91), and Orange (95). These are large industrial, utility, and telecommunication companies, and their sensitivity to global shocks likely reflects exposure to global demand, supply chains, and capital markets. Among financial institutions (indices 109–141), the global factor explains a moderate amount of variability, with somewhat stronger connections observed for insurance companies (indices 109–117). In contrast, several banks, including Dexia (118) and Bank of Ireland (124), exhibit relatively low sensitivity to global shocks.

Sovereign institutions (indices 142–151) tend to show the lowest sensitivity to global factor shocks. This can be attributed to the direct impact of economic problems on the financial and non-financial sectors. However, some sovereigns such as Belgium (143), Italy (147), Portugal (149), and to a lesser extent Spain (150), and the UK (151), exhibit relatively stronger exposure to global shocks. This may be due to their higher debt burdens and prolonged recovery trajectories following the 2008 financial crisis, which made them more susceptible to changes in global financial conditions.

Together, Figure 7 underscores the heterogeneous impact of global shocks across different types and jurisdictions of institutions, highlighting the particularly strong transmission to large non-financial corporations and certain sovereigns with elevated post-crisis vulnerabilities.

4.2 Variance decomposition of a shock in the idiosyncratic components

Once the effect of a shock to the global and block factors is taken into account, any connectedness in response to idiosyncratic shocks can be interpreted as a measure of the pure spillover effects among institutions. Figure 8, panel (a), presents the heatmap of the variance decomposition matrix of the idiosyncratic components without the inclusion of block factors, while panel (b) shows the respective matrix when block factors have been taken into account. Panels (c) and (d) are a zoom-in version of panels (a) and (b), respectively, to emphasize only the lower right part of the matrix focusing on the financial and the sovereign institutions. Each square in the heatmap represents the percentage contribution of a shock to the institution in the column to the 10-day forecast error variance of the institution in the corresponding row. In other words, the heatmap captures the directional connectedness from column to row. Similarly to the previous heatmap figures, darker heatmap colors represent stronger relative connections. This is to say that the same color on different graphs may represent different absolute values but the same ranking.

Some key insights appear in Figure 8. The heatmap is asymmetric, confirming that spillovers are directional: some institutions are net transmitters, others are net receivers. In addition, the matrices are not dense, suggesting that most institutions are only connected to a few others, supporting the idea of sparse idiosyncratic spillovers. In particular, while non-financial firms were highly sensitive to global shocks in Figure 7, they exhibit relatively low levels of idiosyncratic connectedness both between themselves and with banks. This supports the idea that their linkages are primarily driven by shared economic exposures (captured by global/block factors), not firm-to-firm contagion. In general, Figure 8 underscores that even after eliminating common shocks, idiosyncratic spillovers remain concentrated within certain blocks, especially among periphery financial institutions. This highlights their vulnerability not only to systemic risk, but also to local dynamics that amplify distress through tight informal channels.

Looking into more details in panels (a) and (b), we observe that, overall, the percentage of the 10-day forecast error variance is stronger for institutions around the matrix diagonal, which means that institutions that belong to the same sub-sector are more interconnected. This pattern is particularly evident among financial institutions (indices 109–142, especially 109–117) and sovereign entities (indices 142-151), where spillovers within the group are more pronounced. In panel (a), the vertical belt formed by the institutions by the indices 109-142 show that, in the one-block model, shocks in the financial sector are correlated with the non-financial sector. This pattern is no longer visible in panel (b) after the block factors are extracted, suggesting that this correlation was due to group factors rather than individual correlations.

Additionally, in panel (a), insurance companies (109-117) seem to have strong connections among each other relatively to any other sub-sector institutions. Companies 109-117, composed mainly of large European insurance and reinsurance companies, appear strongly interconnected in the model without block factors (Figure 8a). This is likely due to shared exposures to regulatory, interest rate, and credit market conditions specific to the insurance sector. In the absence of block-level controls, these shared dynamics are misattributed to direct idiosyncratic spillovers. Once block factors are introduced, these sector linkages disappear, highlighting more the interconnectedness between insurance firms and the rest of the financial firms and revealing that much of the observed connectedness within this group was driven by sector-wide forces rather than firm-specific contagion. Similarly, banks (119–141) appear tightly interconnected in the model without block factors (panels (a)-(c)), with widespread estimated spillovers between institutions. This reflects the dense linkages within the European banking sector. However, once block-level effects are accounted for (panels (b)-(d)), the estimated idiosyncratic spillovers are markedly reduced. This suggests that much of the observed connectedness among banks arises from common sectoral and regional dynamics, rather than from direct firm-to-firm contagion. Ignoring block factors risks overestimating systemic risk by conflating common shocks with idiosyncratic transmission. Finally, panels (b) and (d) emphasize the interconnectedness between sovereigns, highlighting the importance of the financial health of each individual sovereign for the rest of sovereigns.

Figure 3 zooms into the financial sector for both models, panel (a) and panel (b), respectively. In addition to the relative strength represented by the colors' intensity, the heatmap now includes estimated variance decomposition. For example, the square in row 110 and column 114 shows a value of 7.5%, which means that a shock to institution 114 explains 7.5% of the 10-day forecast error variance of institution 110.

Figure 3 illustrates how the inclusion of block factors reshapes our understanding of spillovers between financial institutions. Notably, the heatmap becomes more asymmetric once block factors are included, reflecting the fact that shared within-group comovements, often symmetric by nature, are absorbed by the block structure. What remains are more directional and idiosyncratic spillovers between institutions. The magnitude of estimated forecast error variance contributions also shifts. For example, the directional connectivity from Unicredit (128) to Intesa Sanpaolo (125), two major Italian banks, increases from 7.8% in the no-block model to 9.2% in the model with blocks. This suggests that, once common financial dynamics are accounted for, Unicredit emerges as a stronger idiosyncratic transmitter of risk to Intesa. In contrast, the connection from Barclays (137) to Royal Bank of Scotland (135), both UK banks, remains largely unchanged (8.5% vs 8.7%), indicating a robust bilateral linkage not driven primarily by broader block factors. This comparison underscores the value of controlling for block-level comovement to more accurately identify institution-specific spillovers.

Focusing on sovereigns, Figure 4(a) shows that, absent block controls, Austria (142), France (144), and Germany (145) exhibit extremely high levels of bilateral connectedness. For example, a shock to Austria explains more than 26% of France's 10-day forecast error variance, and similar magnitudes are observed in both directions. Similarly, Austria accounts for 21.5% of Germany(145)'s 10-day forecast error variance, while Germany accounts for 19.9% of Austria's 10-day forecast error variance. These elevated connections likely reflect shared exposure to common euro area dynamics, such as monetary policy, capital flows, and safe-asset demand. However, once block factors are introduced (Figure 4(b)), the picture changes dramatically: the strongest connections shift to Italy (147), Portugal (149), and Spain (150), and the overall magnitudes decrease (the strongest connection goes from 26.5% to 11.7%). This suggests that the core sovereigns, Austria, Germany, and France, primarily drive systemic block-level shocks, while more idiosyncratic residual spillovers remain concentrated among peripheral countries. Ignoring block structure would thus overstate the bilateral risk transmission between the core sovereigns and understate the localized vulnerability of the periphery.

Overall, our results clearly show that the interpretation of our measure of connectedness changes when block factors are taken into account. Both the model with block factors and the model without them can be used to measure connectedness, but they capture different dimensions of it: the version with block factors isolates more idiosyncratic firm-to-firm spillovers, while the version without block factors includes shared dynamics within economic or institutional blocks. Each provides distinct but complementary insights into the structure and sources of connectedness in the system.

4.3 Variance decomposition of a shock in the block factors

Figure 10 illustrates the 10-day forecast error variance of a shock in each of the block factors and how this correlates with each institution. Note that this is an inverted plot; now the shocks are in rows and are transmitted across the columns. Thus, we can infer that a shock in each block is mostly transmitted to industries within that same block to varying degrees. Figure 10 reveals that shocks to financial and sovereign block factors contribute more substantially to the 10-day forecast error variance of institutions than shocks to industry block factors. This pattern aligns with the structural role of these sectors within the European financial system. Sovereign institutions, particularly in Austria, France, and Germany, anchor market expectations for fiscal stability and serve as safe assets during periods of stress.

The financial sector similarly functions as a transmission hub, amplifying and distributing shocks due to deep interconnections between banks and insurance companies. In contrast, shocks to industry blocks, such as energy or telecommunications, tend to be more contained, reflecting more idiosyncratic or sector-specific dynamics. These results reinforce the importance of distinguishing between systemic block-level shocks and localized spillovers, and they highlight the centrality of the sovereign-financial nexus in driving connectedness across the euro area.

Figure 11 illustrates the relative importance of global and block-level shocks by showing the variance decomposition of a unit shock in each. The figure reveals that global shocks exert stronger influence on non-financial firms, particularly those in the automotive and industrial sectors (indices 0 to 39). As expected, the global factor shocks explain a higher percentage of the 10-day ahead forecast error variance than the block factor shocks. In particular, the directional connectivity from the sovereign block factor to the core sovereign institutions, Austria, France, and Germany, is relatively weak. This reflects the fact that these countries are key drivers of the sovereign block itself. Since their dynamics are already embedded in the construction of the block factor, they exhibit minimal additional response to a shock in that factor. In contrast, peripheral sovereigns respond slightly more strongly, suggesting that they absorb the systemic effects transmitted by core institutions.

5 Conclusions

This paper proposes a novel decomposition of financial connectedness across European sovereigns, financial institutions, and non-financial firms by separating global shocks, block-level (sector or region-specific) shocks, and purely idiosyncratic spillovers. Using CDS spreads as a forward-looking measure of credit risk, we show that traditional estimates of spillovers when block-level dynamics are not accounted for tend to overstate the extent of bilateral contagion by conflating it with common sectoral or regional trends.

Our results reveal several important patterns. First, global shocks play a dominant role in shaping risk for non-financial institutions, especially in sectors like automotive and industrials. In contrast, block-level shocks are more relevant for financial and sovereign institutions, where sectoral co-movement is particularly strong. Second, including block factors in the model leads to a more asymmetric pattern of residual connectedness, underscoring that firm-specific risk transmission is directional and not necessarily reciprocal. Third, sovereign institutions in core countries such as Austria, France, and Germany appear not only as highly interconnected but as drivers of systemic block-level sovereign shocks, rather than recipients of contagion.

Our findings underscore the importance of distinguishing between systemic, group-specific, and institution-specific spillovers in assessing financial stability. The model without block factors captures overall interconnectedness, including common exposures, while the model with block factors isolates true firm-to-firm idiosyncratic spillovers. Both views are complementary and provide valuable insights: the former is useful for monitoring broad systemic risk, while the latter helps identify targeted channels of contagion.

This layered perspective has practical implications for macro-financial surveillance and crisis management. Stress testing exercises, resolution planning, and regulatory interventions may benefit from incorporating global and block-level dynamics to better anticipate how shocks propagate and which institutions are likely to amplify them. As interconnectedness continues to evolve, adapting surveillance frameworks to capture these nuanced spillover mechanisms will be essential to maintaining financial stability in an increasingly complex world.

6 Declaration of generative AI and AI-assisted technologies in the writing process

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During the preparation of this work, the authors used ChatGPT and Writefull in the writing process to improve the readability and language of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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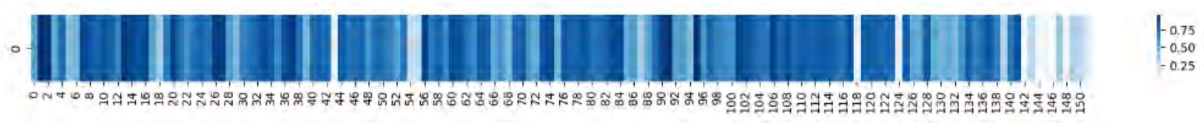
Lag	**AIC**	**BIC**	**FPE**	**HQIC**
0	6.507	6.516	669.7	6.510
1	6.394	6.459*	598.0	6.417
2	6.365	6.487	581.3	6.408*
3	6.355	6.533	575.6	6.418
4	6.342	6.575	567.7	6.424
5	6.344	6.633	569.1	6.446
6	6.332*	6.677	562.2*	6.454

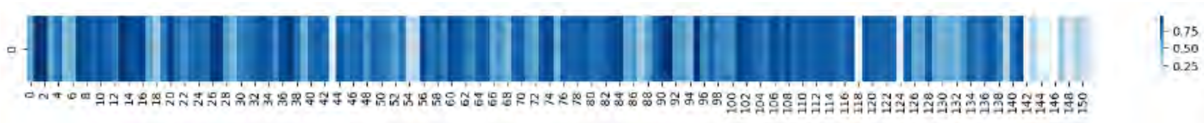
Table 1: Information criteria for different lag lengths. Asterisks (*) indicate the minimum value for each criterion.

Figure 1: Variance decomposition of a shock in the global factor with and without block factors.

(a) Variance Decomposition (no block factors)



(b) Variance Decomposition (block factors)



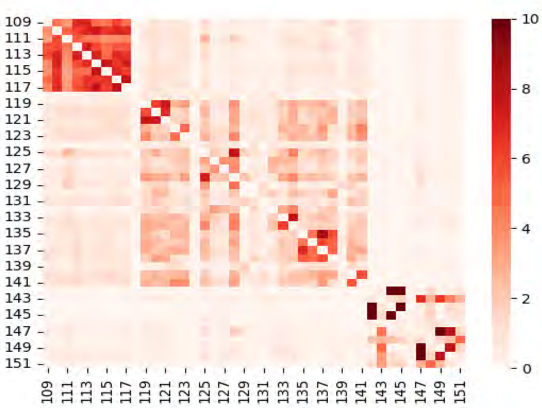
Note: From index 0 to 108 are European industry, index 109 to 141 are Financial institutions and, 142 to 151 are Sovereigns. See Appendix A for institution index and name correspondence.

Figure 2: Variance decomposition of a shock in the idiosyncratic components with and without block factors

(a) Connectedness (no block factors)

(b) Connectedness (block factors)

(c) Financials and sovereigns (no block factors)



(d) Financials and sovereigns (block factors)

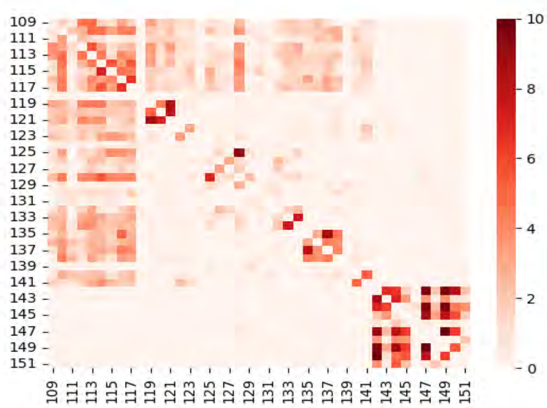
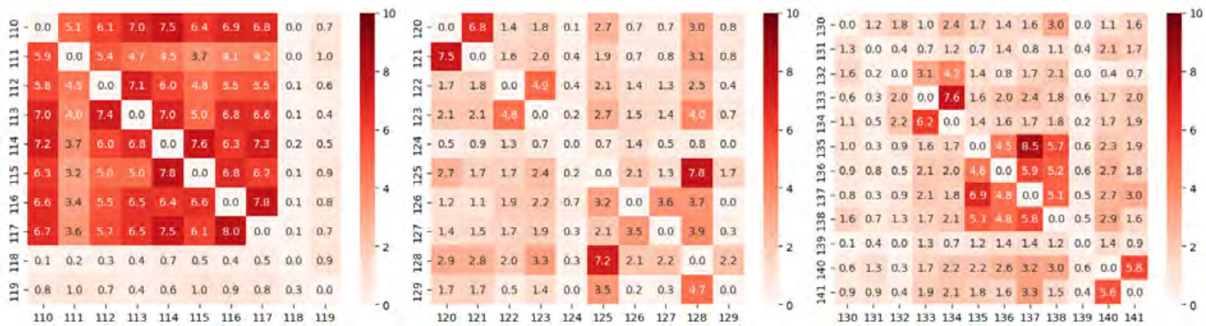


Figure 3: Variance decomposition of a shock in the idiosyncratic components for the financial sector. (values are in percentages)

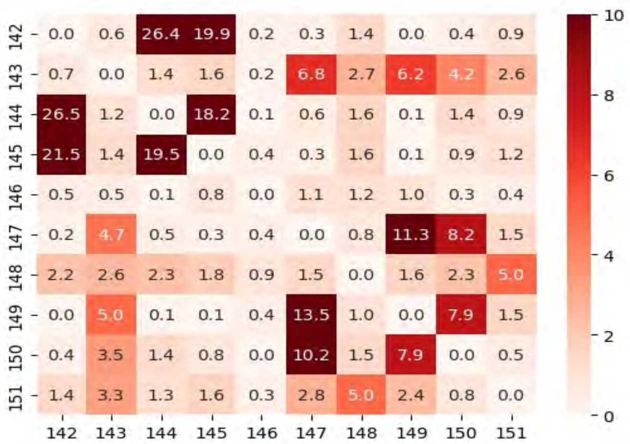
(a) Financials (no block factors)



(b) Financials only (block factors)

Figure 4: Variance decomposition of a shock in the idiosyncratic components (Sovereigns only)

(a) Sovereigns only (no block factors)



(b) Sovereigns only (block factors)

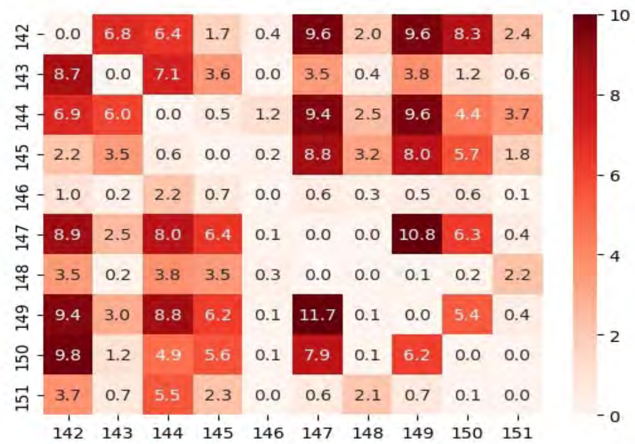
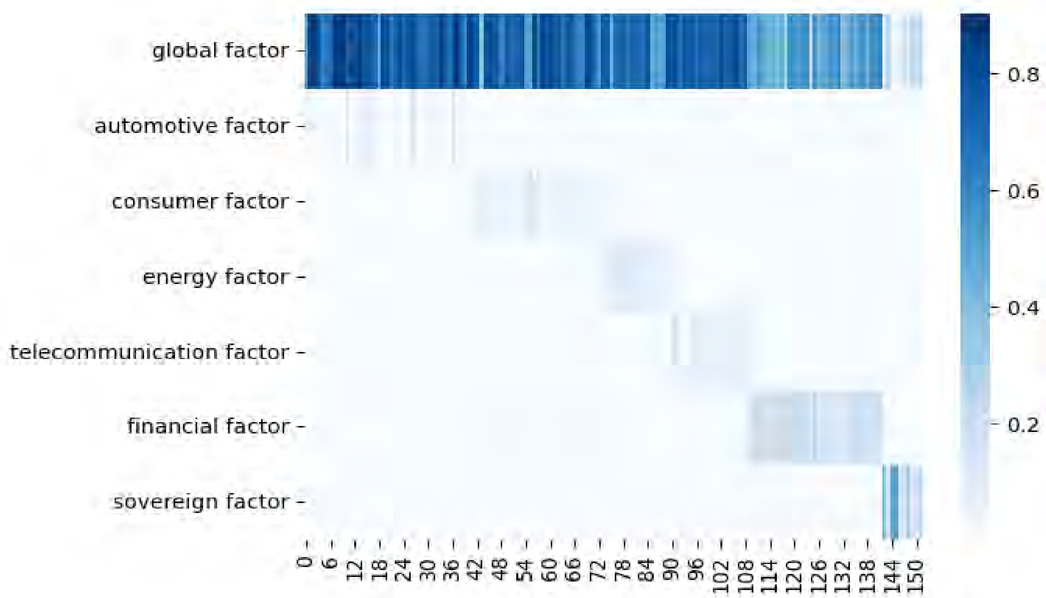


Figure 5: Variance decomposition of a shock in each block factor

Note: This figure depicts variance component due to a shock in the six block factors.

Figure 6: Variance decomposition of a shock to global and block factors



Note: This figure depicts variance component due to a shock to the six block factors and the global factor.

7 Appendix A

Table 2: List of CDS entities in the panel dataset

Index	Entity Name	Sector	Sub-Sector	Country	Name Code
0	Adecco	Non-financial	Autos & Industrials	Switzerland	ADE
1	Volvo	Non-financial	Autos & Industrials	Sweden	VOL
2	Akzo Nobel	Non-financial	Autos & Industrials	Netherlands	AKN
3	Alstom	Non-financial	Autos & Industrials	France	ALS
4	Anglo American	Non-financial	Autos & Industrials	UK	ANA
5	Astrazeneca	Non-financial	Autos & Industrials	UK	ASZ
6	Atlantia	Non-financial	Autos & Industrials	Italy	ATL
7	Bae Systems	Non-financial	Autos & Industrials	UK	BAE
8	BASF	Non-financial	Autos & Industrials	Germany	BAS
9	Bayer	Non-financial	Autos & Industrials	Germany	BAY
10	BMW	Non-financial	Autos & Industrials	Germany	BMW
11	Bouygues	Non-financial	Autos & Industrials	France	BOU
12	Clariant	Non-financial	Autos & Industrials	Switzerland	CLA
13	Saint-Gobain	Non-financial	Autos & Industrials	France	SAG
14	Michelin	Non-financial	Autos & Industrials	Switzerland	MIC
15	Continental	Non-financial	Autos & Industrials	Germany	CON
16	Daimler	Non-financial	Autos & Industrials	Germany	DAI
17	Deutsche Post	Non-financial	Autos & Industrials	Germany	DPO
18	Evonik	Non-financial	Autos & Industrials	Germany	EVO
19	Finmeccanica	Non-financial	Autos & Industrials	Italy	FME
20	GKN Holding	Non-financial	Autos & Industrials	UK	GKN
21	Glencore	Non-financial	Autos & Industrials	Switzerland	GLC
22	Koninklijke DSM	Non-financial	Autos & Industrials	Netherlands	DSM
23	Air Liquide	Non-financial	Autos & Industrials	France	AIR
24	Lanxess	Non-financial	Autos & Industrials	Germany	LAX
25	Linde	Non-financial	Autos & Industrials	Germany	LIN
26	Peugeot	Non-financial	Autos & Industrials	France	PEU
27	Renault	Non-financial	Autos & Industrials	France	REN
28	Rentokil Initial	Non-financial	Autos & Industrials	UK	REI
29	Rolls-Royce	Non-financial	Autos & Industrials	UK	ROR
30	Sanofi-Aventis	Non-financial	Autos & Industrials	France	SAA
31	Siemens	Non-financial	Autos & Industrials	Germany	SIE
32	Stora Enso Oyj	Non-financial	Autos & Industrials	Finland	SEO
33	Solvay	Non-financial	Autos & Industrials	Belgium	SOL
34	ThyssenKrupp	Non-financial	Autos & Industrials	Germany	THK
35	UPM-Kymmene Oyj	Non-financial	Autos & Industrials	Finland	UPM
36	Valeo	Non-financial	Autos & Industrials	France	VAL
37	Vinci	Non-financial	Autos & Industrials	France	VIN
38	Volkswagen	Non-financial	Autos & Industrials	Germany	VOL
39	Wendel	Non-financial	Autos & Industrials	France	WEN
40	Accor	Non-financial	Consumers	France	ACC
41	Electrolux	Non-financial	Consumers	Sweden	ELE
42	Auchan	Non-financial	Consumers	France	AUC
43	Alliance Boots	Non-financial	Consumers	UK	ALL
44	Carrefour	Non-financial	Consumers	France	CAR
45	Casino Guichard	Non-financial	Consumers	France	CAG
46	Compass	Non-financial	Consumers	UK	COM
47	Danone	Non-financial	Consumers	France	DAN
48	Lufthansa	Non-financial	Consumers	Germany	LUF
49	Diageo	Non-financial	Consumers	UK	DIA
50	Experian Finance	Non-financial	Consumers	UK	EXF

(Table 2 continued)

Index	Entity Name	Sector	Sub-Sector	Country	Name Code
51	Henkel	Non-financial	Consumers	Germany	HEN
52	Ladbrokes	Non-financial	Consumers	UK	LAD
53	Imperial Brands	Non-financial	Consumers	UK	IMB
54	ISS Global	Non-financial	Consumers	Denmark	ISS
55	J Sainsbury	Non-financial	Consumers	UK	JSA
56	Kering	Non-financial	Consumers	France	KER
57	Kingfisher	Non-financial	Consumers	UK	KIN
58	Koninklijke Ahold Delhaize	Non-financial	Consumers	Netherlands	AHO
59	Koninklijke Philips	Non-financial	Consumers	Netherlands	PHI
60	LVMH	Non-financial	Consumers	France	LVM
61	Marks & Spencer	Non-financial	Consumers	UK	M&S
62	Metro	Non-financial	Consumers	Germany	MET
63	Nestlé	Non-financial	Consumers	Switzerland	NES
64	Next	Non-financial	Consumers	UK	NEX
65	PernodRicard	Non-financial	Consumers	France	PER
66	Safeway	Non-financial	Consumers	UK	SAF
67	Svenska Cellulosa	Non-financial	Consumers	Sweden	SCE
68	Swedish Match	Non-financial	Consumers	Sweden	SWM
69	Tate & Lyle	Non-financial	Consumers	UK	T&L
70	Tesco	Non-financial	Consumers	UK	TES
71	Unilever	Non-financial	Consumers	UK	UNI
72	BP	Non-financial	Energy	UK	BP
73	Centrica	Non-financial	Energy	UK	CEN
74	EON	Non-financial	Energy	Germany	EON
75	Edison	Non-financial	Energy	Italy	EDI
76	Energias de Portugal	Non-financial	Energy	Portugal	EDP
77	Electricité de France	Non-financial	Energy	France	EDF
78	ENBW	Non-financial	Energy	Germany	ENB
79	ENEL	Non-financial	Energy	Italy	ENE
80	ENGIE	Non-financial	Energy	France	ENG
81	Fortum OYJ	Non-financial	Energy	Finland	FOY
82	Gas Natural SDG	Non-financial	Energy	Spain	SDG
83	Iberdrola	Non-financial	Energy	Spain	IBE
84	National Grid	Non-financial	Energy	UK	NGR
85	Royal Dutch Shell	Non-financial	Energy	Netherlands	RDS
86	RWE	Non-financial	Energy	Germany	RWE
87	Statoil	Non-financial	Energy	Norway	STA
88	Total	Non-financial	Energy	France	TOT
89	United Utilities	Non-financial	Energy	UK	UNU
90	British Telecom	Non-financial	TMT	UK	BTE
91	Deutsche Telekom	Non-financial	TMT	Germany	DTE
92	Hellenic Telecom	Non-financial	TMT	Greece	HTE
93	ITV	Non-financial	TMT	UK	ITV
94	Nokia	Non-financial	TMT	Finland	NOK
95	Orange	Non-financial	TMT	France	ORA
96	Pearson	Non-financial	TMT	UK	PEA
97	Publicis	Non-financial	TMT	France	PUB
98	Relx	Non-financial	TMT	UK	REL
99	St Microelectronics	Non-financial	TMT	Switzerland	STM
100	Ericsson	Non-financial	TMT	Sweden	ERI
101	Telefonica	Non-financial	TMT	Spain	TEF
102	Telekom Austria	Non-financial	TMT	Austria	TEA

(Table 2 continued)

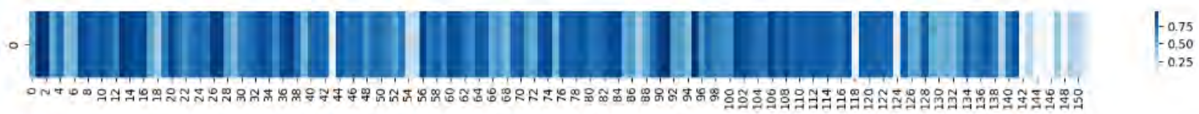
Index	Entity Name	Sector	Sub-Sector	Country	Name Code
103	Telenor	Non-financial	TMT	Norway	TEL
104	Telia	Non-financial	TMT	Sweden	TEI
105	Vivendi	Non-financial	TMT	France	VIV
106	Vodafone	Non-financial	TMT	UK	VOD
107	Wolters	Non-financial	TMT	Netherlands	WOL
108	WPP	Non-financial	TMT	UK	WPP
109	Aegon	Financial		Netherlands	AEG
110	Allianz	Financial		Germany	ALL
111	Generali	Financial		Germany	ALL
112	Aviva	Financial		Italy	GEN
113	AXA	Financial		UK	AVI
114	Hannover Rueck	Financial		France	AXA
115	Munich RE	Financial		Germany	HRE
116	Swiss RE	Financial		Germany	MRE
117	Zurich Insurance	Financial		Switzerland	SRE
118	Dexia	Financial		Switzerland	ZIN
119	BNP Paribas	Financial		Belgium	DEX
120	Crédit Agricole	Financial		France	BNP
121	Société Générale	Financial		France	CAG
122	Deutsche Bank	Financial		France	SOG
123	Commerzbank	Financial		Germany	DBA
124	Bank of Ireland	Financial		Germany	COB
125	Intesa Sanpaolo	Financial		Ireland	BOI
126	Banca Monte Di Paschi	Financial		Italy	BMP
127	Banca Popolare	Financial		Italy	BPO
128	Unicredit	Financial		Italy	UNI
129	Mediobanca	Financial		Italy	MED
130	ING	Financial		Netherlands	ING
131	Rabobank	Financial		Netherlands	RAB
132	Banco Comercial Port.	Financial		Portugal	BCP
133	Santander	Financial		Spain	SAN
134	BBVA	Financial		Spain	BBV
135	Royal Bank of Scot.	Financial		UK	RBS
136	HSBC Bank	Financial		UK	HSB
137	Barclays Bank	Financial		UK	BAB
138	Lloyds Bank	Financial		UK	LLB
139	Standard Chartered	Financial		UK	SCH
140	UBS	Financial		Switzerland	UBS
141	Credit Suisse	Financial		Switzerland	CSU
142	Austria	Sovereign		Austria	AUT
143	Belgium	Sovereign		Belgium	BEL
144	France	Sovereign		France	FRA
145	Germany	Sovereign		Germany	GER
146	Ireland	Sovereign		Ireland	IRE
147	Italy	Sovereign		Italy	ITA
148	Netherlands	Sovereign		Netherlands	NED
149	Portugal	Sovereign		Portugal	POR
150	Spain	Sovereign		Spain	ESP
151	UK	Sovereign		UK	UK

8 Appendix B

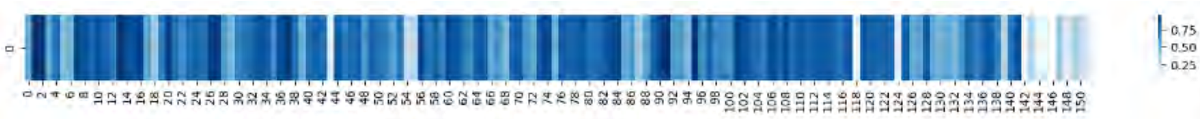
The following graphs show the estimated connectedness when only three factors are used (non financial, financial and sovereign).

Figure 7: Variance decomposition of a shock in the global factor with and without block factors.

(a) Variance Decomposition (no block factors)



(b) Variance Decomposition (block factors)



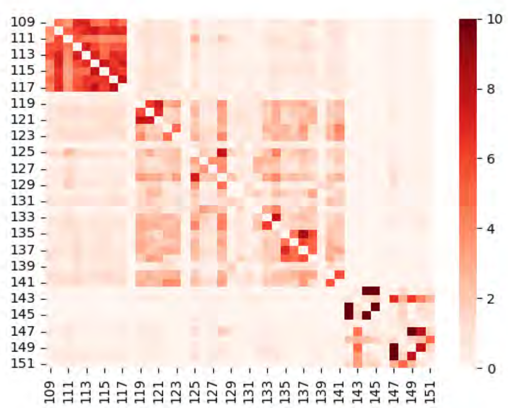
Note: From index 0 to 108 are European industry, index 109 to 141 are Financial institutions and, 142 to 151 are Sovereigns. See Appendix A for institution index and name correspondence.

Figure 8: Variance decomposition of a shock in the idiosyncratic components with and without block factors

(a) Connectedness (no block factors)

(b) Connectedness (block factors)

(c) Financials and sovereigns (no block factors)



(d) Financials and sovereigns (block factors)

Figure 9: This figure compares the variance decomposition of a shock in the idiosyncratic components for sovereigns only with and without block factors. See Appendix A for institution index and name correspondence.

(a) Sovereign Only (no block factors)

(b) Sovereign Only (block factors)

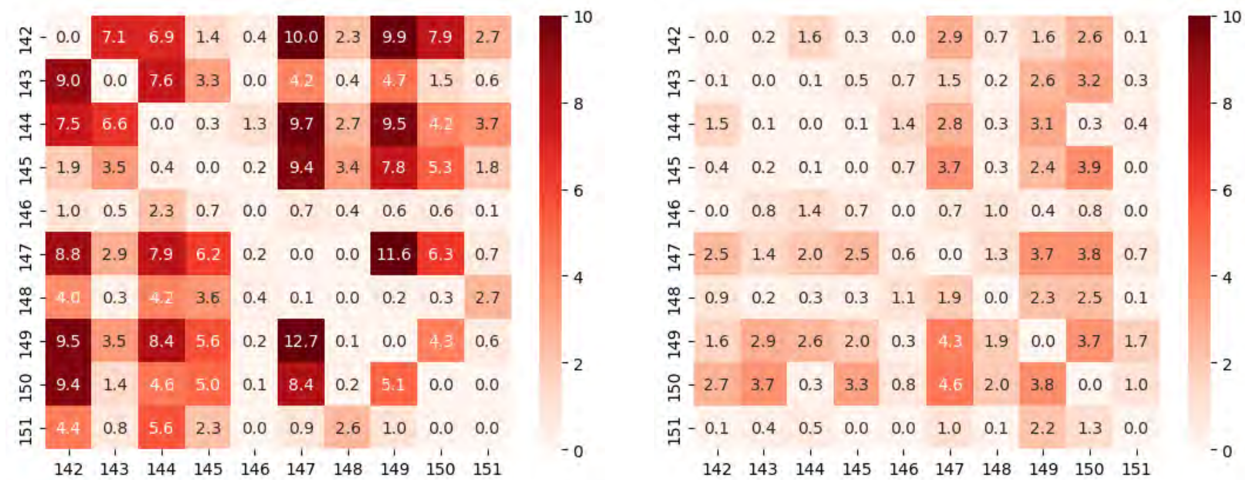
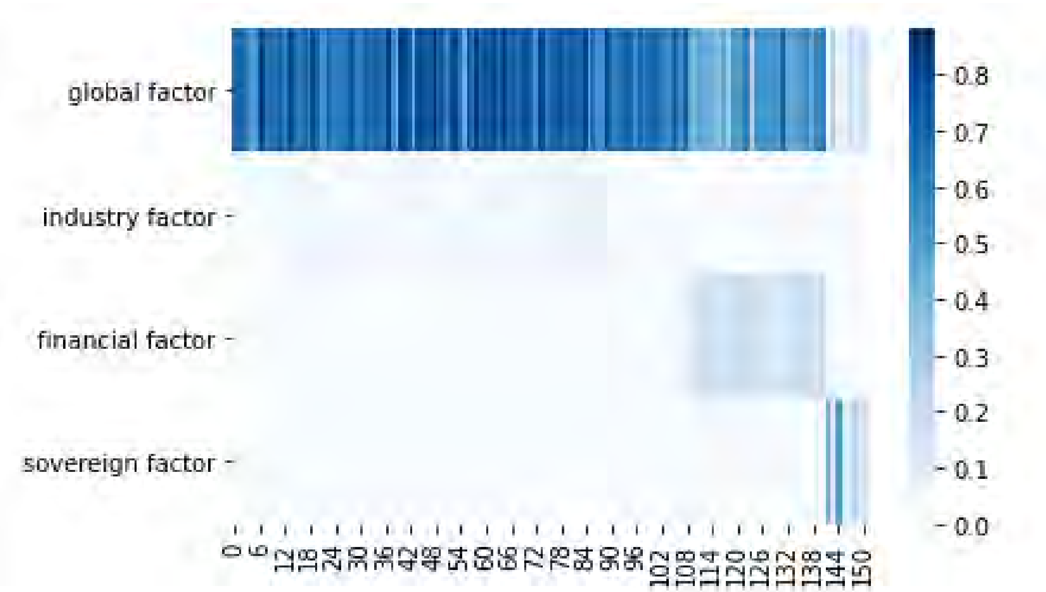


Figure 10: Variance decomposition of a shock in each block factor

Note: This figure depicts variance component due to a shock in the three (3) block factors.

Figure 11: Variance decomposition of a shock to global and block factors



Note: This figure depicts variance component due to a shock to the three (3) block factors and the global factor.