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Analyzing Credit Risk Transmission to the Non-Financial Sector in Europe: A Network Approach

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Abstract

A high-dimensional network of European CDS spreads is modeled to assess the transmission of credit risk to the non-financial corporate sector in Europe. We build on a network connectedness approach that uses variance decompositions in vector autoregressions (VARs) to characterize the dependence structure in the panel of CDS spreads. Our main findings suggest a sectoral clustering in the CDS network, where financial institutions are located in the center of the network and non-financial as well as sovereign CDS are grouped around the financial center. The network has a geographical component reflected in differences in the magnitude and direction of real-sector risk transmission across European countries. We identify an increase in the transmission of financial and sovereign credit risk to the non-financial sector during the global financial crisis and the European debt crisis. By contrast, we find that the transmission of risk within the non-financial sector remains largely unaffected by crisis events.

JEL Classification: C01, C32, G01, G15

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1 Introduction

As a consequence of the European sovereign debt crisis that followed the 2007-08 financial crisis, the sovereign-bank nexus attracted considerable attention in the literature (e.g., Acharya et al. 2014; Alter and Beyer 2014; De Bruyckere et al. 2013). In contrast, little empirical evidence exists on the degree to which the non-financial corporate sector (real sector) in Europe has been affected by the rise in sovereign and bank credit risk. There are two empirical studies that investigate the impact of sovereign credit risk on the non-financial corporate sector based on European credit default swap (CDS) data (Bedendo and Colla 2015; Augustin et al. 2018). Both studies find significant risk spillovers from sovereigns to corporations in Europe. However, there is to date no formal study focusing on the transmission of credit risk from financial institutions to non-financial corporations during the crisis events. In addition, little attention has been paid to the simultaneous measurement of interactions between all three sectors of the economy (financial, sovereign, and non-financial). Given that a fundamental component in the concept of systemic risk is the notion of negative externalities for the real economy,[1] incorporating these negative real effects in any quantitative measurement of systemic risk should be given greater emphasis.

In order to fill this gap in the literature, this paper conducts a network analysis that captures the linkages among 152 CDS series for European sovereigns, financial institutions and non-financial corporations over the period 2006-2017. Our unified empirical framework incorporates recent techniques to measure systemic risk by quantifying connectedness in high-dimensional networks, similar to the approaches adopted by Barigozzi and Hallin (2017) and Demirer et al. (2017). Specifically, we employ elastic net shrinkage in a vector autoregressive (VAR) setup to overcome the dimensionality problem in large datasets. We also control for common shocks using a dynamic factor approach. We derive static and dynamic measures

[1]Following the report prepared by the International Monetary Fund (IMF), the Financial Stability Board (FSB) and the Bank for International Settlements (BIS) for the G20, systemic risk can be defined 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"(IMF/FSB/BIS 2009, p. 2).

of connectedness to characterize the network of CDS spreads over the sample period. The empirical evidence presented in this paper contributes to a better understanding of the financial *and* real economic effects of the crisis events in the past decade.

Our empirical approach has close ties to recent theoretical work that emphasizes network connectedness in financial or economic contexts. For example, there is a growing body of theoretical studies that illustrate how increasing interconnectedness can pose a serious threat to the stability of the financial system due to contagion and amplification effects (Acemoglu et al. 2015; Elliott et al. 2014; Glasserman and Young 2015; Glasserman and Young 2016). From a real-sector perspective, Acemoglu et al. (2012) show that intersectoral input-output linkages between firms can give rise to aggregate (or economy-wide) fluctuations when idiosyncratic or sectoral shocks propagate, thus leading to network effects that impact the aggregate economy.

The adverse interactions between banks, corporates and sovereigns played a prominent role in the Eurozone crisis (IMF 2013). One transmission channel making corporations vulnerable to changes in sovereign creditworthiness is the so-called "transfer-risk" channel, which implies that distressed governments may be forced to shift some parts of the debt burden to the corporate sector; for example, by raising corporate taxes. An increase in sovereign risk may therefore lead to lower current and future profitability in the corporate sector (Acharya et al. 2014). Another reason to expect a sovereign-corporate link is the joint influence of rating agencies. Borensztein et al. (2013) provide evidence for the existence of "sovereign ceilings" that prevent corporations from being rated above the sovereign. Deteriorations in credit ratings of sovereigns consequently lead to lower ratings for corporations located in the respective country, translating into higher costs of debt capital for the corporate sector (Almeida et al. 2017).

Besides the sovereign-corporate link, there are reasons to assume a relationship between banks and the non-financial corporate sector. Since banks in financial distress need to reduce their credit exposure and/or increase interest rates, corporations are likely to face higher bank funding costs. This can erode the financial health of these firms and increase the probability of default. Abildgren et al. (2013) provide evidence for such a relationship based on micro data for banks and firms in Denmark. Minamihashi (2011) identifies a credit crunch effect resulting from bank failures in Japan, which leads to a substantial decrease in the investment activity of client firms.

Our goal is to quantify the extent of credit risk transmission to the non-financial sector in Europe by making use of recent advances in the econometrics of networks. We estimate and visualize our corporate-financial-sovereign network both statically (full-sample period) and dynamically (rolling-window). For the static framework we find that our network is characterized by a dominant financial sector located in the center of the network, while non-financial corporations and sovereigns are grouped in sectoral clusters around the financial center. The aggregation of spillover effects to the non-financial sector at the country-level reveals a strong geographical component in the network, which is reflected in sizeable differences in the pattern of real-sector risk transmission between peripheral European countries and countries located in the geographical center of Europe. Based on the dynamic estimation framework we identify an increase in the transmission of financial and sovereign credit risk to the non-financial sector during the global financial crisis and the European debt crisis. By contrast, we find that the transmission of risk within the non-financial sector remained largely unchanged during the crisis events. We conclude that financial and sovereign risk were main drivers of European corporate credit risk during the period considered.

The remainder of this paper is organized as follows. Section 2 outlines the econometric methodology for estimating and visualizing the networks. Section 3 describes the data used in our analysis. In Section 4 we present and discuss our results. Finally, we provide a brief conclusion and an outlook in Section 5.

2 Econometric Methodology

We use variance decompositions in VAR models to assess the interconnectedness of CDS returns. Diebold and Yilmaz (2014) show that the classical VAR framework can be used to model the network structure for a panel of time series by defining the weight associated with edge (i, j) in the network as the proportion of the h-step-ahead forecast error variance of variable i that is accounted for by the innovations in variable j. While this methodology is in principle applicable to a wide range of different settings, it is constrained by curse-of-dimensionality problems, as classical VAR estimation becomes unstable in high-dimensional networks. Demirer et al. (2017) tackle the dimensionality problem of the Diebold-Yilmaz approach by estimating the network using the LASSO ("least absolute shrinkage and selection operator"), a penalized regression method that allows to select and shrink the VAR parameters in optimal ways. Barigozzi and Hallin (2017) propose to remove the effect of common shocks before applying LASSO or related penalized regression techniques, as the presence of collinearity badly affects estimation stability.

Following these recent developments in the econometric modelling of networks, we apply a 'factor plus sparse VAR' approach in our analysis of credit risk transmission.

2.1 Removing Common Shocks

Similar to Barigozzi and Hallin (2017), we use dynamic factor methods to separate common shocks from idiosyncratic shocks before estimating the network structure. For our $n \times T$ panel of logarithmic CDS returns $\boldsymbol{Y} = (Y_{1t}, Y_{2t}, ..., Y_{nt})'$, we consider the generalized dynamic factor model representation by Forni et al. (2000, 2015, 2017) and Forni and Lippi (2001), which admits the decomposition of $\boldsymbol{Y} := Y_{it}$, for all i and t, into a *common* component X_{it} and an *idiosyncratic* component Z_{it}:

$$Y_{it} = X_{it} + Z_{it}. \tag{1}$$

It is further assumed that the common component is driven by q factors defined as an orthonormal unobservable white noise vector $\boldsymbol{u_t} = (u_{1t}, u_{2t}, ..., u_{qt})'$, such that X_{it} can be expressed as an auto-regressive representation $X_{it} = \sum_{k=1}^{q} b_{ik}(L)u_{kt}$, where the filters $b_{ik}(L)$ are one-sided and square summable. To determine the number of factors q, we apply the Hallin and Liška (2007) criterion, which favors $q = 1$. Consequently, we choose to conduct our analysis with one common factor. Using frequency-domain principal components (Brillinger 1981), Forni et al. (2015, 2017) show how to recover the common and idiosyncratic components based on an estimator for the spectral density of X_{it}.

A key motivation underlying our approach of disentangling idiosyncratic from common drivers of variation in our dataset of CDS returns is that we are interested in measuring the "pure" contagion risk component of systemic risk. Contagion risk can be defined as "an initially idiosyncratic problem that becomes more widespread in the cross-section, often in a sequential fashion" (ECB 2011, p. 141). Our empirical framework thus separates contagion risk from a second form of systemic risk: the common exposure to shocks in financial markets or the macroeconomy (De Bandt et al. 2009; ECB 2011). Moreover, by focusing on idiosyncratic dependencies of CDS returns, our empirical strategy is also closer to the theoretical concept of financial networks, in which the origin of contagion is a shock to an individual institution that is subsequently transmitted to other institutions through the web of obligations (Glasserman and Young 2016).[2]

2.2 Characterizing Networks via Variance Decompositions

To obtain empirical measures that help to characterize the network of CDS returns, we build on the econometric framework proposed by Diebold and Yilmaz (2014) and Demirer et al. (2017), which is based on variance decompositions in large-dimensional VAR models.[3]

[2]An alternative approach to control for common shocks is to include observable market variables as exogenous regressors in the econometric model. However, the drawback of this strategy is that these relevant market variables need to be identified a priori by the researcher with the consequence that the results might be dependent upon the particular set of chosen market variables.

[3]An earlier but less general version of this methodology is outlined in Diebold and Yilmaz (2009, 2012).

Specifically, we write the following covariance stationary VAR with n endogenous variables, representing the n estimated idiosyncratic components $Z_t = (Z_{1t}, Z_{2t}, ..., Z_{nt})'$ as defined in Eq. (1):

$$Z_t = \sum_{k=1}^{p} \Phi_k Z_{t-k} + \varepsilon_t, \tag{2}$$

where $\varepsilon_t \sim (0, \sum)$, Φ_k is a parameter matrix of dimension $n \times n$, and the lag length is two ($p = 2$).

The model in Eq. (2) can be expressed in its moving average representation as follows:

$$Z_t = \sum_{k=0}^{\infty} A_k \varepsilon_{t-k}, \tag{3}$$

where A_k is the matrix of moving average coefficients at lag k. These moving average coefficients are crucial for assessing the dynamics of the system. Using forecast error variance decompositions for h steps ahead enables to determine how much of the variance of each variable Z_i, for $i = 1, 2, ..., n$, is due to shocks to another variable included in the system. In calculating variance decompositions we adopt the generalized impulse-response framework of Koop et al. (1996) and Pesaran and Shin (1998). This approach accounts for correlated shocks across markets by using the historically observed distribution of the shocks. As a consequence, all estimation results are invariant to the ordering of variables in the VAR. We use a forecast horizon of $h = 10$ days in all our estimations.

Defining θ_{ij} as the h-step-ahead error variance in forecasting variable Z_i that is due to shocks to variable Z_j, where $i, j = 1, 2, ...n$, we can obtain the relative contribution (in percent) of each variable Z_j to the forecast error of variable Z_i by normalizing by the sum of all row entries in the variance decomposition matrix:

$$\gamma_{ij} = \frac{\theta_{ij}}{\sum_{j=1}^{n} \theta_{ij}} \times 100. \tag{4}$$

Each element γ_{ij} has a value between 0 and 100 and provides a quantitative measure for the *pairwise directional connectedness* from CDS entity j to CDS entity i. Based on the estimates for pairwise directional connectedness, it is possible to construct a range of informative connectedness measures by summing the elements γ_{ij} at different levels of aggregation, from individual (firm- or sovereign-level) to aggregate connectedness (system-wide).

At the individual level, total directional connectedness to entity i "from" all other entities j is defined as:

$$\gamma_{i\leftarrow\bullet} = \frac{\sum_{j=1 j\neq i}^{n} \gamma_{ij}}{\sum_{i,j=1}^{n} \gamma_{ij}} = \frac{\sum_{j=1 j\neq i}^{n} \gamma_{ij}}{n}. \tag{5}$$

Conversely, total directional connectedness from entity i "to" all other entities j can be constructed as follows:

$$\gamma_{\bullet\leftarrow i} = \frac{\sum_{j=1 j\neq i}^{n} \gamma_{ji}}{\sum_{i,j=1}^{n} \gamma_{ji}} = \frac{\sum_{j=1 j\neq i}^{n} \gamma_{ji}}{n}. \tag{6}$$

Note that the individual measures can also be restricted to a subset of entities j. For example, we will be interested in the total directional connectedness from (to) entity i to (from) all sovereign/financial/non-financial entities j.

The most aggregate measure of connectedness (*system-wide connectedness*) is obtained by summing all individual measures of total directional connectedness:

$$\gamma^{Total} = \frac{\sum_{i,j=1 i\neq j}^{n} \gamma_{ij}}{\sum_{i,j=1}^{n} \gamma_{ij}} = \frac{\sum_{i,j=1 i\neq j}^{n} \gamma_{ij}}{n}. \tag{7}$$

Besides these measures, we can construct additional aggregate measures including *sectoral connectedness* by aggregating pairwise connectedness measures at the sector-level and *geographical connectedness* by aggregating pairwise connectedness at the country-level.

2.3 Elastic Net Shrinkage

Since our VAR needs to be estimated in very high dimensions (152 variables), it is essential to reduce the number of parameters to be estimated in order to circumvent the "curse of dimensionality". In our network analysis we use elastic net shrinkage (Zou and Hastie 2005), which is a variant of LASSO methods[4], to shrink, select and estimate our VAR model. Elastic

[4]See Tibshirani (1996) for an introduction to LASSO.

net solves the following least-square estimation problem:

$$\widehat{\beta} = \underset{\beta}{\operatorname{argmin}} \left(\sum_{t=1}^{T} (Z_{it} - \sum_{k=1}^{p} \boldsymbol{\beta}'_{\boldsymbol{k,i}} \boldsymbol{Z_{t-k}})^2 + \lambda \sum_{k=1}^{p} \left[(1-\alpha)|\boldsymbol{\beta_{k,i}}| + \alpha |\boldsymbol{\beta_{k,i}}|^2 \right] \right), \tag{8}$$

where $i = 1, ..., n$, and $\boldsymbol{Z}$ is the matrix of idiosyncratic returns. Zou and Hastie (2005) define the function $(1-\alpha)|\boldsymbol{\beta_{k,i}}| + \alpha|\boldsymbol{\beta_{k,i}}|^2$ as the elastic net penalty, which is a combination of the "LASSO penalty" and the "ridge penalty". The elastic net penalty is controlled by α that takes a value between 0 and 1. For $\alpha = 1$, the elastic net becomes simple ridge regression, and for $\alpha = 0$, we obtain the LASSO penalty. The tuning parameter λ controls the overall strength of the penalty. We select α and λ jointly for each equation by 10-fold cross validation over a grid of possible values, using the values for α and λ that produce the lowest mean squared error for the model.

2.4 Network Visualization

Because of the high-dimensional nature of our network, consisting of 152 nodes and $152 \times 151 = 22,951$ links, presenting the results in an informative manner is challenging. In what follows, we characterize the estimated networks by means of graphical representations that visualize the results according to data characteristics and estimated connectedness measures.

Node Names and Colors: Each node represents one variable abbreviated by a three-digit name code (see Table A.2 in the Appendix for a detailed list of all name codes). The color of each node is defined by the sectoral affiliation of each entity: Financial Institutions are yellow, Sovereigns are red, Autos & Industrials are blue, Consumers are green, Energy corporations are purple, and TMT (Technology, Media & Telecommunications) firms are light salmon.

Node Size: Node size is a linear function of total directional connectedness "to others" (Eq. 6). Hence, entities that contribute relatively more credit risk to other entities are represented by bigger nodes in the network. Node size can be interpreted as a direct visual measure of systemic importance of the respective firm or sovereign.

Node Location: We use the force-directed algorithm of Fruchterman and Reingold (1991) to determine node location. The algorithm positions the nodes in the two-dimensional space in such a way that repelling and attracting forces among the set of nodes exactly balance. While repulsive forces tend to separate the nodes in space, the links simultaneously attract the pair of nodes they connect. The force of repulsion and attraction between two nodes is determined by pairwise directional connectedness "to" and "from". CDS entities that are linked through high pairwise directional connectedness are thus positioned close to each other, while CDS entities that are linked through low pairwise directional connectedness are drawn further apart. As a result, CDS entities with many strong links to other CDS entities will be located in the network's center (i.e., these entities are more systemically important), while nodes for CDS entities with weak links to others will be located in the network's periphery (less systemically important).

Link Thickness: Each link is a linear function of pairwise directional connectedness such that a relatively thicker link between two nodes indicates strong pairwise connectedness.

3 Data

Our data set comprises 152 daily CDS series of European sovereigns, financial institutions, and non-financial corporations. CDS spreads provide a more accurate measure of credit risk (i.e., the risk of an entity defaulting on its debt) than bond yields for three main reasons. First, CDS contracts are standardized products with pre-specified and fully documented credit derivatives agreements (Augustin et al. 2014), whereas bond terms and conditions are heterogeneous and depend on various features, including maturity, issue amount and coupon structure. Second, CDS markets are typically less influenced by liquidity effects relative to bond markets. Longstaff et al. (2005), for example, find that a large proportion of bond spreads is related to measures of bond-specific illiquidity such as bid-ask differentials.[5] Third, CDS spreads provide a timelier market-based indicator of credit risk, as documented by empirical studies showing that CDS markets lead bond markets in the price discovery process (Blanco et al. 2005; Palladini and Portes 2011).

We consider CDS spreads with a maturity of five years, which is typically the contract specification with the highest liquidity. We choose CDS quotes for euro-denominated senior unsecured debt with the modified-modified restructuring clause for firms and the cumulative restructuring clause for sovereigns. These types of contracts represent the conventional terms for CDS contracts in Europe. The sample period runs from October 23, 2006 to July 28, 2017, thus covering both the global financial crisis and the European sovereign debt crisis.[6] We source our data through Datastream and Bloomberg.[7]

Our sample includes sovereign CDS quotes from the following 10 countries: Austria, Belgium, France, Germany, Ireland, Italy, Netherlands, Portugal, Spain and the UK.[8] To ensure that our sample comprises the most relevant European corporate CDS entities, we consider only data from financial and non-financial corporations that were part of the Markit iTraxx Europe index over the sample period.[9] The Markit iTraxx Europe refers to the 125 most actively traded European corporate entities with investment grade credit ratings. The index contains corporate CDS from five different sectors: Autos & Industrials, Consumers, Energy,

[5]While recent theoretical and empirical evidence suggests that CDS prices are influenced by liquidity effects too (Bongaerts et al. 2011; Corò et al. 2013), the magnitude of these effects is likely to be greater for bond markets than for CDS markets. Comparing the magnitude of the liquidity premium across CDS and bond markets, Bühler and Trapp (2009) estimate that 35 percent of bond spreads is attributable to liquidity, whereas in CDS markets the liquidity component is only 4 percent.

[6]The starting date of our sample is dictated by data availability. Using an earlier starting date would result in a substantially smaller sample of CDS series due to missing data.

[7]Our procedure in collecting the data is as follows: we first check data availability for a specific CDS entity in Datastream; if the data are available, we include them in our sample; if the data are not available in Datastream, we check data availability in Bloomberg and add the series to our sample if the data are available.

[8]Data for Greece are not available for the full-sample period, because trading of Greek CDS contracts was suspended from March 9, 2012, when a so-called "credit event" was declared by the International Swaps and Derivatives Association as a consequence of the Greek debt restructuring agreement. We therefore omit Greek CDS from our analysis.

[9]The constituents of the iTraxx Europe are revised twice a year, such that there are frequent changes in the composition of the index. We decide to consider a company for inclusion in our sample if it was at least once part of the iTraxx Europe index during our sample period.

TMT (Technology, Media & Telecommunications) and Financials. The group of financial CDS entities includes both banks and non-bank financial intermediaries (insurance companies). Our analysis thus addresses the need expressed by regulators to include insurance companies in systemic risk assessments.[10]

After excluding all corporate CDS series for which more than 15 percent of the observations are stale values, our final sample consists of CDS spreads for 109 non-financial corporations, 33 financial institutions, and 10 sovereigns. Table A.1 in the Appendix reports summary statistics (by country) of our data set and Table A.2 provides a full list of all companies and countries included in our analysis.

4 Empirical Results

We first recover the idiosyncratic components from our panel of logarithmic CDS returns to control for common shocks and to capture the "pure" contagion effects as described above. We then characterize the CDS network both statically (full-sample) and dynamically (rolling-window) based on variance decompositions in a large-dimensional VAR to analyze the transmission of credit risk to the non-financial sector in Europe.

4.1 Static Estimation of the CDS Network

4.1.1 Full-Sample Individual CDS Network

Figure 1 shows the full-sample CDS network using the force-directed algorithm by Fruchterman and Reingold (1991) to determine node locations. We observe a strong sectoral clustering of corporates and sovereigns, as nodes of CDS entities from the same sector tend to bunch together. Financial institutions are all located in the center of the network, whereas non-

[10]Insurance companies can be important for financial stability because they are major investors in financial markets, insurers and banks are increasingly interconnected and insurance companies insure the (financial) risks of households and firms (ECB 2009). G20 governments reacted to the growing importance of insurers for financial stability by asking the Basel Financial Stability Board (FSB) to consider insurers alongside banks in the development of a policy framework to specifically address the systemic risks associated with systemically important financial institutions (FSB 2011).

financials and sovereigns are located around the center, indicating the systemic importance of the financial sector in Europe. The central role of the financial sector is also evidenced by the large node size of financial institutions relative to non-financial corporations and sovereigns.[11] Non-financial companies in the sectors Consumers, Autos & Industrials and TMT show the strongest links to the financial sector, while Energy corporations are located closer to the sovereign sector.

[FIGURE 1 about here]

To provide a more detailed account of the most important individual transmitters of sovereign and bank credit risk to the non-financial sector, we present a ranking of the largest senders of credit risk in Table 1. The ranking is based on aggregating all pairwise directional connectedness measures "to" non-financial corporations for each individual financial institution and sovereign, respectively. The ranking can be interpreted as a quantitative indicator for the systemic importance of each financial and sovereign entity to the real economy. Conversely, we also present a ranking for the largest receivers of credit risk from sovereigns and financials in Table 1. It is shown that the ranking for the senders of financial risk is headed by two major European banks, namely Santander and Crédit Agricole, followed by a major insurance company (Swiss RE). All banks in the top 10 ranking (Santander, Crédit Agricole, Société Générale, BBVA and Unicredit) are designated by the FSB as "global systemically important banks" that are subject to additional capital and other regulatory requirements under the Basel III framework (see FSB (2014) for a complete list of all identified banks).[12] The presence of five insurance companies in the top 10 of financial risk senders underscores the importance of including non-bank financial intermediaries into systemic risk assessments as proposed by regulators (ECB 2009).

[11] As explained above, node size is a function of "to" connectedness. Hence, entities that are more important to the system in terms of credit risk transmission have larger nodes.

[12] In addition, the insurance company Allianz (rank 9 in Table 1) is designated as a "global systemically important insurer (G-SII)" by the FSB (see FSB (2016) for the separate list of all G-SIIs).

[Table 1 about here]

An interesting feature of the financial institutions in our network is that their link size to non-financial firms is positively correlated with their link size to other financial institutions. Figure 2 depicts this relationship by plotting average directional connectedness of individual financial institutions to all non-financial firms (this corresponds to the observations in the ranking of senders in Table 1(a)) on the horizontal axis against average directional connectedness of individual financials to all other financial institutions on the vertical axis. The structure of the estimated network hence reveals that financial institutions which generate the largest contagion effects within the financial system are also the most important transmitters of contagion effects to the real economy.

[Figure 2 about here]

Turning to the largest non-financial receivers of contagion effects from financial institutions (second panel in Table 1(a)), we observe that the top 10 is dominated by corporations from the sectors Autos & Industrials (Air Liquide, Bayer, Akzo Nobel, Svenska Cellulosa) and Consumers (Henkel, Ahold Delhaize, Svenska Cellulosa, Carrefour, Accor, Casino Guichard). A look at the bottom of the ranking indicates that energy corporations, such as RWE, BP and Iberdrola, are less affected by financial risk shocks.

As for the links between sovereigns and the non-financial sector (Table 1(b)), we find that the southern European countries Italy, Portugal and Spain, which were among the most severely stressed countries during the debt crisis, are by far the largest transmitters of credit risk. Sovereigns from the "core" of the Eurozone (Austria, Germany, France, Belgium, Netherlands) as well as the UK are much less important in terms of credit risk transmission. Surprisingly, Ireland is the least important sender despite its central role in the Eurozone crisis.[13] This result can be explained by Ireland's fast recovery from the crisis, especially

[13] After Greece, Ireland was the second country to receive a bailout package from the EU and the IMF in November 2010.

in comparison with the countries from southern Europe. Finally, on the receiving end of the sovereign risk channel (second panel in Table 1(b)), we see that there are mainly energy companies at the top of the ranking. The only exceptions are the TMT companies Telefonica and Hellenic Telecom.

4.1.2 Aggregate Cross-Sectoral Network Connectedness

Building on the findings from the individual CDS network, which already highlighted some sectoral patterns in credit risk transmission, we next move to an aggregate perspective on cross-sectoral connectedness. Our aim is to identify sectoral heterogeneity in the magnitude of contagion effects. Figure 3 shows the sectoral decomposition of directional connectedness from financials and sovereigns to non-financial firms. We observe that the financial sector is a more important contributor of credit risk to the non-financial sector than the sovereign sector. For the non-financial sectors Autos & Industrials, Consumers and TMT, the magnitude of contagion shocks from financial institutions is roughly two to four times stronger relative to sovereigns. Only energy companies are comparatively more affected by contagion shocks from sovereigns (by a factor of roughly 1.5). At the same time, compared with other non-financial sectors, the energy sector is less affected by contagion from financial institutions.

[Figure 3 about here]

An important factor that can explain both the relatively stronger sensitivity of the energy sector to sovereign risk shocks and the lower sensitivity to financial risk shocks is the ownership structure of energy corporations. The energy sector is of great strategic importance to the public sector, which is why sovereign governments are often major shareholders in energy firms to retain influence on corporate decisions. Among the 18 energy firms in our sample, 9 are characterized by a substantial public ownership.[14] By contrast, among the

[14]We define public ownership as substantial if the government owns a company's share of more than 5 percent. We collect information on the ownership structure of the corporations in our sample from publicly available sources (corporate websites, annual reports, etc.).

remaining non-energy firms in the non-financial sector, only 12 percent are characterized by a substantial public ownership. Firms with government ties often receive state-guaranteed loans and are more likely to be bailed out than firms without government ties (Faccio et al. 2006). Our results are consistent with the notion that the energy sector's large proportion of (partially) government-controlled firms, and the superior financing conditions associated with government control, is responsible for the relatively lower exposure of the energy sector to financial risk shocks. At the same time, the prevailing degree of government control in the energy sector creates a stronger link to variations in sovereign risk, as rising concerns about the solvency of sovereigns erodes the credibility of state-guaranteed loans and decreases the likelihood for bailouts.

4.1.3 Geographical Network Connectedness

Despite the common market there exist regional differences across European countries, ranging from cultural differences (including language) to purely economic differences related to e.g., macroeconomic fundamentals, credit ratings and the size of national banking sectors. All of these country-specific factors may give rise to a relationship between the geographical location of firms and sovereigns and the size/direction of credit risk transmission.[15]

[Figure 4 about here]

To provide more detailed insights into the geographical component of the CDS network, we conduct a country-level decomposition of credit risk contagion in Figure 4. We observe in Figure 4(a) that Spain, France, Germany and Switzerland are the main senders of financial risk, as indicated by the size of their financial sector nodes. The main receivers of financial risk (indicated by color-level) are the non-financial sectors of countries located in the core of Europe (Belgium, France, Germany, Netherlands, Sweden, UK), while the non-financial sectors of countries in the southern periphery (Portugal, Spain, Italy, Greece) are less affected

[15] See Ang and Longstaff (2013) and De Santis (2012) for evidence on country-specific risk factors in European sovereign CDS spreads.

by financial risk shocks. Turning to the transmission of credit risk from sovereigns to non-financial firms in Figure 4(b) reveals a very different geographical pattern. Here, the major senders of risk are the southern European countries Portugal, Spain and Italy, while the contribution of core European countries is much less. In addition, the geographical dispersion of sovereign risk shocks is mainly limited to the periphery, since these countries are also the main receivers of shocks as indicated by the magnitude of non-financial connectedness and the link size between peripheral countries. Consequently, our results suggest that real-sector contagion of sovereign risk does not spread from the periphery to the center, but remains predominantly a regional phenomenon.

We next assess whether cross-country contagion effects can be explained by the degree of financial linkages between countries. Theoretical work on financial contagion effects suggests that geographically interrelated claims and liabilities in the banking system can facilitate cross-country transmissions of financial shocks (Allen and Gale 2000). We test whether stronger financial linkages between European countries lead to stronger contagion of financial and sovereign risk to the non-financial sector by using data on bilateral bank claims provided by the Bank for International Settlements (BIS) to proxy financial linkages. We distinguish between two aggregates of bilateral bank claims: (i) bilateral bank claims of country i to all sectors of country j, and (ii) bilateral bank claims of country i to the non-bank private sector of country j. To assess the influence of these two measures of financial linkages on the cross-country dimension of contagion to the non-financial sector, we then run a simple OLS regressions with the country-level pairwise connectedness measures as the dependent variable and one of the financial linkages proxies as the independent variable.

[Table 2 about here]

The results in Table 2 suggest a clear positive relationship between cross-country contagion effects from the financial sector and financial linkages (first column). Countries that share stronger financial linkages experience stronger cross-border contagion between their financial and non-financial sectors than countries with weaker financial linkages. Our results complement empirical findings from studies focusing exclusively on contagion effects within the banking sector. For example, Tonzer (2015) shows that international linkages in interbank markets contribute to the channeling of financial distress across borders. However, our results do not suggest an influence of financial linkages on the magnitude of cross-border contagion effects for sovereign credit risk (second column in Table 2), which highlights again the rather regional nature of the sovereign-real sector risk channel.

4.2 Dynamic Estimation of the CDS Network

To assess the time-varying nature of the CDS network, we next move to a dynamic framework based on rolling-window (200 days) estimations, with repeated cross validation of the penalty parameter λ and the elastic net mixing parameter α in each window.[16] Looking at the evolution of connectedness across time allows us to assess whether the propagation of shocks intensified during crisis events, which is consistent with the concept of "shift-contagion" (Rigobon 2016). Naturally, our emphasis is on the evolution of the network structure following the global financial crisis and the European sovereign debt crisis.

4.2.1 Global Financial Crisis

The critical event in the global financial crisis was Lehman Brother's bankruptcy on September 15, 2008. In Figure 5 we show the CDS network at two different stages for comparison. In (a) the network is depicted for the period before Lehman Brother's bankruptcy (the 200 days window ends on September 1, 2008), while in (b) the network is shown for the period after the Lehman collapse (the 200 days window ends on November 6, 2008).

[Figure 5 about here]

The key pattern that emerges after comparing the two plots is that a large cluster of

[16] We also estimate the idiosyncratic components for each window separately.

financial institutions moves from the periphery to the center of the network after Lehman's collapse, reflecting an increase in connectedness of the financial sector to others. An increase in overall transmission of credit risk to others, i.e., the systemic risk component of the financial sector, can be further deduced from the large node size of many financial institutions, such as UBS, Société Générale (SOG) and Deutsche Bank (DBA). As for Lehman Brother's effect on the non-financial sector, we observe that Autos & Industrials as well as TMT corporations cluster very close to the financial sector, while the energy sector and most consumer corporations are relatively farther away from the financial center after Lehman's bankruptcy.

4.2.2 European Sovereign Debt Crisis

To visualize how the CDS network was transformed following the European sovereign debt crisis, we analyze the network graph before and after the onset of the crisis in Figure 6. We clearly see that connectedness is rather low before the crisis (late-2009), particularly with regards to sovereigns which form their own cluster in the periphery of the network. After the onset of the Eurozone crisis in May 2010 (following the first bailout package for Greece), connectedness increases drastically, thereby fundamentally altering the network's structure. Now we observe that the nodes for sovereign entities moved to the network's center and that the stressed countries Italy, Spain, Ireland and Portugal have very large nodes, which highlights their central role in the crisis. In addition, the sovereign CDS nodes attract a large number of both financial and non-financial corporations that are grouped closely around them. Hence, Figure 6(b) does not only reveal a strong sovereign-financial nexus but it also shows a pronounced contagion effect from sovereigns to non-financial corporations during the European debt crisis.

[Figure 6 about here]

4.2.3 System-Wide Connectedness

Moving from the individual to the aggregate perspective, we depict in Figure 7 the evolution of overall network connectedness, i.e., the degree to which all idiosyncratic CDS returns co-move with each other over time. We observe wide fluctuations in connectedness over the sample period. While system-wide connectedness is at less than 70% at the beginning of the sample, it shows an increasing trend until the Lehman collapse in late-2008. After a downward trend in 2009, network connectedness jumps substantially following the outbreak of the European debt crisis in early-2010. Throughout 2010, system-wide connectedness remains elevated with several pronounced spikes, reflecting the high degree of financial distress and uncertainty in the Eurozone during this period. The culmination is reached in October and November 2010 when the level exceeds 90 percent. This was a crucial stage in the European debt crisis, as concerns about the fiscal strength of Ireland and Portugal prompted markets to expect that a Greek-style program would be extended to these two countries. On October 18, 2010 Angela Merkel and Nicolas Sarkozy agreed in a meeting in the French town of Deauville that future sovereign bailouts would require private investor participation when it comes to 'haircuts' on sovereign bond holdings. Our findings suggest that the surprise announcement of Deauville triggered further contagion in European CDS markets, thus confirming the view that the Deauville proposal increased market pressure due to new uncertainty attached to sovereign debt (Brunnermeier et al. 2016).

[Figure 7 about here]

In the first quarter of 2011, overall contagion risk decreases noticeably, as evidenced by the drop in system-wide connectedness. Two major political events are able to explain this downward shift. The first event was the resignation of Axel Weber from the Bundesbank presidency in February 2011, expressing disagreement with ECB's sovereign bond purchases. With Axel Weber's resignation it was also clear that he would not succeed Jean-Claude Trichet as president of the ECB. The decrease in contagion risk around this event may thus reflect the belief of markets that - after the withdrawal of the major opponent of ECB's decisions on securities markets purchases in the governing council - the ECB would further continue and potentially expand its asset purchase program in the future.[17] A second important event influencing the decline in contagion effects was the agreement of euro area leaders on March 11, 2011 to allow the EFSF (European Financial Stability Facility) and the ESM (European Stability Mechanism) to directly intervene in primary markets for sovereign debt.

Over the remainder of the sample period, system-wide connectedness fluctuates persistently, albeit with smaller swings. There is a mild upward trend in connectedness from mid-2012 until early-2017, reflecting that even after the most severe crisis events came to an end, CDS spreads remained tightly linked to each other across all sectors. This indicates that market participants continued to closely monitor conditions in all CDS markets simultaneously.

4.2.4 Aggregate Cross-Sectoral Network Connectedness

With the goal of focusing specifically on temporal fluctuations in credit risk transmission to the non-financial sector, we conduct a sectoral decomposition of connectedness in Figure 8. The results suggest a large extent of heterogeneity in dynamic connectedness across sectors. As for the credit risk shocks from the financial sector, we observe several spikes throughout the sample period. Financial-real sector connectedness is particularly high during the 07/08 global financial crisis and the 2010-12 European debt crisis, providing evidence for contagion effects to the non-financial corporate sector. Interestingly, the level and fluctuations of connectedness between financial and non-financial corporations both increase toward the end of the sample period (2015-2017).

[Figure 8 about here]

[17] These expectations soon proved to be correct, as the ECB implemented its Securities Markets Programme (SMP) also to Italy and Spain in August 2011.

With regards to sovereign credit risk (second plot), the dynamic connectedness measure reflects a clear trend. Following the start of the European debt crisis, connectedness rises drastically and then remains at this high level during the most stressing stages of the crisis. In early-2011 we observe a considerable decline in the magnitude of sovereign risk transmission. The downward trend continues until early-2014, fluctuations thereafter remain modest. The findings can be interpreted in favor of the European Central Bank's monetary policy stance, as our results suggest that the ECB was successful in curbing the contagion effects to the non-financial sector.

As a comparison, we also present intra-sectoral connectedness of non-financial corporations (last plot in Figure 8). It shows almost no fluctuations over time, reflecting that crisis events influenced only the transmission of credit risk from the financial and sovereign sector, but not the transmission of risk within the non-financial sector.

[FIGURE 9 about here]

So far, our dynamic cross-sectoral connectedness analysis focused on quantifying the magnitude of risk transmission in only one direction, either from financials to non-financials, or from sovereigns to non-financials. However, for both types of contagion there exists the possibility of a feedback channel running from the non-financial sector to financial institutions and sovereigns, respectively. To control for a potential feedback channel, we consider the pure *net* contribution of the financial and sovereign sector in Figure 9 by subtracting the spillover effects originating in the non-financial sector from those operating in the opposite direction. Yet, the dynamic evolution of cross-sectoral connectedness remains almost unaffected by this modification.

[FIGURE 10 about here]

Finally, Figure 10 further breaks down dynamic connectedness by sub-sectors of non-financial corporations. It is shown that each sub-sector displays somewhat different dynamics, suggesting a role for sector-specific factors in risk transmission.

4.2.5 Geographical Network Connectedness

The static network analysis already revealed a strong geographical component in the magnitude and direction of credit risk transmission to the non-financial sector. To further investigate geographical patterns in a dynamic framework, we differentiate between two groups of risk senders at the country-level and calculate the evolution of risk transmission for each group separately. We form a group of GIIPS banks, i.e., financial institutions headquartered in the so-called "GIIPS" countries (Greece, Ireland, Italy, Portugal, Spain) and a group of non-GIIPS banks, i.e., financial corporations headquartered in "non-GIIPS", or "core", countries (Belgium, France, Germany, Netherlands, Switzerland, UK). Moreover, to capture possible geographical differences in the transmission of sovereign risk, we adopt the same grouping procedure for "GIIPS" and "non-GIIPS" sovereigns.

[Figure 11 about here]

Figure 11 shows each country group's contribution to financial and sovereign risk transmission over time. As for the risk transmission from the financial sector to non-financial corporations (first plot), the difference between the two country groups appears to be small. For most of the sample period the two separate connectedness measures move in tandem. In 2010, we observe a relatively stronger contribution from banks in GIIPS countries. In the second half of the sample (2013-2017), financial shocks from non-GIIPS banks are typically stronger than those from GIIPS banks.

Regarding risk transmission from the sovereign sector, the difference in contributions between GIIPS and non-GIIPS is sizeable, as visible in the second plot of Figure 11. With the beginning of the sovereign debt crisis in early-2010, risk shocks from GIIPS sovereigns increased relatively more than risk shocks from non-GIIPS sovereigns. In terms of magnitude, our estimates suggest that at the height of the sovereign debt crisis in 2010, sovereign risk shocks transmitted from GIIPS sovereigns to non-financial corporations are roughly twice as strong as risk shocks transmitted from non-GIIPS sovereigns.

In 2011, connectedness decreases for both country groups. But while connectedness from non-GIIPS sovereigns returns to its pre-crisis level in 2011, that of stressed GIIPS countries remains elevated throughout 2011 as a result of continuing political and economic tensions in these countries. Only in the first half of 2012, the level of sovereign risk transmission from non-GIIPS sovereigns converges back to that of non-GIIPS countries, possibly as an outcome of the more aggressive ECB policy stance under the new president Mario Draghi.[18] From mid-2012 onwards, sovereign connectedness remains relatively stable, with both country groups contributing about the same amount of credit risk. This changes in 2015, where we observe another increase in contagion from GIIPS-sovereigns as a consequence of uncertainties regarding the newly elected Syriza-government in Greece.

5 Conclusions

Motivated by the scant empirical evidence on the propagation of credit risk shocks from financial institutions and sovereigns to the non-financial sector of the economy, we conduct a network analysis using 152 CDS series for European financial institutions, sovereigns and non-financial corporations over the period from October 2006 to July 2017. Our methodology relies on recent techniques to measure and visualize connectedness in large-dimensional systems of financial variables. Our main findings suggest a sectoral clustering in the CDS network, where financial institutions are located in the center of the network and non-financial as well as sovereign CDS are grouped around the financial center, reflecting the systemic importance of the financial sector in Europe. We also detect a geographical component in the network, as evidenced by differences in risk transmission across countries.

[18] After Mario Draghi took office as the new president of the ECB in November 2011, the governing council lowered interest rates in two steps by a combined 0.5 percent to 1 percent over the course of five weeks. In addition to these measures, the ECB announced at the December 2011 meeting two exceptional longer-term refinancing operations (LTRO), which provided unlimited amounts of liquidity to banks with a three-year maturity.

Moreover, we analyze how the network structure of CDS spreads evolves dynamically by conducting rolling-window estimations. We find that both the Lehman bankruptcy and the European debt crisis fundamentally transformed the network structure. We observe that especially Autos & Industrials as well as TMT corporations cluster very close to the financial sector during the global banking crisis, while Energy and TMT corporations cluster around sovereigns during the European debt crisis. By contrast, we find that the transmission of risk within the non-financial sector remained largely unchanged during the crisis events. Taken together, our results indicate that financial and sovereign risk are important drivers of corporate credit risk.

Our network analysis identified the source, direction and relative size of credit risk shocks to the non-financial sector in Europe. Future research could further include the sign of the shocks' impact as additional information in the characterization of the network, as in Dungey et al. (2017). A signed network would reflect whether a shock to one entity has an amplifying or dampening effect on each of the other entities in the system. This approach would take into account that contagion is more likely between nodes that are linked through positive weights rather than negative weights.

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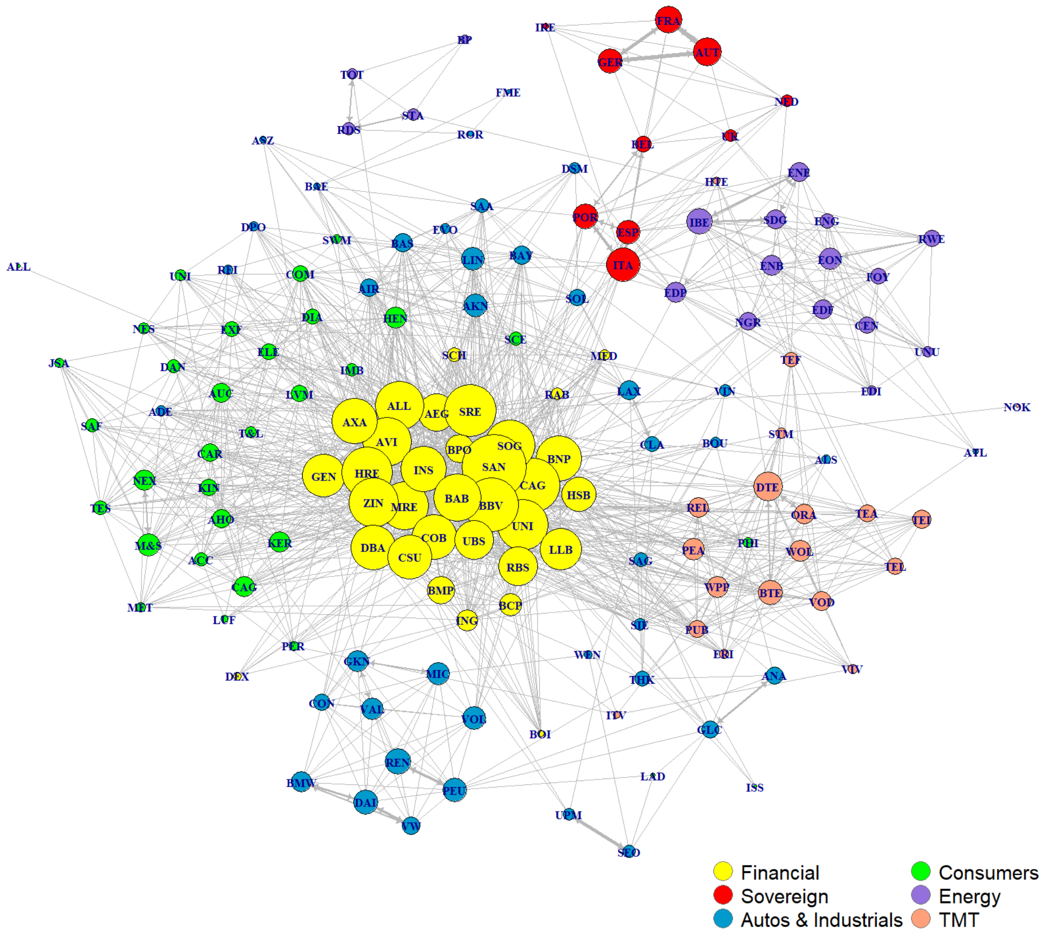
Figure 1: CDS Network Graph for Full-Sample Period (2006-2017)



Note: The network pictured above is estimated using forecast error variance decompositions in a 'factor plus sparse' VAR. The position of links and nodes is determined by the force-directed algorithm of Fruchterman and Reingold (1991).

Table 1: Ranking of Largest Senders and Receivers of Credit Risk

(a) Financial → Non-Financial

Sender

Rank	Name	Connectedness "To"
1	Santander	0.58
2	Crédit Agricole	0.54
3	Swiss RE	0.52
4	Société Générale	0.49
5	BBVA	0.49
6	Hannover Rueck	0.47
7	Zurich Insurance	0.46
8	Munich RE	0.45
9	Allianz	0.44
10	Unicredit	0.43
⋮	⋮	⋮
29	Standard Chartered	0.17
30	Rabobank	0.14
31	Dexia	0.13
32	Mediobanca	0.11
33	Bank of Ireland	0.08

Receiver

Rank	Name	Connectedness "From"
1	Air Liquide	0.81
2	Henkel	0.77
3	Ahold Delhaize	0.73
4	Svenska Cellulosa	0.73
5	Bayer	0.66
6	Akzo Nobel	0.65
7	Carrefour	0.64
8	Accor	0.63
9	Relx	0.63
10	Casino Guichard	0.62
⋮	⋮	⋮
105	Hellenic Telecom	0.07
106	RWE	0.07
107	BP	0.07
108	Iberdrola	0.06
109	Nokia	0.04

(b) Sovereign → Non-Financial

Sender

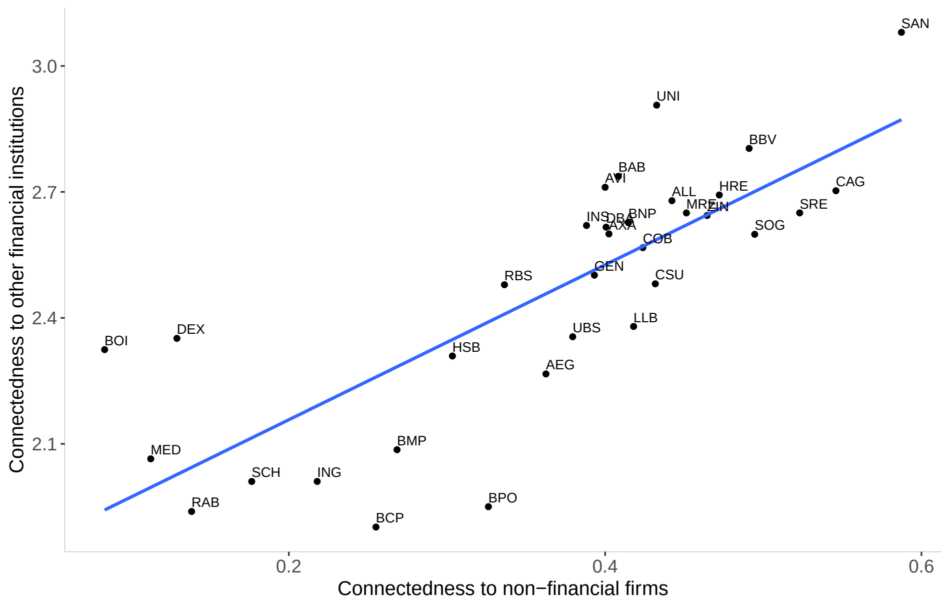
Rank	Name	Connectedness "To"
1	Italy	0.28
2	Portugal	0.22
3	Spain	0.21
4	UK	0.12
5	Austria	0.12
6	Germany	0.11
7	France	0.11
8	Belgium	0.11
9	Netherlands	0.11
10	Ireland	0.09

Receiver

Rank	Name	Connectedness "From"
1	Energias de Portugal	0.56
2	ENEL	0.47
3	Telefonica	0.43
4	National Grid	0.39
5	Électricité de France	0.39
6	Iberdrola	0.36
7	EON	0.35
8	Hellenic Telecom	0.34
9	ENBW	0.34
10	ENGIE	0.32
⋮	⋮	⋮
105	Michelin	0.03
106	Glencore	0.03
107	Metro	0.03
108	Volvo	0.02
109	Alliance Boots	0.01

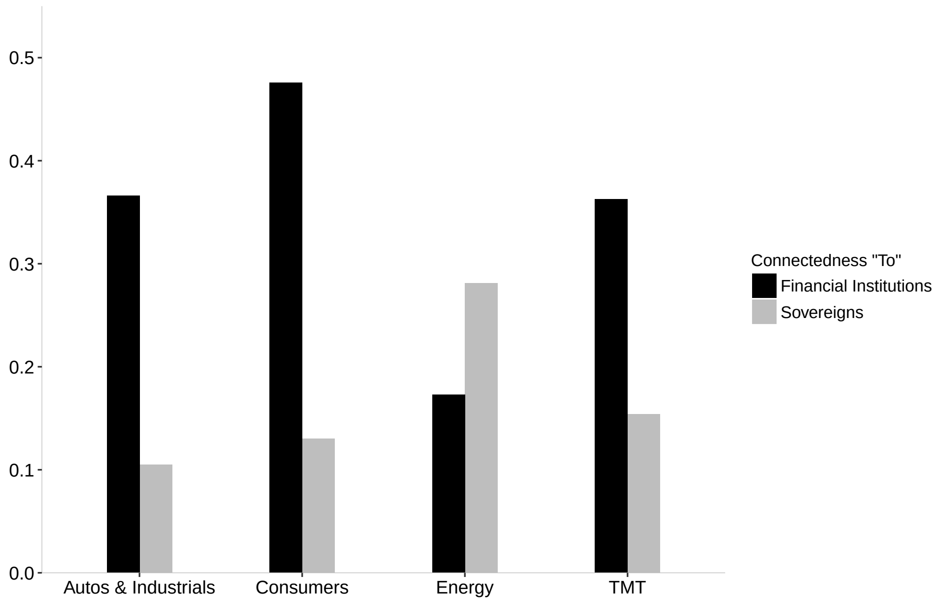
Note: The connectedness measures in all tables above are normalized by the number of entities so that the results represent the average value per entity.

Figure 2: Individual Senders of Financial Risk



Note: The plot shows the relationship between financial institutions' total connectedness to other financial institutions and financial institutions' total connectedness to non-financial firms over the full-sample period (2006-2017).

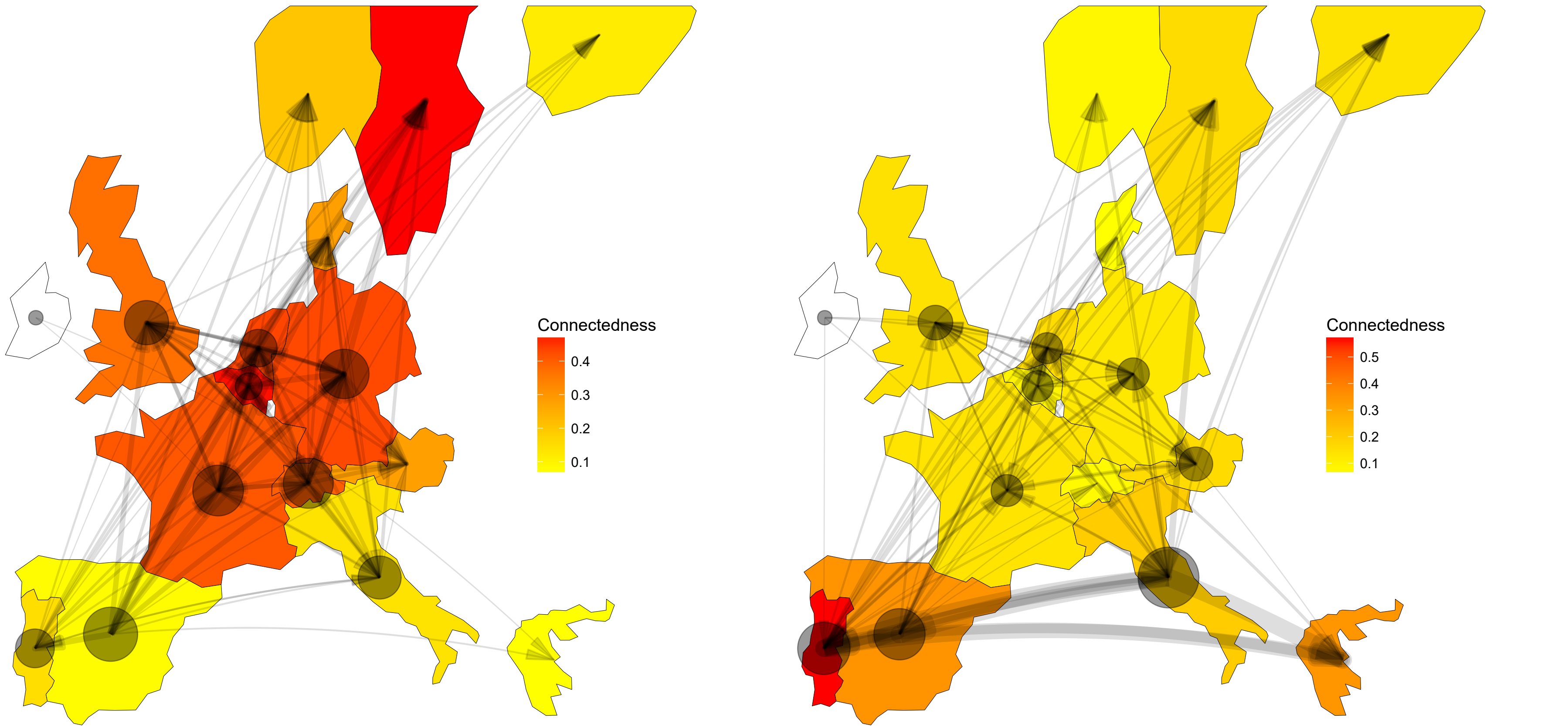
Figure 3: Aggregate Cross-Sectoral Connectedness



Note: The plot shows directional connectedness from financials and sovereigns, respectively, to non-financial firms, aggregated by sector type for the full-sample period (2006-2017). To ensure comparability, the aggregate measures are normalized by the number of entities so that the measures reported above represent average connectedness per entity of the corresponding sector.

Figure 4: Geographical Connectedness

(a) Financial → Non-Financial (b) Sovereign → Non-Financial



Note: The plot shows the geographical (country-level) decomposition of directional connectedness between (a) financial and non-financial entities and (b) between sovereign and non-financial entities. The color level of each country indicates the magnitude of credit risk shocks to non-financial firms headquartered in the corresponding country (country aggregates of "from" connectedness). The size of the black nodes indicates the contribution of (a) financial institutions or (b) sovereigns located in the corresponding country (country aggregates of "to" connectedness). Link thickness reflects the degree of cross-country "from" connectedness of non-financial firms (thicker links between any two countries represent a stronger cross-country risk transfer to non-financials). Ireland is left blank, as there are no non-financial firms from Ireland in our sample. To ensure comparability, all country aggregates are normalized by the number of entities so that the results reported above represent average connectedness by country and sector.

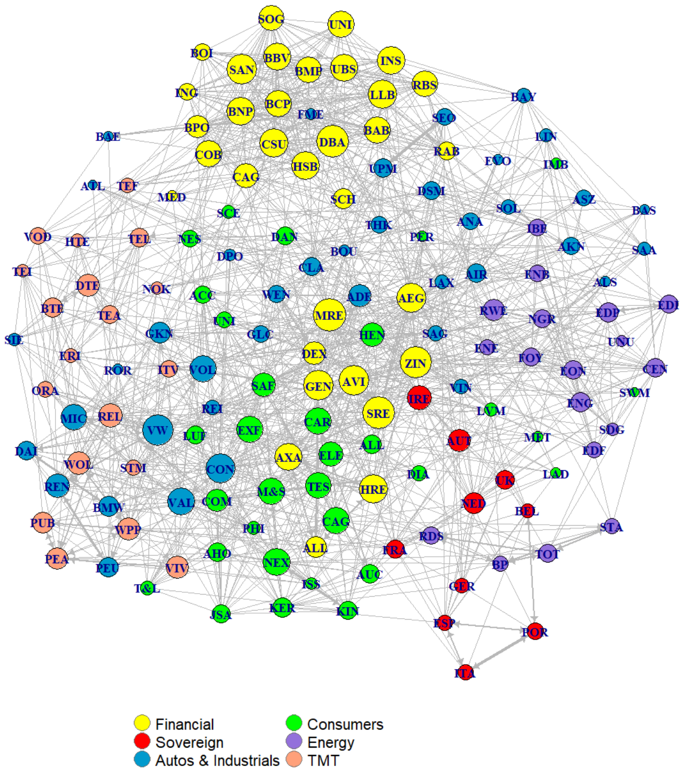
Table 2: Geographical Connectedness and Financial Linkages

	(1) Financial → Non-Financial	(2) Sovereign → Non-Financial
Bilateral bank claims		
(i) All sectors	0.244***	0.034
	(0.065)	(0.086)
(ii) Non-bank private sector	0.341***	0.124
	(0.113)	(0.155)

Note: The table reports the results of regressing the pairwise cross-country connectedness measures on bilateral bank claims from the consolidated banking statistics database of the Bank for International Settlements (BIS). We differentiate between (i) bilateral bank claims of country i to all sectors of country j, and (ii) bilateral bank claims of country i to the non-bank private sector of country j. We divide bilateral bank claims by country j's GDP to control for economy size. The BIS consolidated banking statistics measure banks' country risk exposures by capturing the claims of banks' foreign affiliates (ultimate risk basis). This consolidation approach is consistent with our strategy of aggregating the connectedness measures by the geographical location of a bank's headquarter. Each OLS regression includes a constant and country dummies. Standard errors are in parentheses. *** denotes significance at the 1% level.

Figure 5: CDS Network Before and After Lehman Brother's Bankruptcy

(a) Before: September 1, 2008



(b) After: November 6, 2008

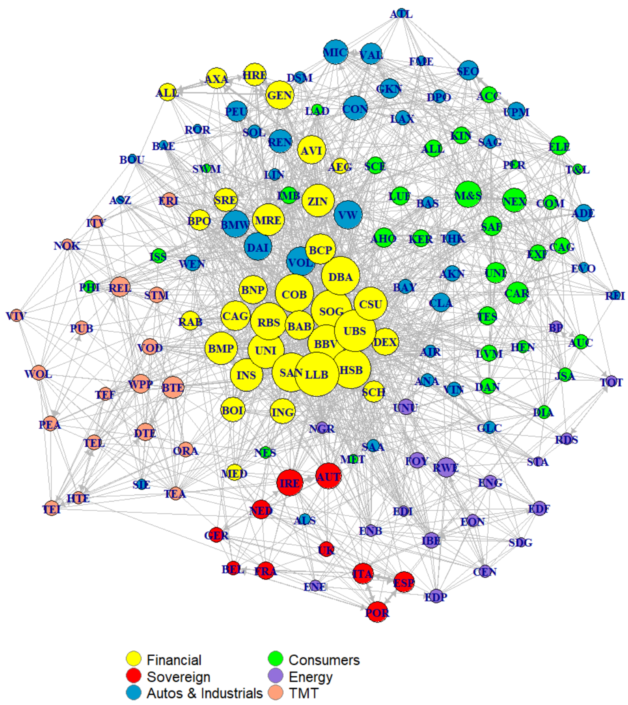
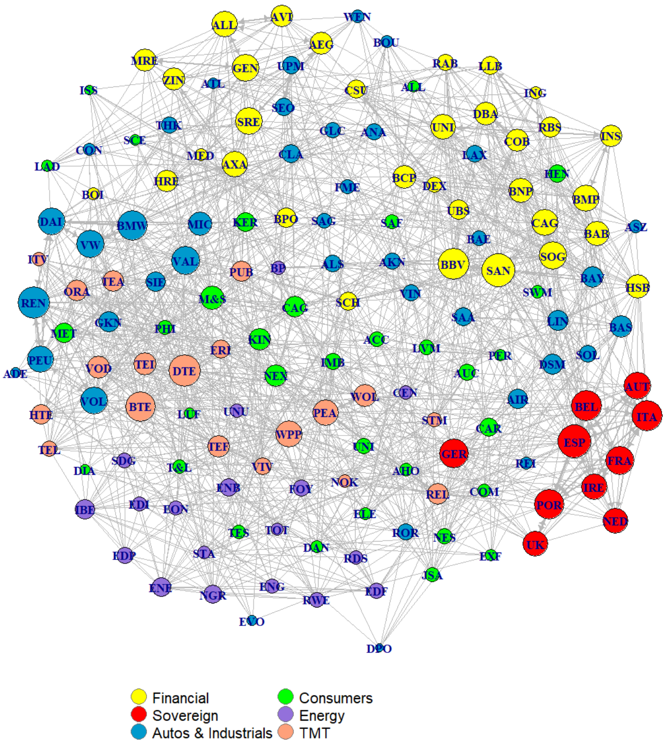


Figure 6: CDS Network Before and After the Onset of the Sovereign Debt Crisis

(a) Before: December 30, 2009



(b) After: May 5, 2010

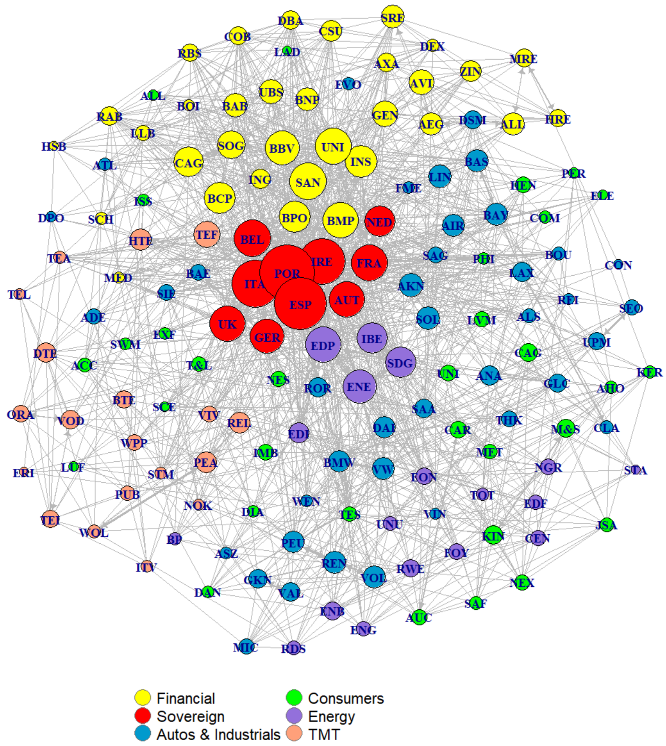
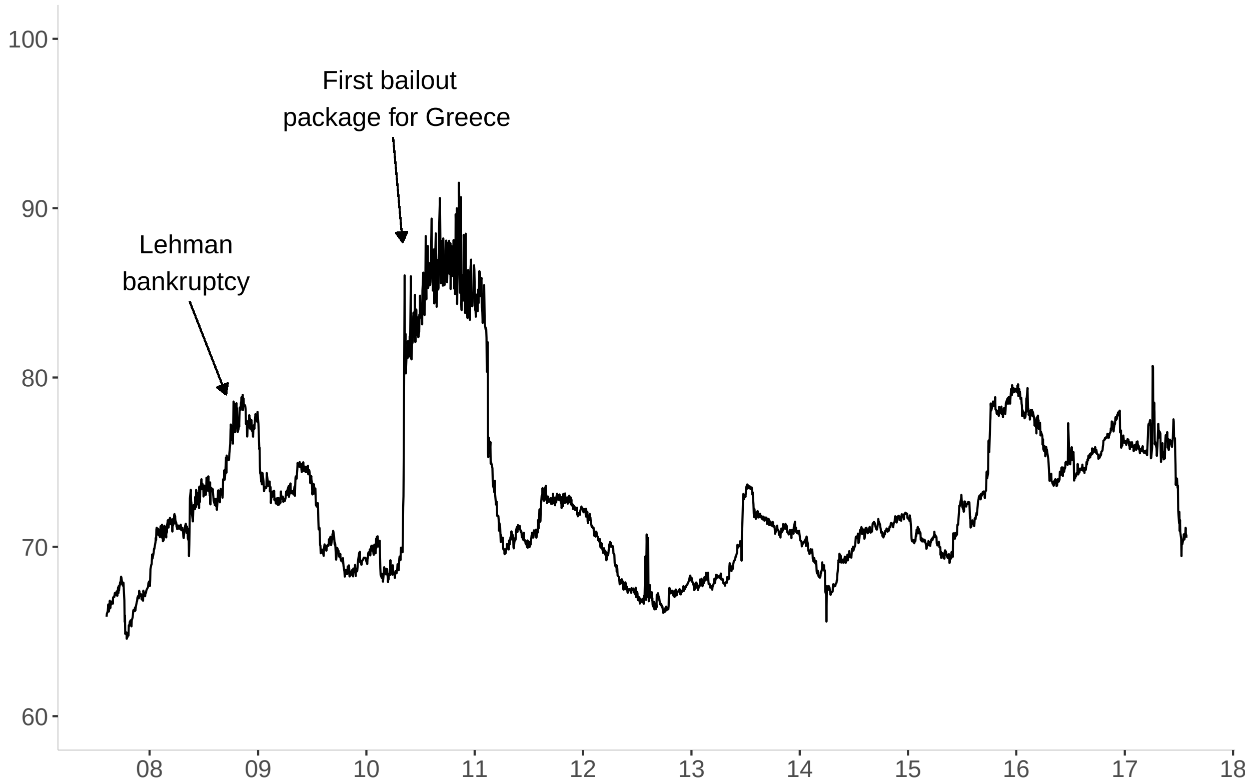
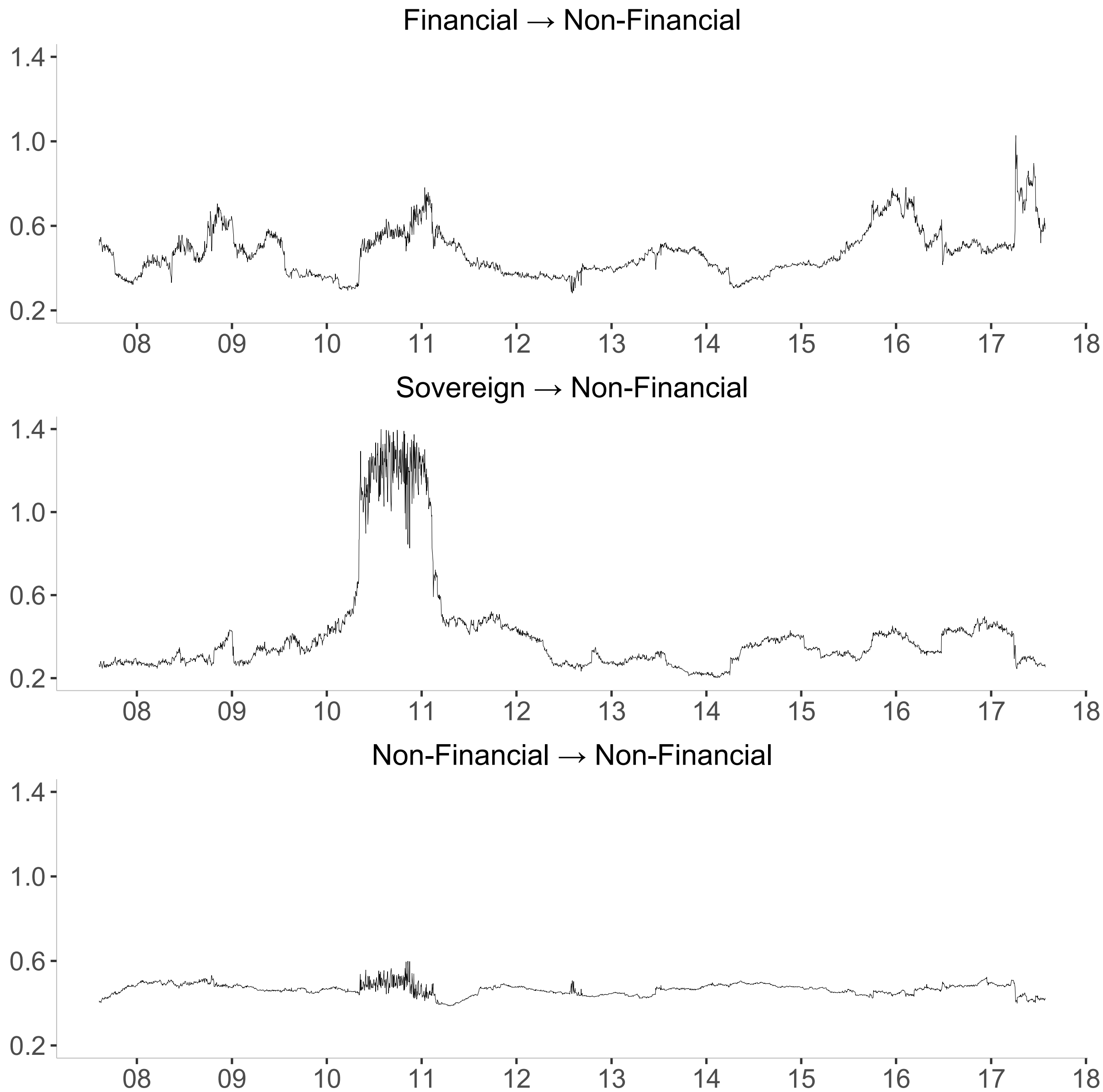


Figure 7: Dynamic System-Wide Connectedness



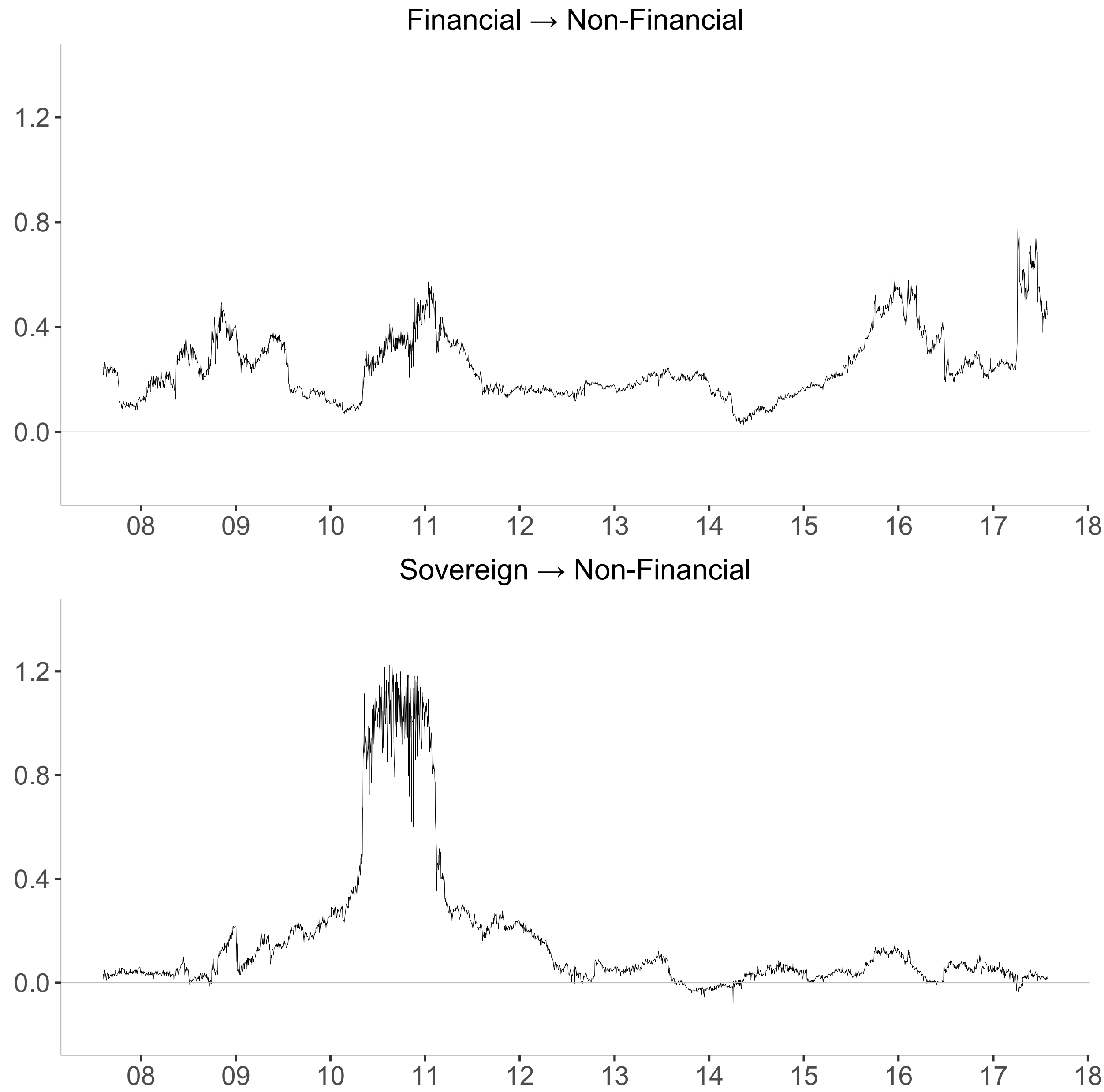
Note: The above figure shows the results from calculating time-varying parameters of the overall connectedness measure written in Eq. (7), using a rolling-window of 200 days.

Figure 8: Dynamic Cross-Sectoral Connectedness



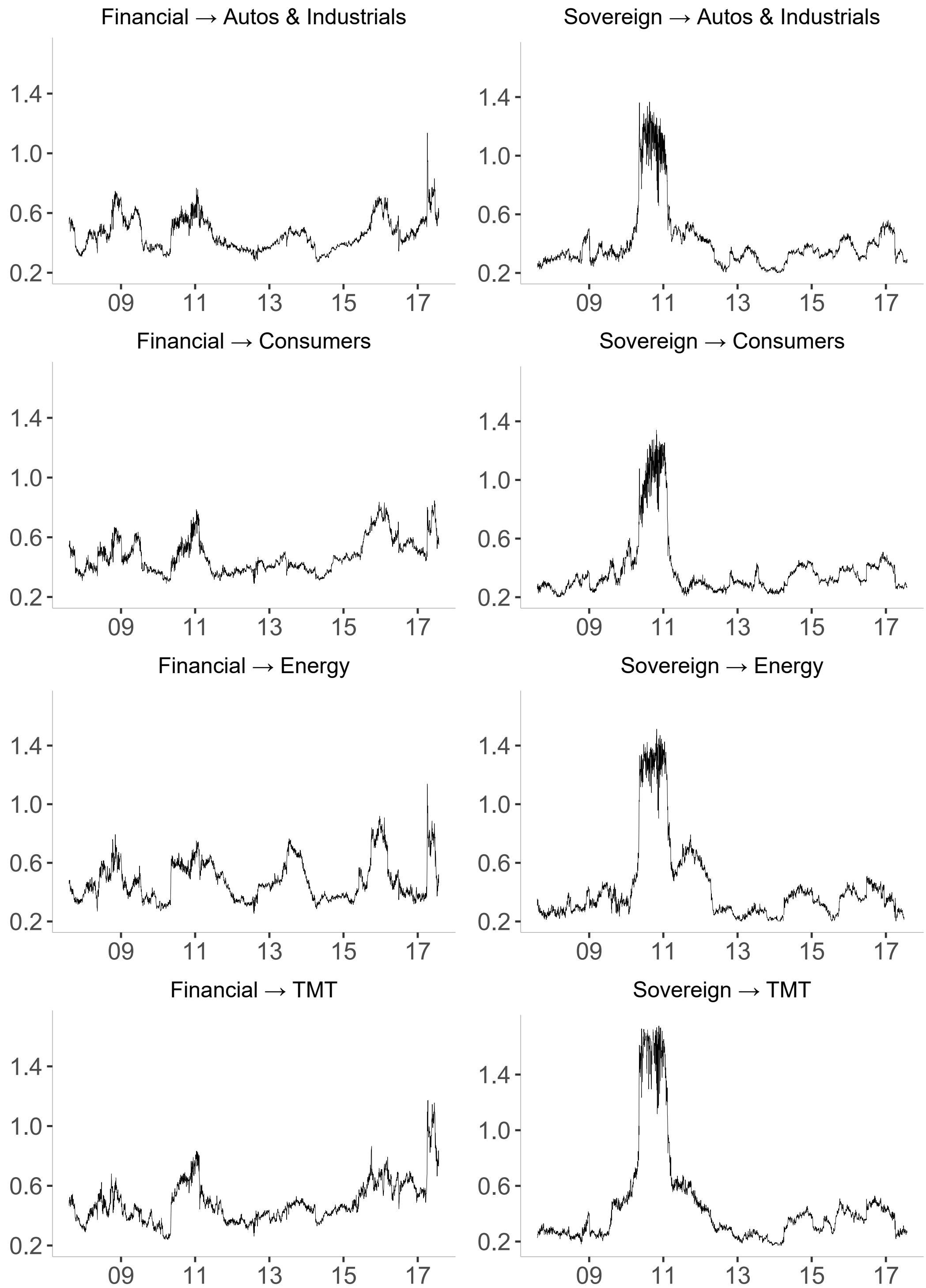
Note: The above figure shows the results from calculating time-varying parameters of the Diebold-Yilmaz connectedness measure aggregated by sector, using a rolling-window of 200 days. Each measure is normalized by the number of entities so that the graph shows the average impact for each sector.

Figure 9: Dynamic Cross-Sectoral Connectedness, Net Contribution



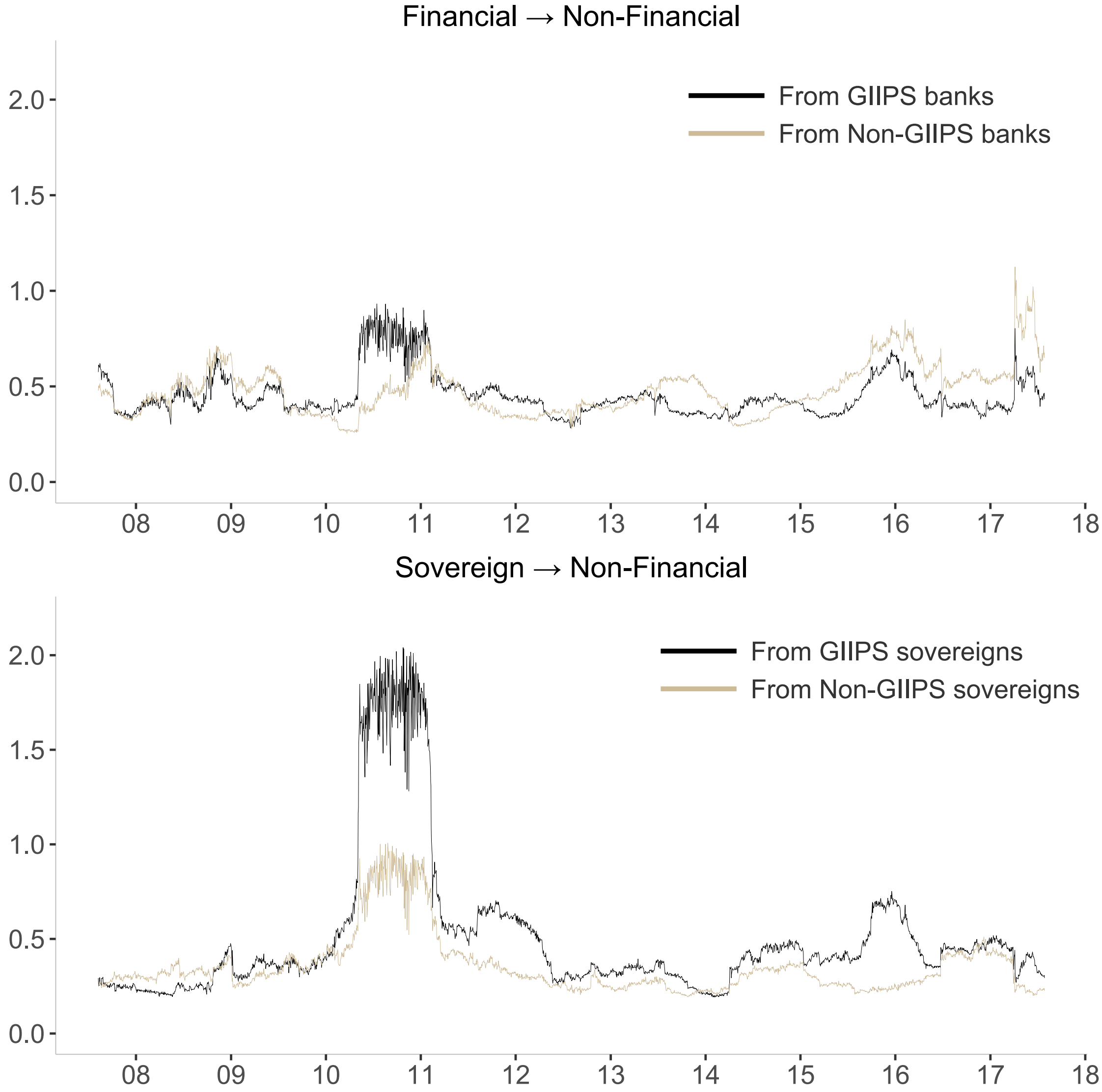
Note: The above figure shows aggregate net contribution of the financial and sovereign sector, respectively, to the non-financial sector in a dynamic framework (rolling window of 200 days). Net contribution of the financial sector is "aggregate connectedness from financial institutions to non-financial corporations" *minus* "aggregate connectedness from non-financial corporations to financial institutions". Net contribution of the sovereign sector is "aggregate connectedness from sovereigns to non-financial corporations" *minus* "aggregate connectedness from non-financial corporations to sovereigns". Each measure is normalized by the number of entities so that the graph shows the average impact for each sector.

Figure 10: Dynamic Cross-Sectoral Connectedness, Sub-Sectors



Note: The above figure shows the results from calculating time-varying parameters of the Diebold-Yilmaz connectedness measure aggregated by sub-sectors, using a rolling-window of 200 days. Each measure is normalized by the number of entities so that the graph shows the average impact for each sub-sector.

Figure 11: Dynamic Network Connectedness across Country Groups



Note: The above figure shows the results from calculating time-varying parameters of the Diebold-Yilmaz connectedness measure aggregated by country group, using a rolling-window of 200 days. (G)IIPS countries are Ireland, Italy, Portugal and Spain (Greece is exluded due to data availability). Each measure is normalized by the number of entities so that the graph shows the average impact for each group of countries.

Appendix: Dataset of CDS spreads

Table A.1: Summary Statistics of CDS Data by Country

Panel A: CDS non-financial corporations

		Levels				Returns			
Country	Entities	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
Austria	1	87.2	37.8	18.9	197.7	0.000	0.031	-0.247	0.251
Belgium	1	82.6	41.9	10.0	251.2	0.000	0.033	-0.249	0.274
Denmark	1	241.3	190.2	51.3	986.3	0.000	0.036	-0.834	0.380
Finland	4	185.2	163.0	7.8	1191.5	0.000	0.034	-0.838	0.377
France	24	113.9	113.4	5.0	1235.4	0.000	0.033	-0.589	0.600
Germany	19	96.4	100.1	7.5	1604.4	0.000	0.034	-0.334	1.032
Greece	1	472.8	586.5	24.0	4018.0	0.001	0.046	-0.331	0.441
Italy	4	137.1	113.0	8.8	702.4	0.000	0.037	-0.536	0.337
Netherlands	6	66.9	31.6	5.1	342.8	0.000	0.032	-0.779	0.807
Norway	2	57.9	30.8	6.6	235.0	0.000	0.031	-0.256	0.299
Portugal	1	224.5	205.4	8.9	929.7	0.001	0.041	-0.390	0.293
Spain	3	136.1	93.3	10.1	563.5	0.000	0.040	-0.399	0.305
Sweden	6	88.1	63.4	19.1	657.0	0.000	0.029	-0.288	0.518
Switzerland	6	134.6	174.7	3.0	3325.5	0.000	0.035	-0.441	0.441
UK	30	109.5	102.5	2.9	1385.4	0.000	0.033	-1.270	1.404

Panel B: CDS financial institutions

		Levels				Returns			
Country	Entities	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
Belgium	1	277.9	210.0	6.5	954.2	0.001	0.044	-0.350	0.866
France	4	107.8	75.1	5.0	434.6	0.000	0.048	-0.439	0.626
Germany	5	81.0	50.0	5.0	361.2	0.000	0.049	-0.476	0.613
Ireland	1	359.0	384.8	5.0	2298.9	0.001	0.058	-0.869	0.604
Italy	6	190.8	156.0	5.4	941.0	0.001	0.047	-0.539	0.753
Netherlands	3	102.8	72.6	3.0	625.0	0.001	0.044	-0.382	0.676
Portugal	1	420.5	373.1	8.0	1875.5	0.001	0.043	-0.354	0.406
Spain	2	151.8	105.4	7.0	510.3	0.000	0.047	-0.457	0.325
Switzerland	4	93.5	72.8	4.0	850.0	0.000	0.045	-0.410	0.562
UK	6	107.5	67.3	3.5	515.0	0.000	0.048	-0.706	0.657

Panel C: CDS sovereigns

		Levels				Returns			
Country	Entities	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
Austria	1	54.7	51.7	0.5	273.0	0.000	0.104	-2.001	1.531
Belgium	1	75.2	74.6	1.4	398.7	0.000	0.044	-0.287	0.305
France	1	56.1	50.3	0.5	245.2	0.000	0.101	-2.001	1.531
Germany	1	29.8	24.4	0.6	118.3	0.000	0.094	-1.335	1.540
Ireland	1	197.2	235.7	1.5	1249.3	0.000	0.164	-2.086	2.071
Italy	1	157.5	124.9	5.3	586.7	0.000	0.042	-0.362	0.331
Netherlands	1	37.7	30.1	1.0	133.8	0.001	0.062	-0.659	0.659
Portugal	1	303.6	322.9	3.4	1600.9	0.001	0.046	-0.512	0.279
Spain	1	150.2	134.2	2.4	634.3	0.000	0.052	-0.570	0.570
UK	1	41.5	30.6	1.5	175.0	0.000	0.044	-0.405	0.936

Table A.2: List of CDS Entities

Entity Name	Sector	Sub-Sector	Country	Name Code
Adecco	Non-financial	Autos & Industrials	Switzerland	ADE
Volvo	Non-financial	Autos & Industrials	Sweden	VOL
Akzo Nobel	Non-financial	Autos & Industrials	Netherlands	AKN
Alstom	Non-financial	Autos & Industrials	France	ALS
Anglo American	Non-financial	Autos & Industrials	UK	ANA
Astrazeneca	Non-financial	Autos & Industrials	UK	ASZ
Atlantia	Non-financial	Autos & Industrials	Italy	ATL
Bae Systems	Non-financial	Autos & Industrials	UK	BAE
BASF	Non-financial	Autos & Industrials	Germany	BAS
Bayer	Non-financial	Autos & Industrials	Germany	BAY
BMW	Non-financial	Autos & Industrials	Germany	BMW
Bouygues	Non-financial	Autos & Industrials	France	BOU
Clariant	Non-financial	Autos & Industrials	Switzerland	CLA
Saint-Gobain	Non-financial	Autos & Industrials	France	SAG
Michelin	Non-financial	Autos & Industrials	Switzerland	MIC
Continental	Non-financial	Autos & Industrials	Germany	CON
Daimler	Non-financial	Autos & Industrials	Germany	DAI
Deutsche Post	Non-financial	Autos & Industrials	Germany	DPO
Evonik	Non-financial	Autos & Industrials	Germany	EVO
Finmeccanica	Non-financial	Autos & Industrials	Italy	FME
GKN Holding	Non-financial	Autos & Industrials	UK	GKN
Glencore	Non-financial	Autos & Industrials	Switzerland	GLC
Koninklijke DSM	Non-financial	Autos & Industrials	Netherlands	DSM
Air Liquide	Non-financial	Autos & Industrials	France	AIR
Lanxess	Non-financial	Autos & Industrials	Germany	LAX
Linde	Non-financial	Autos & Industrials	Germany	LIN
Peugeot	Non-financial	Autos & Industrials	France	PEU
Renault	Non-financial	Autos & Industrials	France	REN
Rentokil Initial	Non-financial	Autos & Industrials	UK	REI
Rolls-Royce	Non-financial	Autos & Industrials	UK	ROR
Sanofi-Aventis	Non-financial	Autos & Industrials	France	SAA
Siemens	Non-financial	Autos & Industrials	Germany	SIE
Stora Enso Oyj	Non-financial	Autos & Industrials	Finland	SEO
Solvay	Non-financial	Autos & Industrials	Belgium	SOL
ThyssenKrupp	Non-financial	Autos & Industrials	Germany	THK
UPM-Kymmene Oyj	Non-financial	Autos & Industrials	Finland	UPM
Valeo	Non-financial	Autos & Industrials	France	VAL
Vinci	Non-financial	Autos & Industrials	France	VIN
Volkswagen	Non-financial	Autos & Industrials	Germany	VOL
Wendel	Non-financial	Autos & Industrials	France	WEN
Accor	Non-financial	Consumers	France	ACC
Electrolux	Non-financial	Consumers	Sweden	ELE
Auchan	Non-financial	Consumers	France	AUC
Alliance Boots	Non-financial	Consumers	UK	ALL
Carrefour	Non-financial	Consumers	France	CAR
Casino Guichard	Non-financial	Consumers	France	CAG
Compass	Non-financial	Consumers	UK	COM
Danone	Non-financial	Consumers	France	DAN
Lufthansa	Non-financial	Consumers	Germany	LUF
Diageo	Non-financial	Consumers	UK	DIA
Experian Finance	Non-financial	Consumers	UK	EXF

(Table A.2 continued)

Entity Name	Sector	Sub-Sector	Country	Name Code
Henkel	Non-financial	Consumers	Germany	HEN
Ladbrokes	Non-financial	Consumers	UK	LAD
Imperial Brands	Non-financial	Consumers	UK	IMB
ISS Global	Non-financial	Consumers	Denmark	ISS
J Sainsbury	Non-financial	Consumers	UK	JSA
Kering	Non-financial	Consumers	France	KER
Kingfisher	Non-financial	Consumers	UK	KIN
Koninklijke Ahold Delhaize	Non-financial	Consumers	Netherlands	AHO
Koninklijke Philips	Non-financial	Consumers	Netherlands	PHI
LVMH	Non-financial	Consumers	France	LVM
Marks & Spencer	Non-financial	Consumers	UK	M&S
Metro	Non-financial	Consumers	Germany	MET
Nestlé	Non-financial	Consumers	Switzerland	NES
Next	Non-financial	Consumers	UK	NEX
PernodRicard	Non-financial	Consumers	France	PER
Safeway	Non-financial	Consumers	UK	SAF
Svenska Cellulosa	Non-financial	Consumers	Sweden	SCE
Swedish Match	Non-financial	Consumers	Sweden	SWM
Tate & Lyle	Non-financial	Consumers	UK	T&L
Tesco	Non-financial	Consumers	UK	TES
Unilever	Non-financial	Consumers	UK	UNI
BP	Non-financial	Energy	UK	BP
Centrica	Non-financial	Energy	UK	CEN
EON	Non-financial	Energy	Germany	EON
Edison	Non-financial	Energy	Italy	EDI
Energias de Portugal	Non-financial	Energy	Portugal	EDP
Electricité de France	Non-financial	Energy	France	EDF
ENBW	Non-financial	Energy	Germany	ENB
ENEL	Non-financial	Energy	Italy	ENE
ENGIE	Non-financial	Energy	France	ENG
Fortum OYJ	Non-financial	Energy	Finland	FOY
Gas Natural SDG	Non-financial	Energy	Spain	SDG
Iberdrola	Non-financial	Energy	Spain	IBE
National Grid	Non-financial	Energy	UK	NGR
Royal Dutch Shell	Non-financial	Energy	Netherlands	RDS
RWE	Non-financial	Energy	Germany	RWE
Statoil	Non-financial	Energy	Norway	STA
Total	Non-financial	Energy	France	TOT
United Utilities	Non-financial	Energy	UK	UNU
British Telecom	Non-financial	TMT	UK	BTE
Deutsche Telekom	Non-financial	TMT	Germany	DTE
Hellenic Telecom	Non-financial	TMT	Greece	HTE
ITV	Non-financial	TMT	UK	ITV
Nokia	Non-financial	TMT	Finland	NOK
Orange	Non-financial	TMT	France	ORA
Pearson	Non-financial	TMT	UK	PEA
Publicis	Non-financial	TMT	France	PUB
Relx	Non-financial	TMT	UK	REL
St Microelectronics	Non-financial	TMT	Switzerland	STM
Ericsson	Non-financial	TMT	Sweden	ERI
Telefonica	Non-financial	TMT	Spain	TEF

(Table A.2 continued)

Entity Name	Sector	Sub-Sector	Country	Name Code
Telekom Austria	Non-financial	TMT	Austria	TEA
Telenor	Non-financial	TMT	Norway	TEL
Telia	Non-financial	TMT	Sweden	TEI
Vivendi	Non-financial	TMT	France	VIV
Vodafone	Non-financial	TMT	UK	VOD
Wolters	Non-financial	TMT	Netherlands	WOL
WPP	Non-financial	TMT	UK	WPP
Aegon	Financial		Netherlands	AEG
Allianz	Financial		Germany	ALL
Generali	Financial		Italy	GEN
Aviva	Financial		UK	AVI
AXA	Financial		France	AXA
Hannover Rueck	Financial		Germany	HRE
Munich RE	Financial		Germany	MRE
Swiss RE	Financial		Switzerland	SRE
Zurich Insurance	Financial		Switzerland	ZIN
Dexia	Financial		Belgium	DEX
BNP Paribas	Financial		France	BNP
Crédit Agricole	Financial		France	CAG
Société Générale	Financial		France	SOG
Deutsche Bank	Financial		Germany	DBA
Commerzbank	Financial		Germany	COB
Bank of Ireland	Financial		Ireland	BOI
Intesa Sanpaolo	Financial		Italy	INS
Banca Monte Di Paschi	Financial		Italy	BMP
Banca Popolare	Financial		Italy	BPO
Unicredit	Financial		Italy	UNI
Mediobanca	Financial		Italy	MED
ING	Financial		Netherlands	ING
Rabobank	Financial		Netherlands	RAB
Banco Comercial Port.	Financial		Portugal	BCP
Santander	Financial		Spain	SAN
BBVA	Financial		Spain	BBV
Royal Bank of Scot.	Financial		UK	RBS
HSBC Bank	Financial		UK	HSB
Barclays Bank	Financial		UK	BAB
Lloyds Bank	Financial		UK	LLB
Standard Chartered	Financial		UK	SCH
UBS	Financial		Switzerland	UBS
Credit Suisse	Financial		Switzerland	CSU
Austria	Sovereign		Austria	AUT
Belgium	Sovereign		Belgium	BEL
France	Sovereign		France	FRA
Germany	Sovereign		Germany	GER
Ireland	Sovereign		Ireland	IRE
Italy	Sovereign		Italy	ITA
Netherlands	Sovereign		Netherlands	NED
Portugal	Sovereign		Portugal	POR
Spain	Sovereign		Spain	ESP
UK	Sovereign		Spain	UK