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Abstract

This paper measures the connectedness in European Economic and Monetary Union (EMU) sovereign and bank CDS between April 2008 and December 2014, in order to understand the transmission of stress during the euro crisis. To this end, we perform a connectedness analysis using the framework proposed by Diebold and Yılmaz (2014). Second, we make use of a dynamic analysis to evaluate the net directional connectedness for each country and bank. Finally, we interpret the policy conclusions that stem from the results. We find that core countries´ contribution to stability was particularly significant since Draghi´s `whatever it takes´ speech. Bank risk played a role in enhancing sovereign risk. However, the systemic impact of banks changes rapidly once a crisis strikes, rendering the ex-ante determination of which banks are systemic and which banks will have a higher impact on the sovereign difficult.

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1. Introduction

The transmission of stress between banks and sovereigns has been the subject of a large literature. Papers often use a panel approach between the CDS (credit default swaps) of banks and sovereigns, or a cross section approach with different states, so as to assess the role that, for example, bank bailouts had in the transmission of risk between banks and sovereigns.

Other papers analyse the connections amongst financial institutions, in order to understand their systemic importance. However, a network approach is usually only used to understand connections in the exposures amongst firms. This, however, has usually not been applied to price indicators.

In this paper we will focus on the interconnection between EMU sovereign debt markets and banks by applying Diebold and Yilmaz (2014)'s indicator of connectedness. The results will shed light on the drivers of the bank-sovereign nexus, the effect of key policy decisions during the sovereign debt crisis and how a bank´s impact on the banking system as a whole changes in crisis times.

A number of papers use extensions of Diebold and Yilmaz (2012)'s methodology to measure the connectedness in different markets. Awartania *et al*. (2013), Lee and Chang (2013), Chau and Deesomsak (2014) and Cronin (2014) use it for the US; Yilmaz (2010), Zhou *etal*. (2012) or Narayan *etal*. (2014) apply ittoAsian economies, while Apostolakisa and Papadopoulos (2014) and Tsai (2014) examine G-7 economies. However, few papers to date have looked at the connectedness and spillover effects between banks and sovereigns in the euro area.

Some authors have analyzed sovereign bond spillovers, like Antonakakis and Vergos (2013), or Claeys and Vašicek (2014), who analyze the links in European sovereign bond markets in 2000-2012; Glover and Richards-Shubik (2014), who study financial networks in sovereign credit default swap spreads among 13 European sovereigns from 2005 to 2011; and Alter and Beyer (2014), who quantify spillovers between sovereign credit markets and banks in the euro area.

Finally, Gomez-Puig et al. (2013) and Gomez-Puig et al. (2014) analyze contagion across sovereign debt markets in a dynamic network, while

Fernandez-Rodriguez et al (2015) employ the framework established by Diebold and Yilmaz (2014) to analyze volatility spillovers within the euro area.

However, to our knowledge, no empirical analyses have been performed of the connectedness in sovereign market with other sovereigns and including in the same framework banks. By including such a network, our paper controls for indirect linkages amongst banks and sovereigns. Therefore, our paper provides a methodological contribution and relevant empirical insights to the assessment of financial stress transmission in EMU sovereign bond and bank CDS.

Diebold and Yilmaz (2014) showed that the connectedness framework was closely linked with both modern network theory (see Glover and Richards-Shubik, 2014) and modern measures of systemic risk (see Ang and Longstaff, 2013 or Acemoglu *et al*., 2014). The degree of connectedness, on the other hand, measures the contribution of individual units to systemic network events, in a fashion very similar to the CoVaR of this unit (see, e. g., Adrian and Brunnermeier, 2008).

After explaining the methodology that will be used in the empirical analysis, we will proceed in three stages. First, in order to estimate system-wide connectedness, we will undertake a full-sample (static analysis) that is not only of intrinsic interest, but will also prepare the way for the second stage, where we analyse connectedness in several subperiods that are of interest because they are marked by different stages in the EMU crisis. Finally, in the last stage we will analyse the implications of the results for several aspects of the literature: the ability to determine ex ante which institutions are systemic, and understanding how the connectedness between banks and sovereigns evolved over time.

Overall, our results confirm the finding that the positive influence of the core on the periphery broke in the height of the crisis, when investors started to differentiate according to country fundamentals. Part of this increase in sovereign risk, we find, was due to an increase in the connectedness from banks to sovereigns in the height of the crisis. Secondly, we find that a bank´s connectivity with its own sovereign changed, as sovereign stress rose and as bank bailouts were announce. Third, starting from the calculation of a bank´s systemic impact, we show how difficult it can be to determine ex ante which banks are systemic, as connectedness changes during crises. Finally, we find that the connectedness between banks and own sovereign is not particularly related to the bank holdings of sovereign bonds.

Consequently, pre-crisis, it was the central countries that triggered net connectedness relationships; in the crisis period, however, there was a major shift and this role was now played by peripheral countries.In addition, bank connectedness changes in crisis periods, and seems to be unrelated to the actual exposures of the banks with the sovereign. Therefore, according to our results, in a context of increased cross-border financial activity in the euro-area, the concern that in turbulent times a shock in one country might have spillover effects into others may be well founded, and financial stability may be threatened.

The rest of the paper is organized as follows. Section 2 presents Diebold and Yılmaz (2014)'s methodology for assessing connectedness in financial market volatility, and the empirical results (both static and dynamic) obtained for our sample of EMU sovereign and bank CDS. In Section 3 we present the empirical results regarding the evolution of connectedness in different subperiods from the outset of the global financial crisis. Section 4 examines the policy implication and our interpretation of the key results. Finally, Section 5 summarizes the findings and offers some concluding remarks.

2. Connectedness analysis

The main tool for assessing connectedness is based on a decomposition of the forecast error variance, which results from first, fitting a standard vector autoregressive (VAR) model. Secondly, we use the data up to and including time t to create an H period-ahead forecast (up to time $t + H$). Finally, we decompose the error variance of the forecast for each component with respect to shocks from the same or other components at time t.

Denote by d^{H}_{ij} the ij-th H-step variance decomposition component (i.e., the fraction of variable i's H-step forecast error variance due to shocks in variable j). The connectedness measures are based on the "non-own", or "cross", variance decompositions, d^{H}_{ij}, $i, j = 1, \dots, N$, $i \neq j$.

Consider an N-dimensional covariance-stationary data-generating process (DGP) with orthogonal shocks: $x_t = \Theta(L)u_t$, $\Theta(L) = \Theta_0 + \Theta_1 L + \Theta_2 L^2 + ...$, $E(u_t, u_t') = I$. Note that Θ_0 need not be diagonal.

Transformation of $\{\Theta_1, \Theta_2, ...\}$ via variance decompositions is needed to reveal and summarize connectedness. Diebold and Yilmaz (2014) use a table such as Table 1 to understand the various connectedness measures and their relationships. Its main upper-left *NxN* block, which contains the variance decompositions, is called the "variance decomposition matrix," and is denoted by $D^H = [d_{ij}]$. The connectedness table increases D^H with a rightmost column containing row sums, a bottom row containing column sums, and a bottom-right element containing the grand average, in all cases for $i \neq j$.

The off-diagonal entries of D^H are the parts of the N forecast-error variance decompositions of relevance from a connectedness perspective. In particular, the *gross pair-wise directional connectedness* from *j* to *i* is defined as follows:

$$C^H_{i \leftarrow j} = d^H_{ij}.$$

Since in general $C^H_{i \leftarrow j} \neq C^H_{j \leftarrow i}$, the *net pair-wise directional connectedness* from *j* to *i,* can be defined as:

$$C^H_{ij} = C^H_{j \leftarrow i} - C^H_{i \leftarrow j}.$$

The off-diagonal row sums in the give the share of the H-step forecast-error variance of variable x_i coming from shocks arising in other variables (all others, as opposed to a single other), while the off-diagonal column sums provide the share of the H-step forecast-error variance of variable x_i going to shocks arising in other variables. Hence, the off-diagonal row and column sums, labelled "from" and "to" in the connectedness table, offer the total directional connectedness measures. In particular, total directional connectedness from others to *i* is defined as

$$C^H_{i \leftarrow \bullet} = \sum_{\substack{j=1 \\ j \neq i}}^{N} d^H_{ij},$$

and *total directional connectedness* to others from *i* is defined as

$$C_{\bullet\leftarrow i}^{H} = \sum_{\substack{j=1 \\ j\neq i}}^{N} d_{ji}^{H}.$$

We can also define *net total directional connectedness* as

$$C_{i}^{H} = C_{\bullet\leftarrow i}^{H} - C_{i\leftarrow\bullet}^{H}.$$

Finally, the grand total of the off-diagonal entries in D^H (equivalently, the sum of the

“from" column or “to" row) measures *total connectedness*:

$$C^{H} = \frac{1}{N}\sum_{\substack{i,j=1 \\ j\neq i}}^{N} d_{ij}^{H}.$$

For the case of non-orthogonal shocks, the variance decompositions are not as easily calculated as before, because the variance of a weighted sum is not an appropriate sum of variances; in this case, traditional Cholesky-factor identification may be sensitive to ordering. So, following Diebold and Yilmaz (2014), a generalized VAR decomposition (GVD), invariant to ordering, proposed by Koop *et al.* (1996) and Pesaran and Shin (1998) is used. The *H*-step generalized variance decomposition matrix is defined as $D^{gH} = \left[d_{ij}^{gH}\right]$, where

$$d_{ij}^{gH} = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e'_{i}\Theta_{h}\Sigma e_{j}\right)^{2}}{\sum_{h=0}^{H-1}\left(e'_{i}\Theta_{h}\Sigma\Theta'_{h}e_{j}\right)}$$

In this case, e_j is a vector with *j*th element unity and zeros elsewhere, Θ_h is the coefficient matrix in the infinite moving-average representation from VAR, Σ is the covariance matrix of the shock vector in the non-orthogonalized-VAR, σ_{jj} being its *j*th diagonal element. In this GVD framework, the lack of orthogonality means that the rows of d_{ij}^{gH} do not have sum unity and, in order to obtain a generalized connectedness index $\tilde{D}^{g} = \left[\tilde{d}_{ij}^{g}\right]$, the following normalization is necessary: $\tilde{d}_{ij}^{g} = \frac{d_{ij}^{g}}{\sum_{j=1}^{N} d_{ij}^{g}}$, where by construction $\sum_{j=1}^{N}\tilde{d}_{ij}^{g} = 1$ and $\sum_{i,j=1}^{N}\tilde{d}_{ij}^{g} = N$

The matrix $\tilde{D}^g = \left[\tilde{d}_{ij}^g \right]$ permits us to define similar concepts as defined before for the orthogonal case, that is, *total directional connectedness*, *net total directional connectedness*, and *total connectedness.*

2.1. Data

We use daily data of CDS spreads built on data collected from the Bloomberg database for six EMU countries: Germany, France, Italy, Spain, Portugal and Ireland. We also use data for the two large banks in each jurisdiction that quote CDS: Deutsche Bank, Commerzbank, Societe Generale, BNP Paribas, BBVA, Santander, ISP, Unicredito, Banco Espirito Santo, BCP, Bank of Ireland and Allied IrishBank. Our sample begins on December 30 2008 and ends on 12 August 2014 (i.e., a total of 1,652 observations), spanning the key events since the start of the global financial crisis.

The full-sample connectedness tables appear as Table 2 and Table 3 for senior and subrogated CDS, respectively. As mentioned above, the *ij*th entry of the submatrix gives the estimated *ij*th pair-wise directional connectedness contribution to the forecast error variance of asset *i*'s yields coming from innovations to asset *j*. The off-diagonal column sums (labelled TO) and row sums (labelled FROM) gives the total directional connectedness to all others from *i* and from all others to *i* respectively. The bottom-most row (labelled NET) gives the difference in total directional connectedness (to-from). Finally, the bottom-right element (in boldface) is total connectedness.

As can be seen, the diagonal elements (own connectedness) are the largest individual elements in the table, but total directional connectedness (from others or to others) tends to be much larger for both banks and sovereigns.

Regarding pair-wise directional connectedness (the off-diagonal elements of the upper-left 11 × 11 submatrix), the highest observed pair-wise connectedness is from BBVA to Santander, and vice versa. In general, the highest value of pair-wise directional connectedness is amongst banks of the same country (ISP and UNI, Santander and BBVA, BNP and SocGen), a sign that, for the whole sample, financial fragmentation in the Eurozone was an issue.

The total directional connectedness from others is highest in Italian, French and Spanish banks. As for the direction connectedness to others, it is also highest in these banks, led by Santander, ISP and BNP, although closely followed by the Italian sovereign.

Finally, for the countries involved, we obtain that connectedness is usually higher amongst countries (this is true of Germany, France, Italy and Spain, whose highest connectors, both in to and from connectedness are other countries), than between countries and banks. However, in the case of the two bailed out countries that received a full sovereign bailout (Portugal and Ireland), the highest connectedness is with their own banks.

Table: Full-sample connectedness

	GER	CMB SNR	DB SNR	FRA	BNP SNR	SGEN SNR	ITA	ISP SNR	UNI SNR	SPA	SAN SNR	BBVA SNR	POR	BES SNR	BCPSNR	IRE	BOI SNR	AIBSNR	Contribution From Others
GER	20.4603	4.7301	4.5182	12.2666	6.6317	6.6314	8.2766	5.3162	5.6580	3.1234	6.2735	6.1966	2.9160	0.7722	1.0346	4.5265	0.5318	0.1362	79.5397
CMB SNR	4.6800	13.5396	5.7271	6.6549	9.2014	8.2286	6.6858	7.4859	8.7482	1.7605	9.1905	8.7908	2.5327	1.5924	1.8251	2.7168	0.6187	0.0211	86.4604
DB SNR	7.5405	7.7660	20.9839	6.2413	6.1046	5.9420	5.0538	4.5534	5.2607	3.0692	7.4675	6.5947	2.7041	2.8664	2.7129	3.9477	1.1665	0.0247	79.0161
FRA	9.5280	5.4233	2.9758	17.0165	8.1613	7.4531	10.1516	6.1698	6.2929	2.4798	7.2821	7.3786	3.4215	0.9334	0.9933	3.7232	0.4700	0.1458	82.9835
BNP SNR	5.3129	7.9046	3.4902	8.2522	12.4400	10.1791	8.5387	7.9522	8.2225	1.8335	8.9115	9.1909	2.7388	0.8385	1.1437	2.3957	0.6320	0.0231	87.5600
SGEN SNR	5.1039	7.8541	3.3357	8.2215	11.2022	12.8059	8.0539	7.8198	7.9030	2.2217	8.7033	8.7393	2.7086	0.9410	1.2139	2.5363	0.6308	0.0051	87.1941
ITA	5.8543	5.5231	2.4905	8.3142	7.1362	6.9356	16.0414	7.2365	6.9304	4.3044	8.2331	8.2512	4.4154	1.2279	1.7881	4.8277	0.4815	0.0084	83.9586
ISP SNR	3.9734	7.1193	2.6533	6.7437	8.7562	7.9030	8.7749	12.4902	11.1327	2.0725	10.2053	10.0718	2.5442	1.1485	1.4273	2.5275	0.4414	0.0148	87.5098
UNI SNR	4.0973	7.1624	2.7762	6.5120	8.6807	7.7739	8.5662	10.7837	14.1188	1.7192	9.9519	9.7082	2.2046	1.3628	1.4545	2.6229	0.4844	0.0204	85.8812
SPA	3.4823	3.8928	2.2785	4.1390	4.3730	4.5415	9.0174	5.1689	4.1541	25.8566	8.7410	9.3592	4.6907	1.6305	2.0111	5.5859	0.9623	0.1153	74.1434
SAN SNR	3.5856	6.9621	3.5652	6.2096	7.8449	7.1486	7.1862	8.4502	7.6625	3.3551	14.7021	13.4474	2.8503	1.6093	1.7762	3.0504	0.5722	0.0219	85.2979
BBVA SNR	3.4775	6.7722	3.4461	6.1961	8.0023	7.0589	7.4299	8.2827	7.4969	3.4891	13.4255	14.7099	3.0303	1.7310	1.7837	3.1233	0.5236	0.0211	85.2901
POR	3.8746	4.6174	2.0288	6.8361	5.5850	5.7133	8.0393	7.0407	4.3339	3.8201	5.7619	7.0415	21.1986	1.6633	1.9387	8.9360	1.3061	0.2646	78.8014
BES SNR	1.8333	4.1420	4.2586	3.2595	4.7497	4.7238	5.0417	5.7836	5.0103	2.8383	7.5279	7.6683	4.6257	22.4666	10.1161	4.0926	1.3927	0.4691	77.5334
BCPSNR	2.4820	4.2069	3.5851	3.6575	5.8990	5.3910	6.4464	5.6719	4.6459	2.4321	7.6338	7.5582	4.4651	9.5228	19.7408	5.0432	1.5550	0.0632	80.2592
IRE	4.6511	4.1258	2.8575	6.7139	4.0717	4.6030	8.3323	5.3591	4.6384	4.3414	5.9387	6.7588	8.6356	1.4782	2.7600	21.5681	2.1096	1.0568	78.4319
BOI SNR	1.3896	1.8726	1.8443	1.8526	2.2860	2.2927	1.5456	1.7985	2.2605	1.0519	3.7763	2.6962	2.9545	1.9308	1.9964	6.6524	61.7556	0.0434	38.2444
AIBSNR	0.4100	1.1071	0.5371	0.4618	0.1449	0.3005	2.2878	1.4807	0.8945	0.9142	1.2361	1.0466	5.5833	0.9124	2.7982	7.5400	0.2970	72.0477	27.9523
Contribution To Others	77.6967	87.0708	71.3929	85.7661	89.7420	88.9247	88.1587	89.4902	87.7616	63.4189	89.8580	89.8698	74.8295	58.8736	66.2636	77.3957	18.6688	3.2950	**77.0032**
Net Contribution (To-From) Others	**-1.8430**	**0.6104**	**-7.6231**	**82.9835**	**2.1820**	**1.7306**	**4.2001**	**1.9805**	**1.8803**	**-10.7244**	**4.5600**	**4.5797**	**-3.9719**	**-18.6598**	**-13.9956**	**-1.0361**	**-19.5756**	**-24.6573**	

Notes: GER, FRA, ITA, SPA, POR and IRE stand for Germany, France, Italy, Spain, Portugal and Ireland respectively. BBVA SNR, SANSNR, UNISNR, ISPSNR, SGEN SNR, BNP SNR, DBSNR, CMB SNR, AIB SNR, BOI SNR, BCP SNR and BES SNR stand for senior CDS for Banco Bilbao Vizcaya Argentaria, Santander, Unicredito, Intesa San Paolo, Societe Generale, BNP Paribas, Deutsche Bank, Commerzbank, Allied Irish Bank, Bank of Ireland, BCP and Banco Espirito Santo

2.2. Sub sample approach

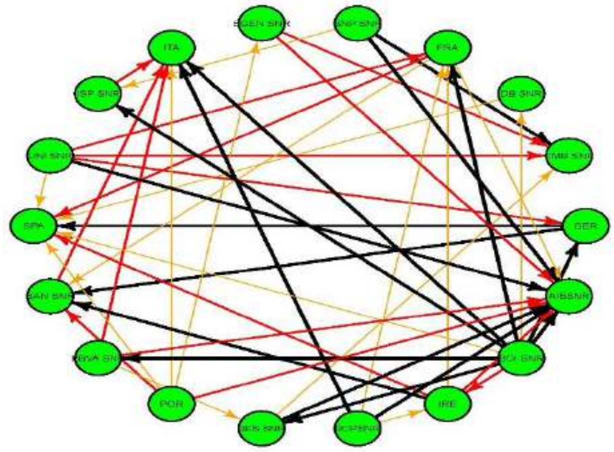
The full-sample connectedness analysis does not provide insights into the connectedness dynamics and its reaction in different time periods and policy changes. This section presents an analysis of connectedness in each of the subperiods identified.

As can be seen in the table, total connectedness changed abruptly in the subsamples studied. In particular, total connectedness declined as market turbulences deepened, and only slowed down in superiod 5, after Draghi´s whatever it takes speech and the implementation of the OMTs. In subperiod 6, possibly related to the Greek bailout, total connectedness declined slightly again.

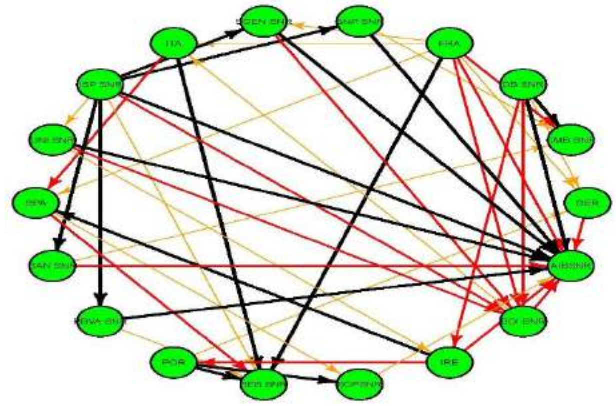
The first sub-period (a), which spans from December 2008 to march 2009, remains as a pre crisis period, in the sense that the bulk of financial turmoil in the euro area was yet to come. Subperiod 2, which ended in April 2010, represents time of building up of risk aversion in markets. Sub-period 3– from April 2010 to October 2011 – marked the first stages of the full-blown euro crisis: Greece (May 2010), Ireland (November 2010) and Portugal (April 2011) were all subject to bailout programs. As noted, the uncertainty continued in European debt markets during sub-period 4 (August 2011 - July 2012). During this phase, Italy was in the middle of a political crisis and the main rating agencies lowered the ratings not only of peripheral countries but of Austria and France as well. In this context of financial distress and huge liquidity problems, the ECB responded by implementing the first round of nonstandard monetary policies (policies that went beyond changing the reference interest rates. In November 2011 and March 2012, the ECB provided banks with a sum close to 500 billion Euros for a three-year period. However, in March 2012 the second rescue package to Greece was approved, and in June 2012 Spain requested financial assistance to recapitalize its banking sector. This was the backdrop to the ECB's President Mario Draghi's statement that he would do "whatever it takes to preserve the euro". Sub-period 5, which starts after that statement in July 2012, clearly reflects the effects of Draghi's spreech since a substantial increase in the level of total connectedness can be observed in EMU sovereign debt markets. Nonetheless, our indicator definitely registered a new slowdown in March 2013, when Cyprus requested financial support. Therefore, the last sub-period (6) spans from that date to the end of the sample (December 2014).

Chart 1: Net pair-wise directional connectedness during the five sub-periods

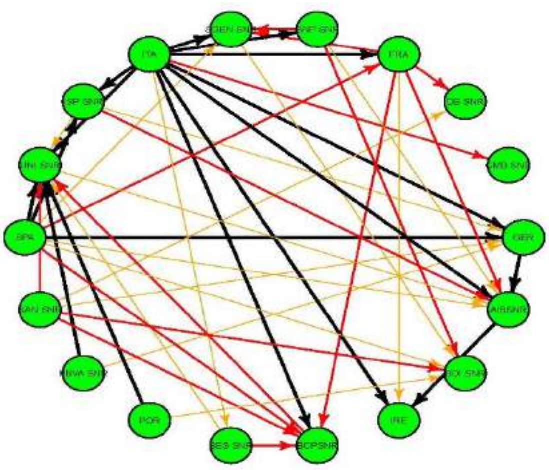
Sub-period 1: 12/30/2008 to 03/18/2009



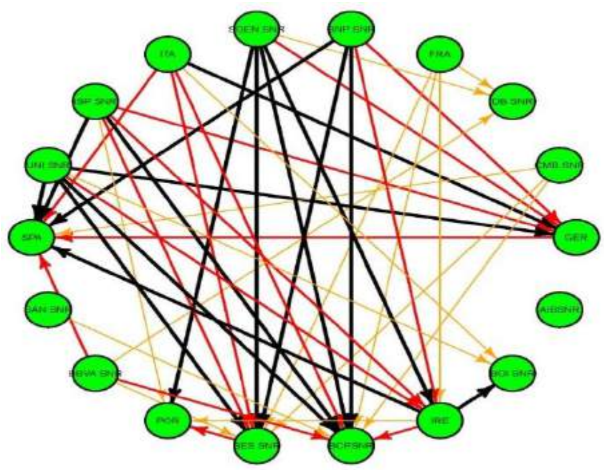
Sub-period 2: 03/19/2009 to 04/22/2010



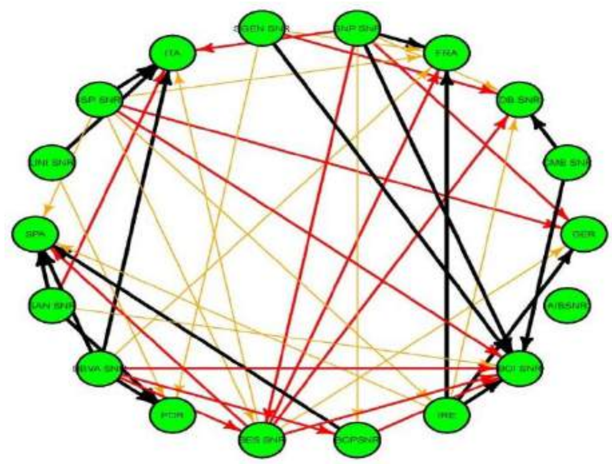
Sub-period 3: 04/23/2010 to 10/07/2011



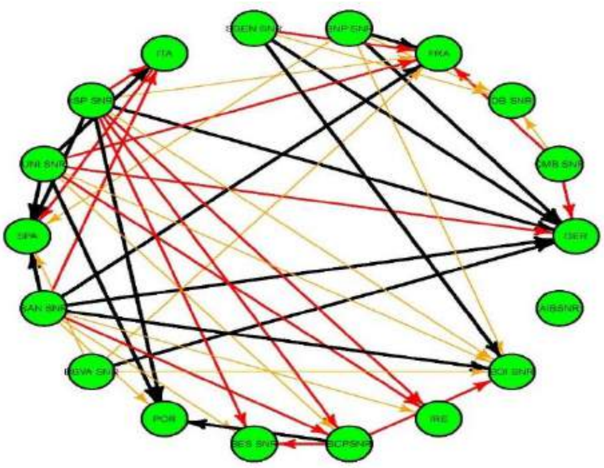
Sub-period 4: 10/08/2011 to 07/26/2012



Sub-period 5: 07/27/2012 to 03/23/2013



Sub-period 6: 03/24/2013 to 12/08/2014



Notes: We show the most important directional connections among the 55 pairs of the 10-year bond yields under study. Black, red and orange links (black, grey and light grey when viewed in grayscale) correspond to the tenth, twentieth and thirtieth percentiles of all net pair-wise directional connections. GER, FRA, ITA, SPA, POR and IRE stand for Germany, France, Italy, Spain, Portugal and Ireland respectively.BBVA SNR, SANSNR, UNISNR, ISPSNR, SGEN SNR, BNP SNR, DBSNR, CMB SNR, AIB SNR, BOI SNR, BCP SNR and BES SNR stand for senior CDS for Banco Bilbao Vizcaya Argentaria, Santander, Unicredito, Intesa San Paolo, Societe Generale, BNP Paribas, Deutsche Bank, Commerzbank, Allied Irish Bank, Bank of Ireland, BCP and Banco Espirito Santo

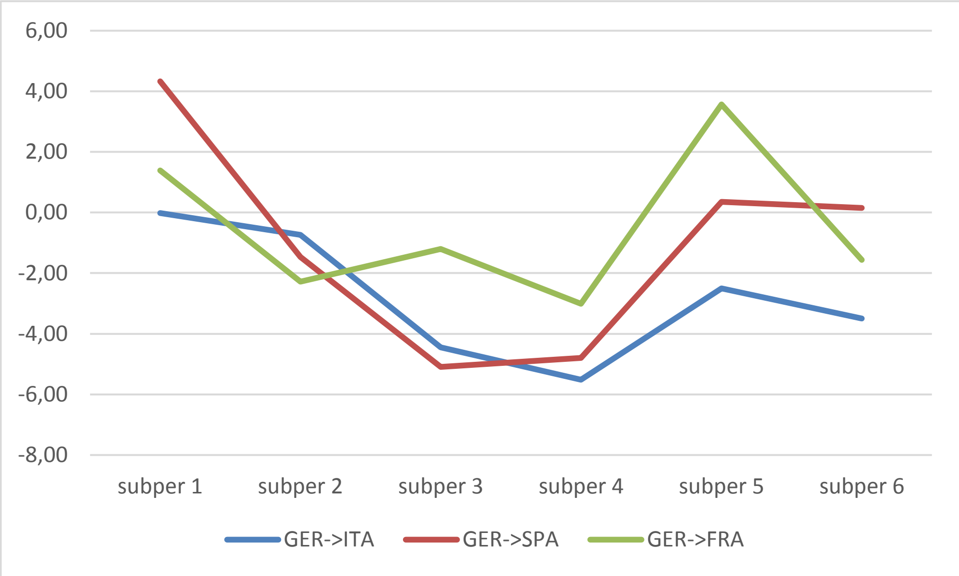
2.3. Net pair-wise directional connectedness

Connectedness rose and then fell. It peaked when whatever it takes was announced, thanks exclusively to a rise in the bank sovereign connectedness. However, this was not driven by a rise in the connectedness between periphery banks and sovereign. The sovereign connectedness rose in the period prior to whatever it takes, partly driven by a rise in the bank-sovereign connectedness

In particular, while the number of significant pairwise connectedness rose from 33 (subperiod 1) to 87 (subperiod 5), this was mainly driven by an increase in the bank-sovereign connectedness in period 5. Also, note that there is a rise in connectivity amongst peripheral countries that recedes in the last period, a sign that investors start to differentiate amongst specific countries in the periphery, given the differences in their stress levels.

Finally, a measure of the disconnect between the periphery and Germany (which we consider a safe asset throughout the period) may give an indication of the level of transfer of risk between the stressed Eurozone countries and the periphery. This transfer of risk can be considered an indication of the resilience of the Eurozone. Note for instance that in the case of Italy, net directional connectedness with Germany turned negative as soon as stress started (in particular, periods 4 and 5, meaning that instead of Germany anchoring Italian CDS, Italian CDS were driving German CDS higher), however, it recovered in subperiod 5, in the wake of whatever it takes, and then worsened, although slightly, in period 6, when some worries about specific periphery countries resurfaced. The results for the Spanish CDS are similar, as can be seen in chart 1.

Chart 2: net direction connectedness from Germany to Italy, France and Spain



3. Policy implications

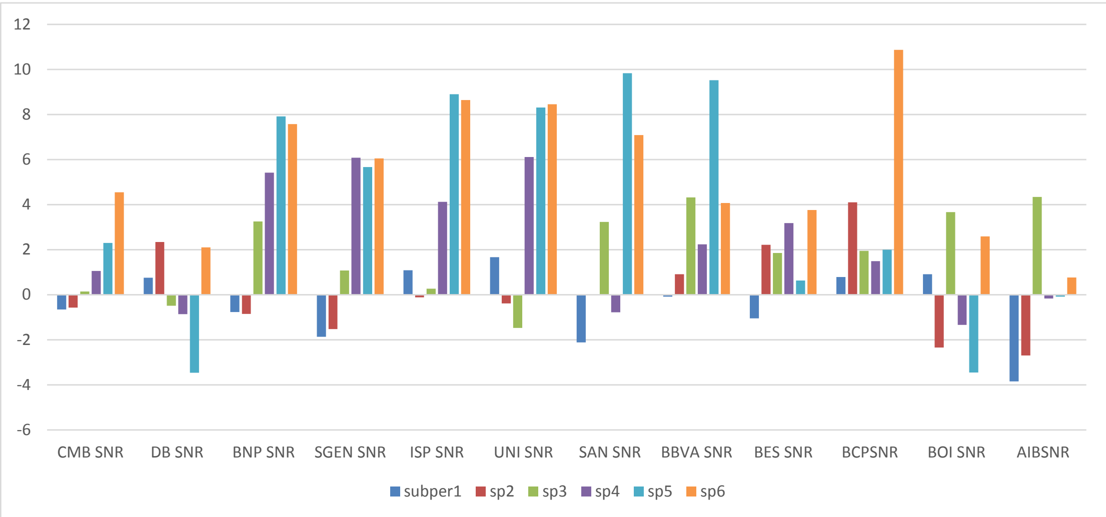
The indicator developed in the above sections has a number of implications for policy. In this section, we use the results from the previous section to shed light on three aspects that have been debated in the academic and policy literature. First, the change in the direction of the spillovers from sovereigns to own country banks. Secondly, we show the difficulty in regulating SIFIs in normal times, as institutions that may not seem SIFIs in normal times can become systemic in times of stress. Finally, we analyse how connectedness between sovereigns and own country banks has strengthened over time, and test two usual determinants: global risk aversion or the increase in the demand for sovereign bonds.

3.1. bank-sovereign connectedness

Acharya (2013) and others show that bank bailout programmers implemented in 2008 led to a change in the risk transfer between sovereigns and banks: before the bailouts, the sovereigns transferred risk to the Banks, but once the market perceived there was a blanket guarantee from the sovereigns to the banks, the directions of causality was the opposite, with the Banks being net issuers of stress to the sovereigns, and the latter going from being net issuers to net receivers. This result has been confirmed by others like Erce (2013).

The following chart shows the net issue of stress for each bank in the sample to its sovereign: in most cases banks went from being net receivers of risk to being net senders of risk from their sovereigns, which is consistent with the hypothesis mentioned above. This was particularly true in period 5, although in some cases, in core countries like France the process started in period 3. What´s more, the chart below shows a relatively similar trend for the banks in a given country, which may be a sign that the connectivity with the sovereign is a function of policies implemented by the latter. This confirms that the bailouts of the banking sector effectively transferred their risk to their sovereign.

Chart 3: net issuance of connectedness from banks to own sovereign



3.2. SIFI status

Another aspect that may be analysed in this framework is whether the Basel III SIFI regulation is appropriate in preparing the banking system for a future downturn. The regulation identifies firms that may have a negative externality on the system because of the systemicity. The interconnectedness of the firms with the system is a key ingredient of SIFI status. As a result, firms that qualify as

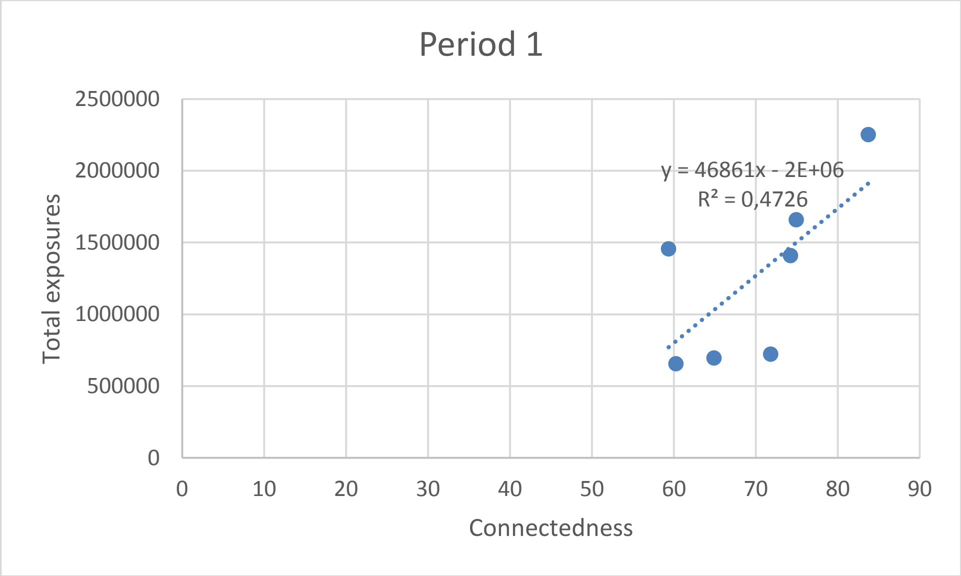
SIFIs are required to hold extra capital, so as to make the failure of one of these banks, which is deemed particularly costly from a social perspective, less likely.

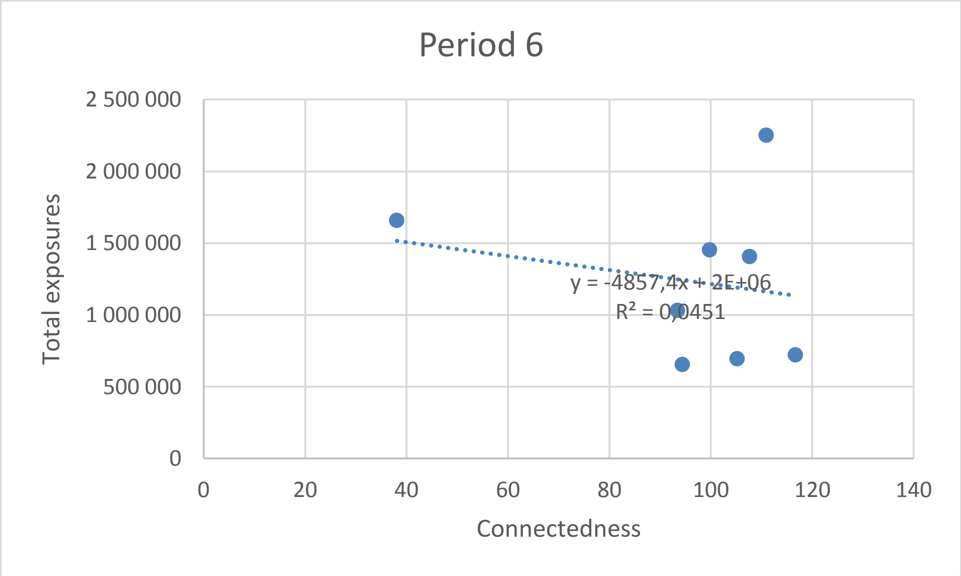
We test the regulation in three ways. First, we compare the total exposures, the key indicator of systemicity, with a firm`s connectedness with the system: this will test whether exposure based indicators of systemicity are good indicators of actual contributions to systemic risk. Secondly, we compare the contribution to systemic risk to the SIFI capital surcharge that firms are subjected to. Finally, we run a simulation, where we show that even for a firm that the systemic contribution in the crisis was rather low, the prevalence of shocks is such that there is a high probability that its contribution to global risk may be larger than that of a SIFI.

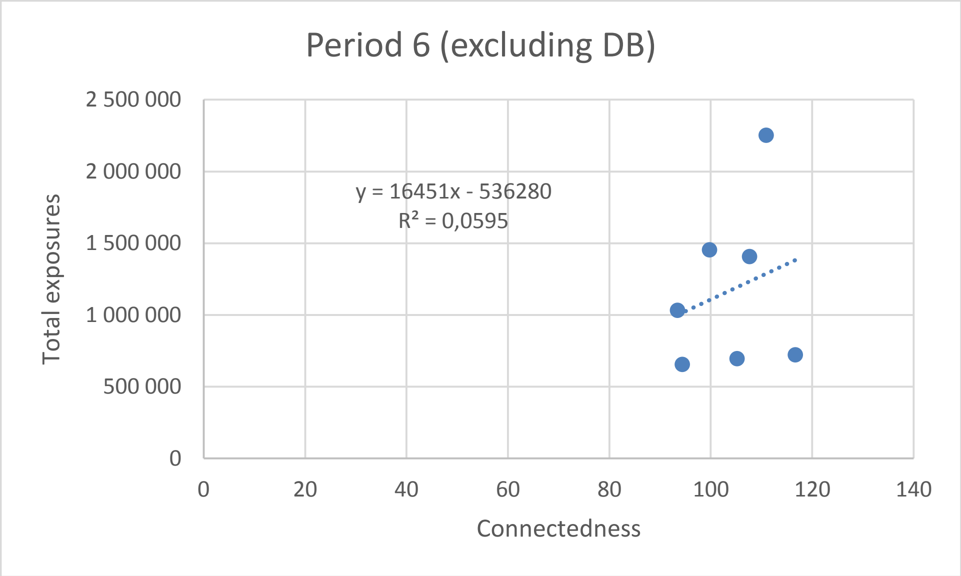
The following chart shows the relationship between the systemic impact and total exposures of the entities. In normal times or in the initial phase of the crisis, there is a positive relationship, such that the banks with a larger exposure are the ones considered more systemic, and so the ones holding more capital on this account. While there are some divergences, overall, the result points to the fact that the more systemic institutions are the ones that have to hold more capital, meaning that, overall, SIFI regulation is well targeted.

After a few years of the crisis and after the broad declines in the connectivity of institutions (e.g. the period 6), the relationship between total exposures and the systemic capital surcharge changes completely: the total exposure is no longer a good predictor of connectivity. Note that the R^2 is low even when an apparent outlieris taken out of the simple. Therefore, the current regulation of SIFIs might not be appropriate in times of crisis, when a relatively small bank can have systemic consequences once crisis mode sets in and the systemic impact becomes less related to bank exposures.

Chart 4. Total bank exposures (Mn EUR) and connectedness







These results suggest that the changing nature of connectivity makes the ex-ante determination of which bank is systemic difficult. In other to further research this point we compare the impact on financial system stress a given institution during the global financial crisis with the capital surcharge that is meant to internalize the costs of the contribution to systemic stress.

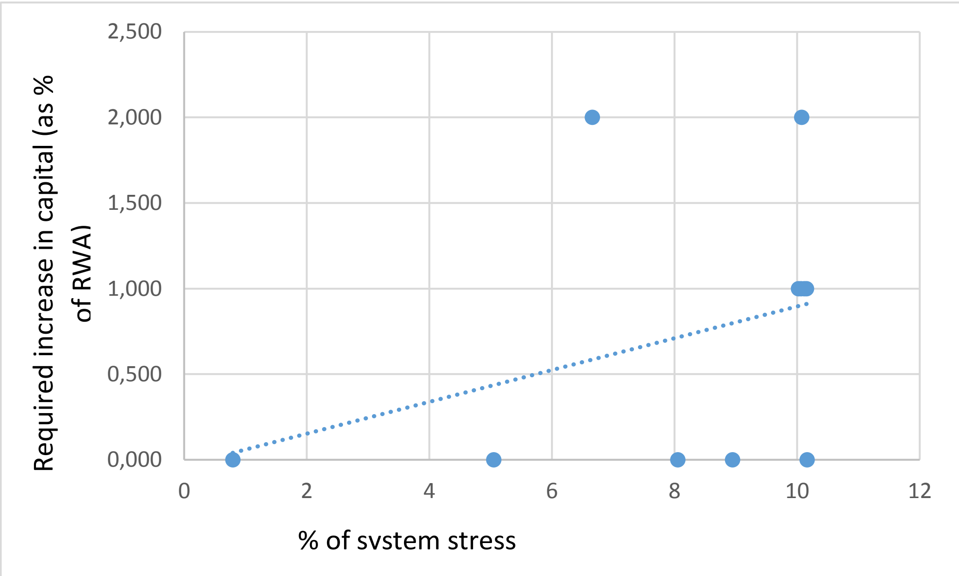
	Initial CDS	Stressed CDS	% of stress caused by banks
CMB SNR	86,5	361,8	9,9
DB SNR	101,078189	186,79	6,7
BNP SNR	70,5	354,24	10,1
SGEN SNR	107,5	426,2	10,0
ISP SNR	112	607,89	10,2
UNI SNR	124	678,31	10,2
SAN SNR	103	490	10,1
BBVA SNR	99	513,5	10,1
BES SNR	94	1277,02	8,1
BCP SNR	104	1878,54	8,9
BOI SNR	245	2218,702	5,0
AIB SNR	206	19483,279	0,8

Secondly, we calculate the additional capital that Basel III regulation requires SIFIs to hold on accounts of their systemic impact.

	Aditional capital	% of RWA of additional CEQ
CMB SNR	0	0
DB SNR	7458,16	2
BNP SNR	11551,18	2
SGEN SNR	345,07	1
ISP SNR	0	0
UNI SNR	4477,34	1
SAN SNR	5586,07	1
BBVA SNR	3320,34	1
BES SNR	0	0
BCP SNR	0	0
BOI SNR	0	0
AIB SNR	0	0

As the chart below shows, firms that had a substantial systemic impact on stress will not be considered systemic, while other with a similar impact will be considered systemic.

Chart 5: Systemic capital requirement and contribution to systemic stress (%)



The above analysis shows that first, the institutions that have a systemic impact in stress may be different to those in normal times, and, secondly, the current SIFI systemic capital requirement regulation would treat firms that in 2008 had the same systemic impact differently. The question that emerges is whether there can be indicators that can be more reliable.

In order to answer this question, we run a simulation to test the circumstances under which a non-systemic institution may become systemic. In order to do this, we test the probability of systemic stress of a not SIFI is superior to a SIFI systemic stress.

We analyze two firms: BOI and Unicredito. The first generates 5.5% of the stress of the system, the second a 10.15%. The first is not SIFI according to the classification used by Basel III, the second is. In this case, one could argue that this classification is correct, given the large difference in their contribution to systemic risk. However, even in such cases, the systemic contribution is similar enough that, subject rather standard shocks, the non SIFI can become more systemic than the SIFI.

We assume that an increase in the CDS of unicredito of 1% increases on average the CDS from the system in 0,1015%. In the second case this figure is 0,055%. This is the interpretation of the result that 5.5% of the stress of the system is because BOI-10.15% to UNI.

Effect on System CDS

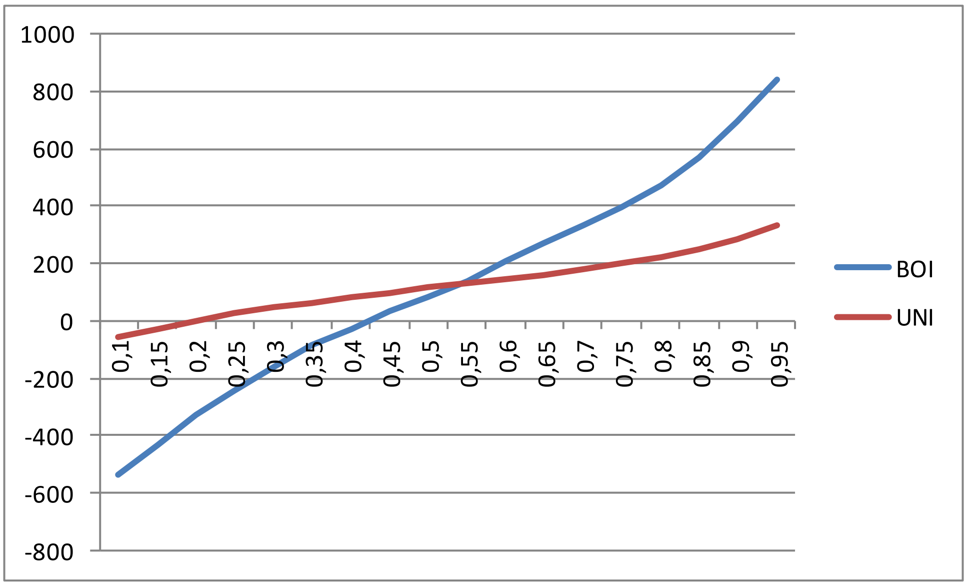
1% shock	Start	Finish
to BOI	100	105
to UNI	100	110

Where start and end are the CDS of the system in one case and another, to shock: a worsening of the BOI CDS increases the system CDS 5 and UNI CDS increased increases the CDS from the system by 10%, in line with the results obtained previously.

We assume that the BOI and UNI CDS that generated this increased systemic risk are subject to a few shocks, with the probability distribution of each shock corresponding to the historical probability distribution. From this distribution, you can obtain the probability that BOI suffers a shock such that their CDS contributes to the system more than the shock from UNI. We run a Monte Carlo simulation to see the possible shocks that may arise and their probability distribution.

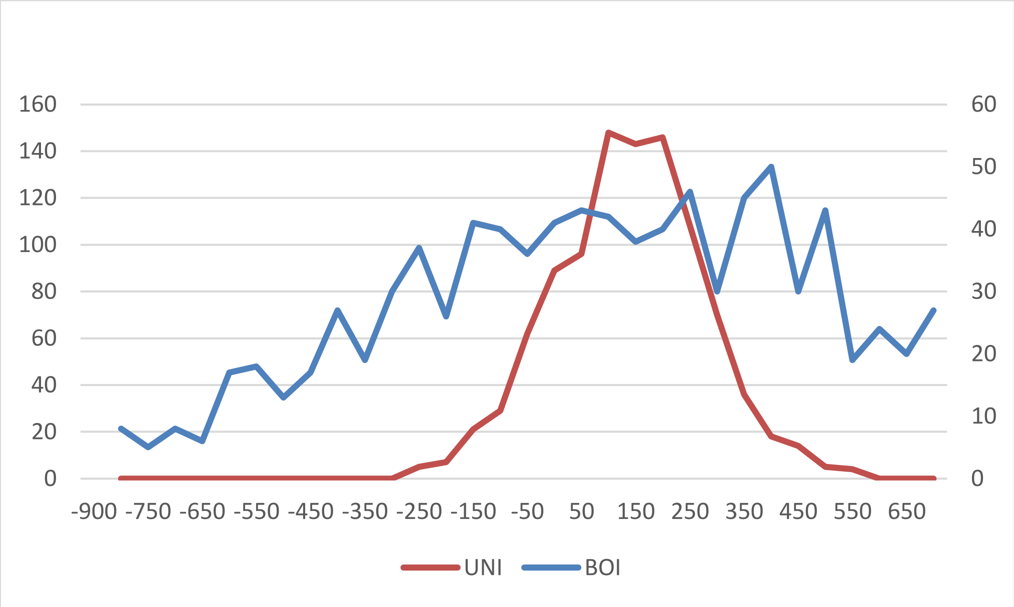
The graph below shows the systemic contribution of each of the banks, when subjected to shocks. The probability distribution of a given shock (shown here as a certain contribution to system risk) is shown in the chart. As can be seen in the graph, there is a 45% chance of that contribution to systemic risk of BOI is greater than the Unicredito. Where start and end are the CDS of the system in one case and another, to shock.

Chart 6. Systemic contribution of the CDS of Bank of Ireland and Unicredit (basis points, probability distribution)



This exercise shows that even banks that a priori have a very different systemic importance, can be subject to shocks such that, with a probability close to 50%, the non-systemic institution has more systemic impact than the a priori systemic institution. This is due to the large differences in the probability distribution of the shocks: in this case, BOI has a much large standard deviation, which results in a different frequency distribution of the shocks.

Chart 7: frequency distribution of 1000 draws of the BOI (right axis) and UNI CDS (draws taken using the historical average and standard deviation distribution of shocks)



The difficulty in determining ex ante the systemic institution, as shown in the examples above, can be taken as evidence that a non-systematic approach to SIFI may be warranted. Alternatively, the focus can be set on swift bank resolution rather than the ex-ante determination of which institutions are systemic. The difficulties of this approach have already been highlighted by Chen (2010), and Brownlees (2011).

3.3. The role of sovereign debt holdings in sovereign-bank connectedness

Finally, an aspect that our indicator can help us shed light on is the role of home bias. Much has been written about the retrenchment of capital in crisis times. Some have argued that this retrenchment, articulated through banks´ increased holdings of sovereign bonds, is at the root of the reinforcement of the bank-sovereign nexus, which is costly in that it creates an inefficient allocation of resources and that it leads to perverse incentives (Uhlig, 2014; Broner, 2013).

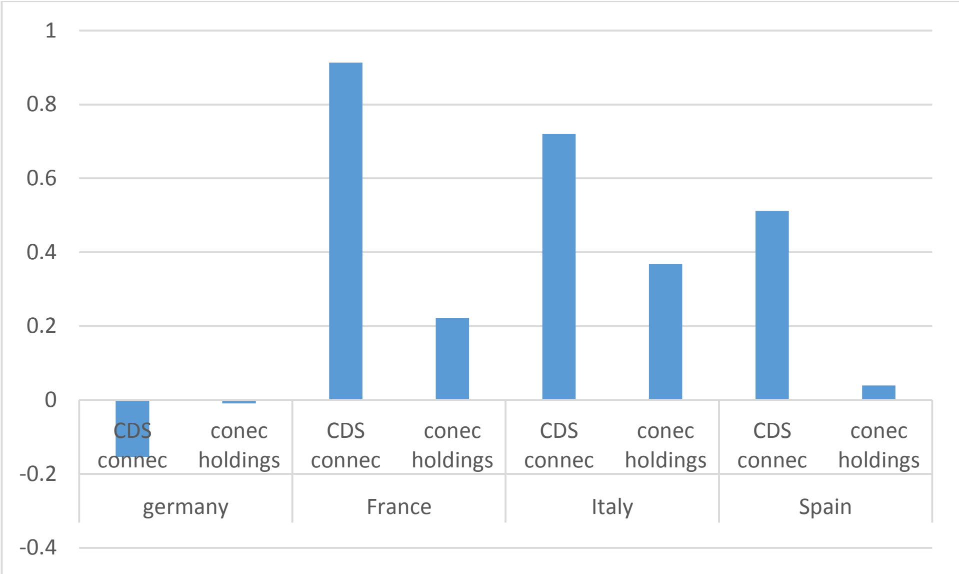
In order to test this, we compare our interconnectedness indicator, which can be considered an indicator of market perception of sovereign-bank connectedness, and actual holdings of government bonds.

As the chart below shows, there does not seem to be a clear relationship between the holdings of sovereign debt and the connectivity with its own Bank. As can be seen in the chart, the holdings of sovereign bonds seem to follow a rising path, while connectivity between Banks and sovereigns peaks around 2013. This suggests that there could be other driving forces of connectedness. For instance, the absence of a lender of last resort could reinforce the nexus. In this light, the ability of the ECB to quell stress in the 2013-2014 (and its lack of intervention in the early stages of the crisis), thus reducing the perceived probability of default, may be a more robust explanation.

Chart 8: domestic bond holdings (orange line, million EUR) and sovereign-bank connectivity (blue line, right axis, index)

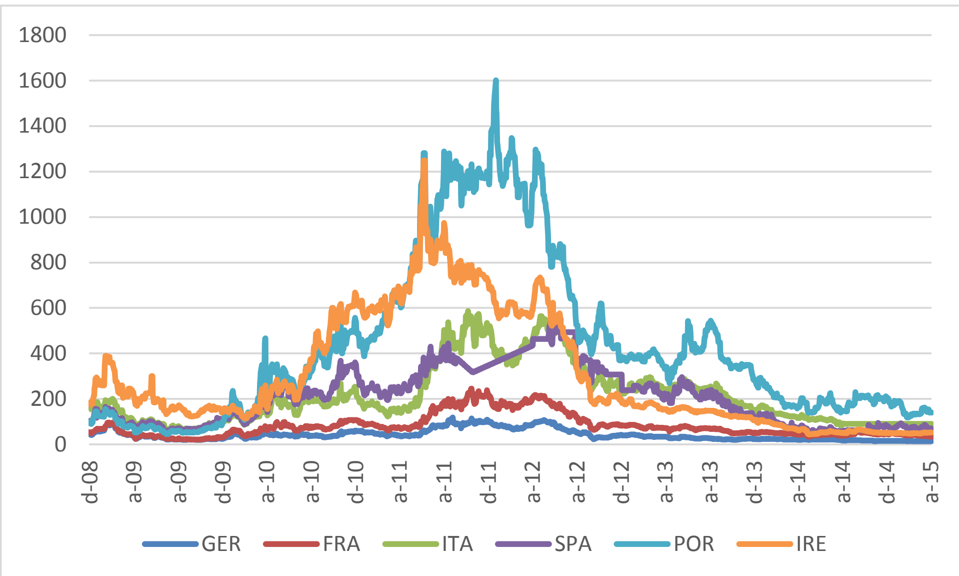
Indeed, the driver of connectedness could be volatility or the deterioration in sovereign solvency conditions: to the extent that Banks and sovereigns become healthier, the probability of a bank rescue that leads to the bankruptcy of both the bank and the sovereign becomes lower. As can be seen in the chart below, connectedness is more correlated with country stress indicators (in this case, the CDS), than with domestic bond holdings.

Chart 9: correlation coefficient, sovereign-bank connectivity with sovereign CDS level and domestic bond holdings



An alternative explanation may lie in the role played by the central bank: if markets perceive that there is a lender of last resort, this could justify lower connectedness between Banks and sovereigns, as the former do not depend on the latter to survive but rather on the liquidity provision by the central bank.

Chart 10: sovereign CDS, selected Eurozone countries (basis points)



4. Concluding remarks

The analysis above sheds light on interconnectedness across banks and sovereigns in the Eurozone. The results show the importance of the links both between banks and sovereigns and across sovereign in determining the developments in sovereign risk. The main takeaways are, first, the role played by the transmission of risk between core and periphery countries, and secondly, the changing importance of banks in relation to their own sovereign. It is important to note that even when controlling for bank CDS, the pattern between core and periphery remains similar to those of other studies (like Gomez Puig and Sosvilla).

Furthermore, the elaboration of a connectedness indicator shows, first, the difficulty involved in determining ex ante the systemic impact of banks. Second, it suggests that the link between banks and sovereigns in probably more related to stress in the sovereign than to other factors, like increased bank holdings of sovereign debt.

From a policy perspective, the main takeaways, are, therefore, that the characterization of the EMU sovereign debt crisis as a crisis of confidence in the Eurozone is appropriate, but this was solved by upgrading the role of the ECB in this context. Secondly, in a more pessimistic note, while our results show that bank stress can be quite significant in determining sovereign stress, they suggest that it is difficult to determine which banks are systemic, and as a result, require higher capital for these institutions, which in turn should minimise their negative impact on sovereign risk.

One way of dealing with this uncertainty is to deepen the current working of the EMU. By creating a true banking union, the nexus between a bank and its own sovereign should decline. Secondly, the difficulty in assessing systemicity calls for a quick, structured framework for bank resolution after a crisis. Assuring that resolution authorities have the resources and the mandate to tackle issues from wherever they might arise can be essential, given the difficulties in understanding the origins of systemic risk

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