Dynamic Connectedness between European Credit Default Swap Premia

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Abstract

This study examines the spillover dynamics of Credit Default Swap (CDS) premia between four major European countries (Germany, France, Italy, and Spain) from 2012 to 2022. A rolling-window Vector Autoregressive (VAR) model is used. Original CDS data from each country contains 716 monthly observations, with the first 147 lost in the burn-in process of the rolling-window VAR model. Generalized forecast error variance decompositions are used to compute various connectedness measures that are independent of the ordering of the model variables. Results indicate that countries experiencing economic instability are more prone to be transmitters of shocks, and that total and pairwise connectedness levels vary significantly over the sample period. The study then regresses connectedness measures against the EUROSTOXX 50 Volatility Index (VSTOXX), the European equivalent of the Chicago Board of Exchange Volatility Index (VIX), and finds that variations in connectedness among CDS premia are positively related to the Europe-wide level of uncertainty. Shock transmissions are intensified around major events that heighten investor concerns.

Keywords: comovement; European markets; financial instability; rolling-window Vector Autoregressive model; spillovers

1. Introduction

Through the last decade, Credit Default Swap (CDS) premia have been increasingly used to assess the financial health of corporations, banks and sovereign states. During financial turmoil periods, increasing levels of CDS premia have received much attention from academics and practitioners, as such periods are marked by heightened levels of investors' fear. It is now well known that return volatilities and correlations increase during turbulent periods (Ang & Bekaert, 2002). Ceylan (2021) shows that a positive shock to the Chicago Board of Exchange Volatility Index (VIX), a measure for the market-wide uncertainty and fear, leads to increases in correlations among major stock markets.

Since the 2008 global financial crisis, European countries have gone through several instabilities including the Eurozone sovereign debt crisis, Brexit and the Covid-19 pandemic. The widening of the European Sovereign CDS spreads around these events may be linked to country- specific factors or to contagion dynamics. Therefore, understanding the connectedness among sovereign CDS premia has become an important issue for policymakers and investors.

This study examines the spillover dynamics of the CDS premia of four major European countries (Germany, France, Italy, and Spain) through a rolling-window Vector Autoregressive (VAR) model. Various connectedness measures are computed based on the generalized forecast error variance decompositions following the methodology introduced by Diebold and Yılmaz (2009, 2012, 2014). Results indicate significant variations in total and pairwise connectedness levels through the sample period. These connectedness measures are then regressed against the EUROSTOXX 50 Volatility Index (VSTOXX), the European reciprocal of the VIX. It is found that variations in the connectedness among the CDS premia are positively related to the Europe-wide level of uncertainty.

The remainder of this study is organized as follows: Section 2 describes the data. Section 3 presents the empirical methodology. Results are provided and discussed in Section 4. Finally, Section 5 concludes the study.

2. Data

For the empirical study, weekly CDS premia data for Germany, France, Italy and Spain are collected. The data period spans from July 2008 to April 2022. Natural logarithm of the data is considered in the study to obtain smoother variations in the model variables. The maturity of the contract is chosen as 5 years as this is the most liquid and representative maturity category for CDS contracts. By the same token, data does not include the period before July 2008, as the European sovereign CDS market was not liquid enough at the time.

In addition, VSTOXX index data are also collected for the linear regression analysis. The VSTOXX index is constructed based on the near-term EUROSTOXX 50 options that are traded on the Eurex exchange. It measures the 30-day implied volatility, and used as a proxy for the uncertainty and fear across European markets.

The Table 1 provides the descriptive statistics for the CDS and VSTOXX data. All the data are taken in natural logarithmic form. CDS premia for Italy and Spain have significantly higher values in the sample period while Germany has the lowest default risk. All the series, including the VSTOXX are right skewed. The last column reports the excess kurtosis values. It may be seen that only Italian CDS premia and VSTOXX series have fat tails.

Table 1: Descriptive statistics for the CDS and VSTOXX data.

	Minimum	**Maximum**	**Mean**	**Median**	**Std. Dev.**	**Skewness**	**Kurtosis**
GERMANY	1.909	4.768	3.048	2.953	0.682	0.611	-0.517
FRANCE	2.398	5.502	3.699	3.619	0.679	0.612	-0.270
ITALY	3.657	6.334	5.023	4.956	0.503	0.414	0.152
SPAIN	3.379	6.390	4.608	4.458	0.758	0.494	-0.664
VSTOXX	2.370	4.308	3.005	2.981	0.324	0.666	0.546

The first 147 observations of the CDS data are lost in burn-in process while constructing the time-varying connectedness measures through rolling-window VAR model. Thus, only 569 observations of VSTOXX series are employed in the regression while the original CDS series had 716 observations.

CDS premia and VSTOXX series are depicted in the Figure 1 and Figure 2 respectively. Simultaneous jumps may clearly be observed in all series during the Eurozone sovereign debt crisis and at the Covid-19 outbreak. There are also idiosyncratic jumps in CDS premia series like the one for France at the beginning of 2017 that is marked by heightened concerns about an unpredictable presidential election.

Figure 1: CDS premia (Logged values).

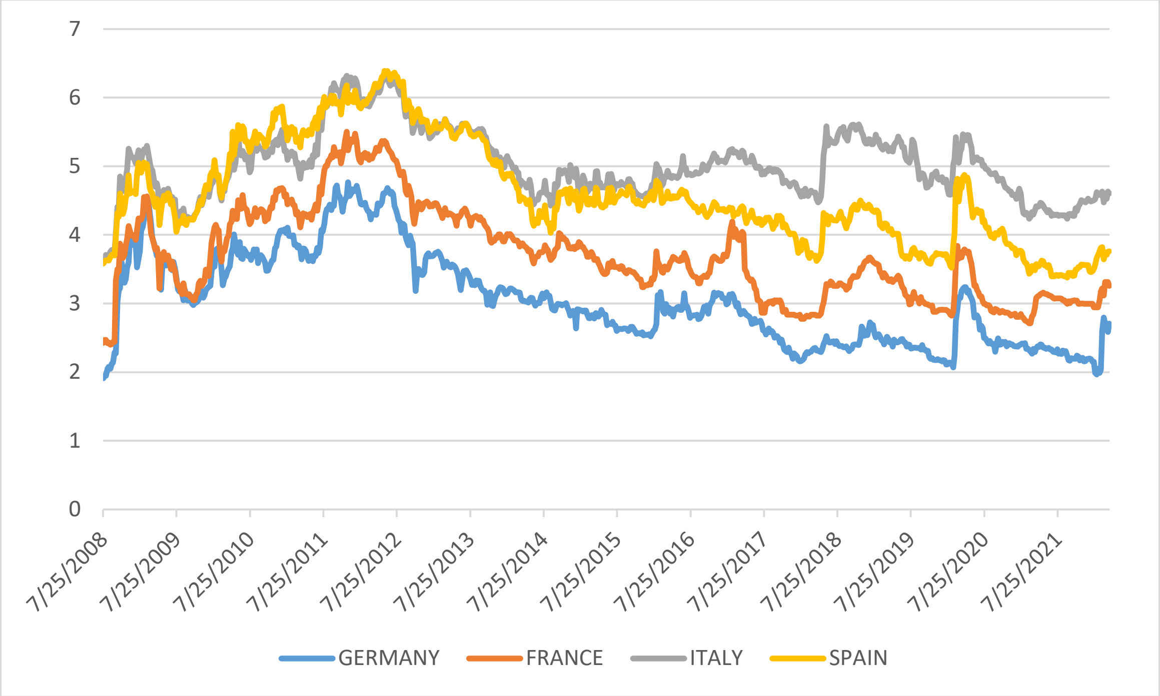
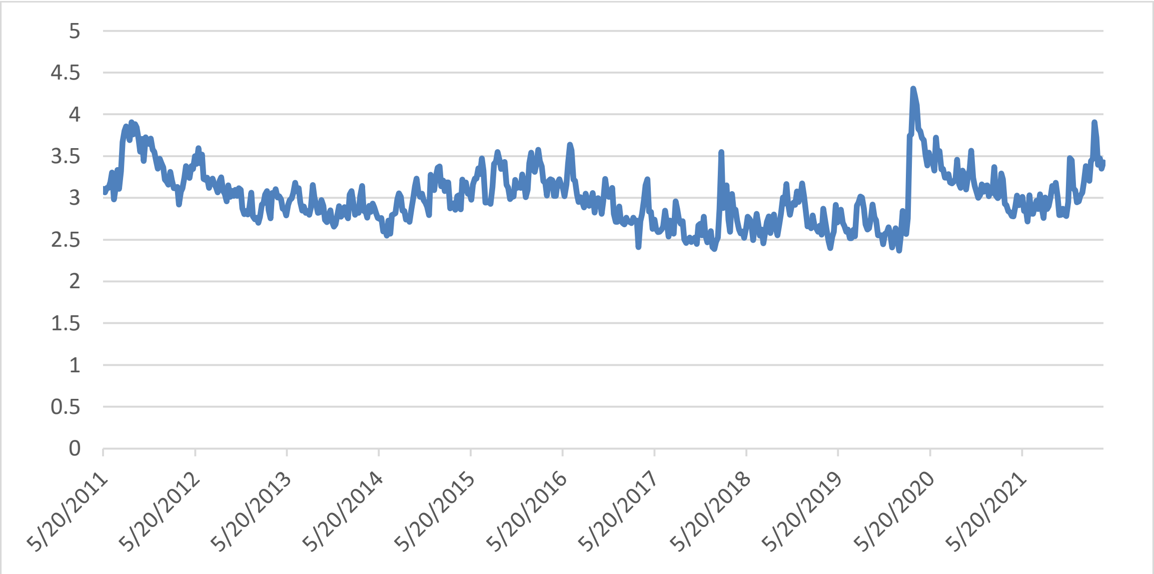


Figure 2: The VSTOXX index (Logged values).



The variables used in the VAR model are tested for stationarity. Augmented Dickey-Fuller (Dickey and Fuller, 1979) and DF-GLS (Elliott et al. 1996) tests are employed. Test statistic values are reported in the Table 2. Results show that the null hypothesis of unit root is rejected at the %1 significance level for each of the variables.

Table 2: Stationarity test results
The critical values for the ADF test are -2.86 and -3.43 for 5% and 1% significance levels respectively.
The critical values for the DF-GLS test are -1.94 and -2.57 for 5% and 1% significance levels respectively.
** and ** denote significance at the 5% and 1%, respectively.*

	GERMANY	FRANCE	ITALY	SPAIN
ADF	-17.8394**	-17.4942**	-19.533**	-19.1853**
DF-GLS	-9.0281**	-8.0007**	-11.2419**	-10.209**

3. Empirical Methodology

The interrelations between the CDS premia are studied through a vector autoregressive (VAR) model formulated as follows:

$$Y_t = \sum_{i=1}^{p} \theta_i Y_{t-i} + \varepsilon_t$$

where Y_t is a *(4x1)* vector of logged CDS premia, p is the VAR order, θ_i are the *(4x4)* coefficient matrices and ε_t is a vector of innovations. Based on the Bayesian information criterion p is set to 2. Akaike's information criterion and Hannan-Quinn information values also suggest the same lag order for the VAR model as shown in the Table 3.

Table 3: Lag order selection for the VAR model

Lag order	AIC	BIC	HQ
0	-8.9573	-8.9573	-8.9573
1	-21.3266	-21.2244	-21.2872
2	**-21.9165**	**-21.7120**	**-21.8375**
3	-21.9134	-21.6068	-21.7950
4	-21.8987	-21.4899	-21.7409
5	-21.8820	-21.3710	-21.6846
6	-21.8620	-21.2488	-21.6252
7	-21.8272	-21.1118	-21.5509
8	-21.7961	-20.9785	-21.4804

Provided that the covariance stationarity condition is satisfied, this VAR model, may be rewritten as an infinite moving average representation:

$$Y_t = \sum_{i=0}^{\infty} A_i \, \varepsilon_{t-i}$$

where the (4x4) coefficient matrices, $A_i$may be obtained through the following recursive relation:

$$A_i = \theta_1 A_{i-1} + \theta_2 A_{i-2} + \cdots \theta_p A_{i-p}$$

with A_0 an identity matrix.

Generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD) are generated based on these moving average coefficients. An impulse response describes the time profile of the effect of a hypothetical shock in variable *j* (δ_j) on the K-step ahead values of all variables in the VAR system (Koop et al., 1996).

$$GIRF(K, \delta_j, I_{t-1}) = E\left(Y_{t+K} \middle| \varepsilon_{j,t} = \delta_j, I_{t-1}\right) - E(Y_{t+K} | I_{t-1})$$

where I_{t-1} is the information set at time t.

Assuming that ε_t is Gaussian, and setting $\delta_j = \sigma_{jj}^{\frac{1}{2}}$, the standard deviation of ε_{jt}, it follows that

$$E\left(\varepsilon_t \middle| \varepsilon_{j,t} = \sigma_{jj}^{\frac{1}{2}} = \boldsymbol{\Sigma e_j} \sigma_{jj}^{\frac{-1}{2}}\right)$$

where $\boldsymbol{\Sigma}$ is the positive definite *(4x4)* covariance matrix, and $\boldsymbol{e_j}$ is the *(4x1)* selection vector with unity at position *j*, and zeros otherwise. The scaled GIRF ($\Psi_j^g(K)$) which measures the effect of one standard deviation shock to the variable *j* on the VAR system may thus be computed as follows:

$$\left(\Psi_j^g(K)\right) = \sigma_{jj}^{\frac{-1}{2}} A_K \boldsymbol{\Sigma e_j}$$

The GIRFs are employed to derive generalized forecast error variance decompositions (GFEVD) that capture the share of K-step ahead forecast error variance of variable *i* due to a shock in variable *j*.

$$(\Phi_{ji}^{g}(K)) = \frac{\sigma_{ii}^{-1}\sum_{l=0}^{K-1}(\boldsymbol{e_i}'A_l\boldsymbol{\Sigma e_j})\text{^}\mathbf{2}}{\sum_{l=0}^{K-1}(\boldsymbol{e_i}'A_l'\boldsymbol{\Sigma e_i})}$$

In the above formulation variance decomposition shares do not sum up to one. A more useful version of GFEVD can be obtained through normalizing the GFEVD as follows:

$$(\Phi_{ji}^{gn}(K)) = \frac{\sum_{l=0}^{K-1}\Psi_{ji}^{2,g}(K)}{\sum_{i=1}^{m}\sum_{l=0}^{K-1}\Psi_{ji}^{2,g}(K)}$$

so as to have $\sum_{i=1}^{m}\Phi_{ji}^{gn}(K) = 1$ and $\sum_{i,j=1}^{m}\Phi_{ji}^{gn}(K) = m$.

Based on the GFEVD, several measures may be computed to evaluate the connectedness level between the model variables. Total Connectedness Index (TCI) measures the weight of the volatility spillovers across all the variables in the total forecast error variance.

$$TCI(K) = \frac{\sum_{\substack{i,j=1 \\ j\neq i}}^{m}\Phi_{ji}^{gn}(K)}{\sum_{i,j=1}^{m}\Phi_{ji}^{gn}(K)} \text{ x } 100 = \frac{\sum_{\substack{i,j=1 \\ j\neq i}}^{m}\Phi_{ji}^{gn}(K)}{m} \text{ x } 100$$

GIRF and GFEVD measures allow one to assess directional connectedness as they are invariant to the ordering of the model variables contrarily to their orthogonalized versions that are generated by using Cholesky decomposition (Pesaran & Shin (1998)). As a first directional connectedness measure, the total spillover that is from variable j to all other model variables is calculated as follows:

$$C_{j\rightarrow i}(K) = \sum_{i=1,j\neq i}^{m}\Phi_{ij}^{gn}(K)$$

In a similar fashion, the total directional connectedness from others to variable j is defined as

$$C_{j\leftarrow i}(K) = \sum_{i=1,j\neq i}^{m}\Phi_{ji}^{gn}(K)$$

The net total directional connectedness is calculated by subtracting the total directional connectedness FROM others from the total directional connectedness TO others.

$$C_j(K) = C_{j\rightarrow i}(K) - C_{j\leftarrow i}(K)$$

The interpretation of the net total directional connectedness measure is straightforward. The variable j would be considered net transmitter if $C_j > 0$, and net receiver if $C_j < 0$. A net transmitter (receiver) influences the system more (less) than being influenced by it.

The net total directional connectedness may be further decomposed in order to analyze the bidirectional relationships. The net pairwise directional connectedness (NPDC) between the variables *j* and *i* measures the net volatility spillover from variable *j* to *i*.

$$NPDC_{ji}(K) = \Phi_{ij}^{gn}(K) - \Phi_{ji}^{gn}(K)$$

In the same manner, the total connectedness index may be decomposed to obtain the pairwise connectedness index that measures the degree of bilateral interconnectedness between variables *i* and *j*.

$$C_{ij}(K) = 2 * \frac{\Phi_{ij}^{gn}(K) + \Phi_{ji}^{gn}(K)}{\Phi_{ii}^{gn}(K) + \Phi_{ij}^{gn}(K) + \Phi_{jj}^{gn}(K) + \Phi_{ji}^{gn}(K)}$$

These connectedness measures are first computed for the full sample to obtain average connectedness levels for the sample period. However, it is now widely known that the magnitude of spillovers between markets varies over time (See for example, Ceylan (2017), Bostancı and Yılmaz (2020), Antonakakis et al. (2020)). To obtain the time-varying connectedness measures, a rolling-window VAR model is employed by setting the window size to 150. The forecast horizon for which the GFEVDs are computed is set to 12 as all the variance shares tend to be stabilized at that horizon. The estimated time-varying total connectedness index and each of the pairwise connectedness indexes are then regressed against the VSTOXX levels (in natural log terms) as follows:

$$Index_t = \alpha + \beta * VSTOXX_t + \varepsilon_t$$

4. Empirical Results

The average connectedness measures that are computed based on the full-sample VAR model are reported in the Table 4. The variables of which the variance is decomposed are given in the rows. The columns provide the impulse variables. For instance, total variance spillovers from Germany TO all other variables in the system is very low (0.34%), while 73.98% of the variance in German CDS is explained by the variance spillovers FROM

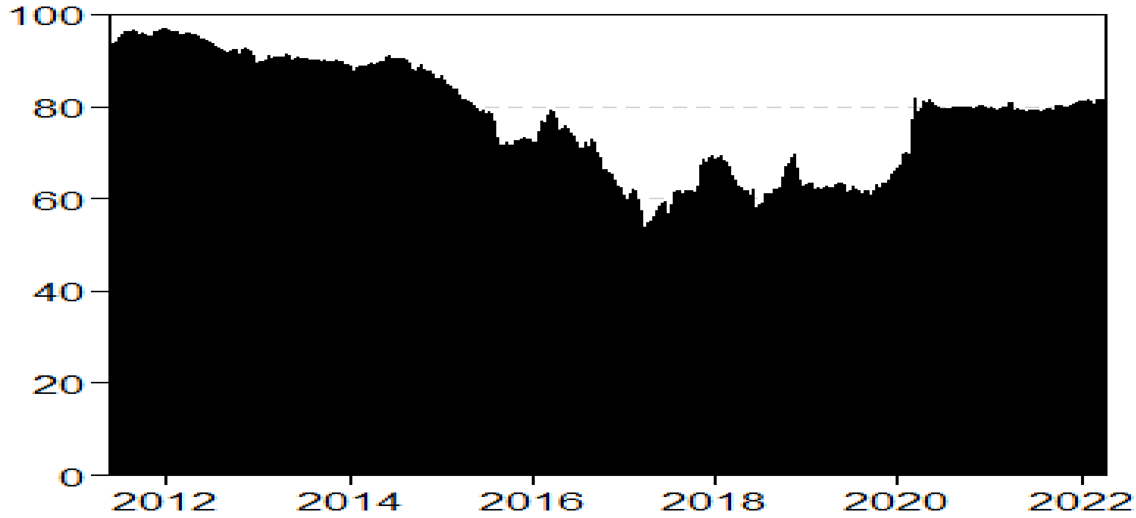
France (33.73%), Italy (17.44%) and Spain (22.81%). Thus, it can easily be concluded that Germany is a net receiver of shocks as it receives much more spillovers than it transmits. All the other variables are net transmitters, with Spain being the most important transmitter of shocks.

Table 4: Average connectedness measures based on the full-sample VAR model (in percentages).

	GERMANY	FRANCE	ITALY	SPAIN	FROM
GERMANY	26.02	33.73	17.44	22.81	73.98
FRANCE	0.18	48.12	22.39	29.31	51.88
ITALY	0.14	20.12	46.67	33.07	53.33
SPAIN	0.02	23.67	29.20	47.12	52.88
TO	0.34	77.51	69.03	85.19	232.07
NET	-73.65	25.63	15.70	32.31	

A more detailed view is provided through time-varying connectedness measures. Figure 3 depicts the total connectedness index levels during the sample period. It can be seen that the system had been very highly connected following the Eurozone sovereign debt crisis. Connectedness levels tend to decrease gradually with some short-lived pikes until the Covid-19 outbreak where the total connectedness index jumped to a high and persistent level again.

Figure 3: Total connectedness index.



The Figure 4 shows the strength of spillovers from the depicted country TO all others while the Figure 5 presents the total spillovers FROM all other countries to the depicted country. The resulting net spillovers from each country are given in the Figure 6. Here also, conforming to the average connectedness measures that are computed based on the full sample VAR, Germany is found to be the only net receiver of shocks. Being the most vulnerable countries during the Eurozone sovereign debt crisis, Italy and Spain had been the most important sources of instability for the system at the beginning of the sample period. France followed these countries with fast increasing spillover transmission levels by the end of 2012.

Figure 4: Total spillovers from the depicted country TO all others in the system.

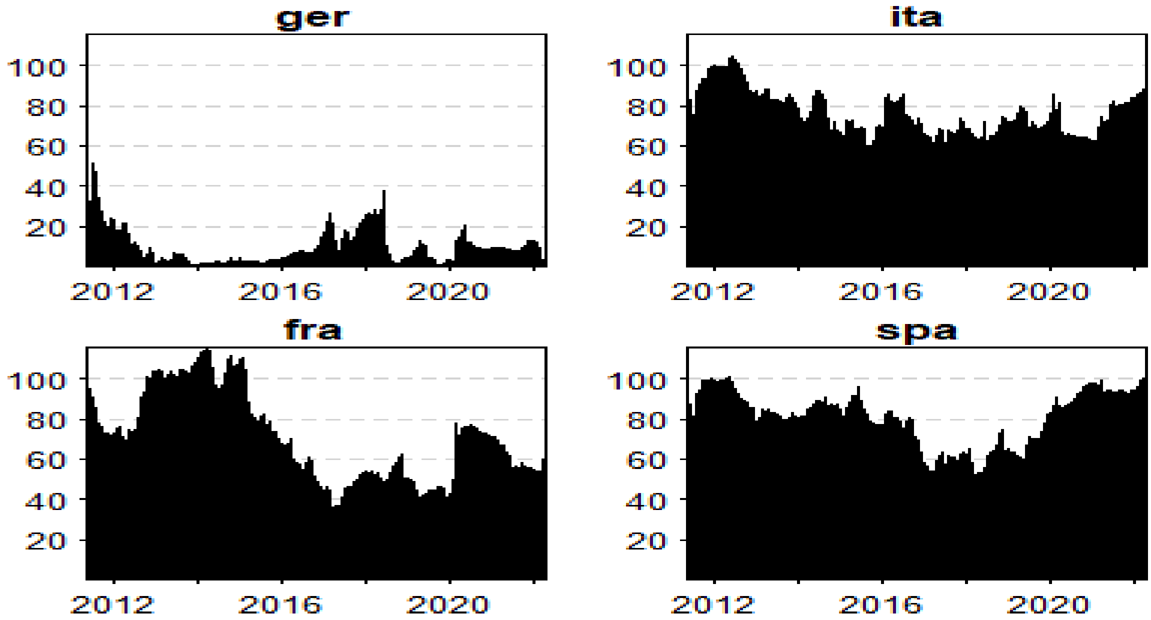


Figure 5: Total spillovers FROM all the other countries to the depicted country

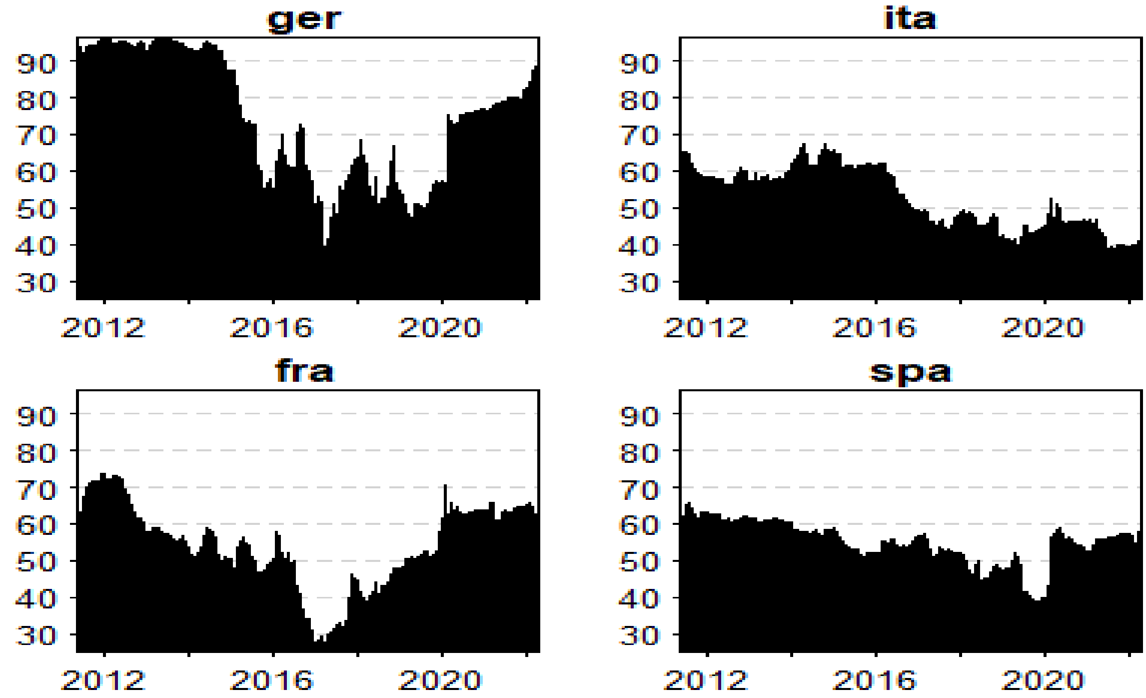
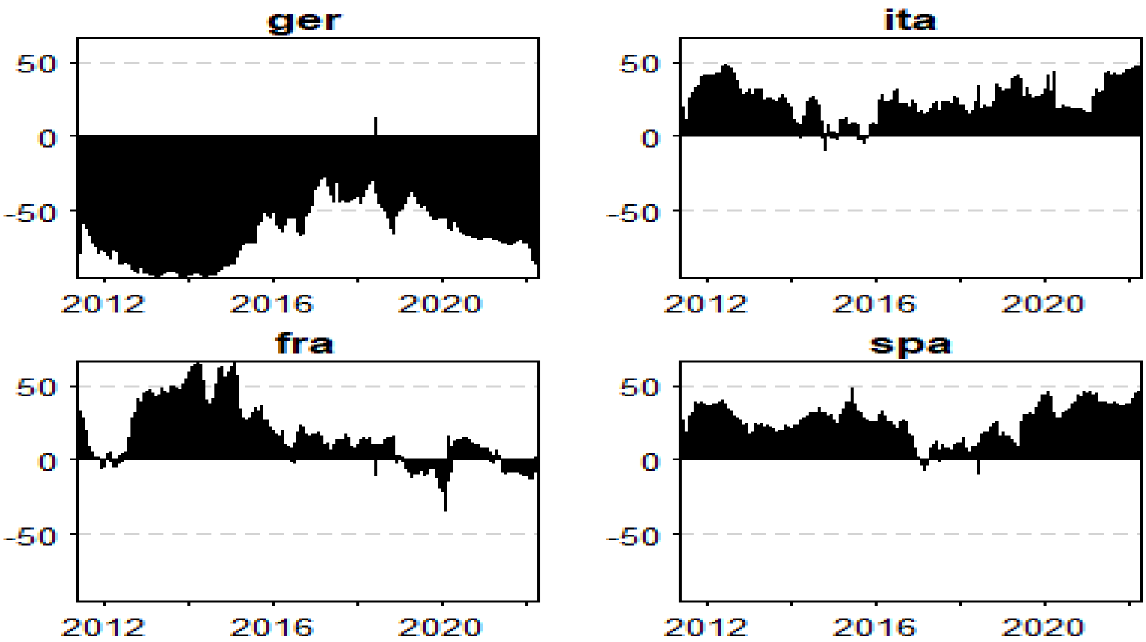
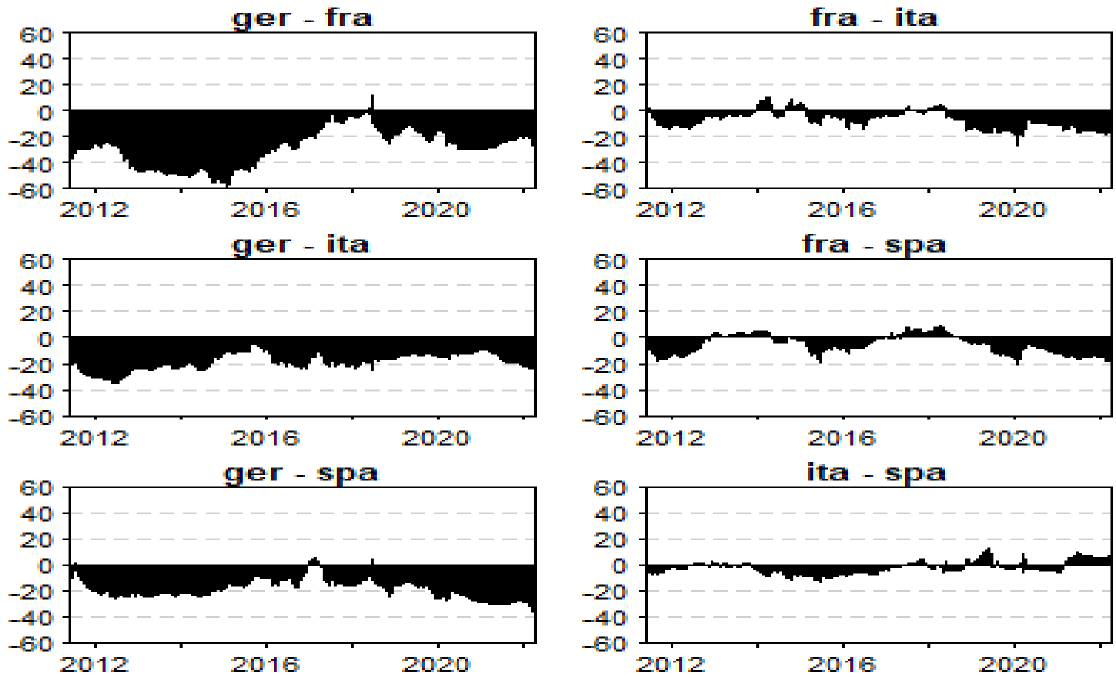


Figure 6: Net spillovers from each country.



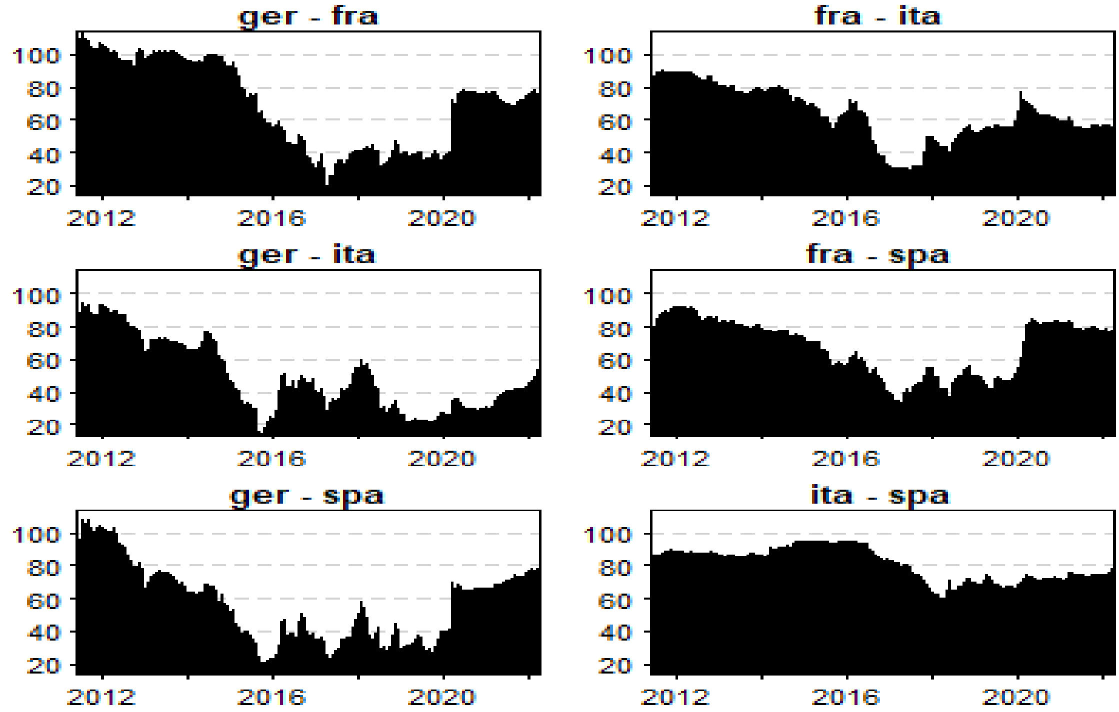
Net pairwise directional connectedness measures provide a closer look at the net spillovers. The Figure 7 depicts the net spillovers at the bilateral level. The left panel of the figure shows that the net spillover received from each of the other countries vary through time, and that France has a significantly higher influence on Germany especially during the first half of the sample period. France becomes a net receiver against Italy and Spain during most of the period. The relation between Italy and Spain vary through time.

Figure 7: Net pairwise directional connectedness.



Pairwise connectedness index series are presented in the Figure 8. Not surprisingly, these bilateral versions of the net connectedness index increase at the beginning, decrease through the middle of the period, and increase again at the end. Yet, it is worth to note for instance that the Brexit referendum held in mid-2016 gave rise to a remarkable increase in connectedness levels between Germany and Italy, Germany and Spain, France and Italy, and to a lesser extent, between France and Spain. The connectedness levels between Italy and Spain had been relatively more stable as these economies were both similarly vulnerable to such events. Another significant point is that the French presidential elections that led to a jump in CDS levels in France caused only a slight increase in spillovers from that country. On the other hand, pairwise connectedness indexes between France and other countries hit rock bottom levels around the elections, making one think that this had been an important local source of uncertainty for France.

Figure 8: Pairwise connectedness indexes.



Lastly, OLS regression models are set for the total connected index and pairwise connectedness indexes taking the VSTOXX index as the independent variable. Regression results are reported in the Table 5. Although the intercepts for two regression equations are not statistically significant, one can conclude that the total and pairwise indexes are all positively related to the VSTOXX index. CDS markets become more connected in the periods of high uncertainty.

Table 5: OLS regression results.
Estimated models are specified as follows: $Index_t = \alpha + \beta * VSTOXX_t + \varepsilon_t$
** and ** denote significance at the 5% and 1%, respectively.*

		Pairwise Connectedness Indexes					
	TCI	GER-FRA	GER-ITA	GER-SPA	FRA-ITA	FRA-SPA	ITA-SPA
A	24.27**	-38.20**	-0.02	-41.16**	-0.20	-14.20*	47.82**
B	17.80**	35.48**	15.96**	32.22**	20.91**	26.97**	10.89**

5. Conclusion

This study examines the connectedness of the CDS premia of Germany, France, Italy, and Spain through a rolling-window VAR model for the period 2012-2022. A variety of connectedness measures are computed based on the generalized forecast error variance decompositions that are independent of the ordering of the model variables.

In the first step, the average connectedness measures are computed based on the full-sample VAR model. Germany, the most stable economy in Europe is revealed to be the only net receiver of shocks during the whole period. All the other countries are net transmitters, with Spain being the most important transmitter of shocks. These preliminary results suggest that the countries that go through periods of economic instability are more prone to be transmitters of shocks.

The second step of the analysis provides a more detailed view through time-varying connectedness measures. Results show significant variations in total and pairwise connectedness levels through the sample period. Connectedness among the sovereign CDS premia tend to increase during the periods of high uncertainty, such as the Eurozone debt crisis and the Covid-19 pandemic. The effect of Brexit on the connectedness levels is of a relatively limited extent while the French presidential elections are marked as an important but local source of uncertainty. These connectedness measures are then regressed against the VSTOXX index, and it is found that variations in connectedness among the CDS premia are positively related to the Europe-wide uncertainty level as measured by the VSTOXX index. Shock transmissions are intensified around major events that heighten investors’ concerns.

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