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ORIGINAL ARTICLE

Systemic risk spillovers in sovereign credit default swaps in Europe: a spatial approach

Mehdi Mili[1]

Abstract This paper explores systemic risk spillovers between sovereign credit default swaps (CDS) returns in Europe during the period 2006–2016. We model spillovers using a spatial regression approach that allows us to analyze the effects of the movements of CDS returns in terms of spillovers and externalities. The spatial model decomposes the CDS returns into a systemic, systematic and idiosyncratic risk premium. We perform also stress testing to capture the impact of extreme events on CDS portfolios. Our results reveal significant impact of systemic risk spillover on sovereign CDS in Europe. Using Monte Carlo simulation, we show that spillovers between CDS markets increase the risk of CDS portfolios and the risk increases for high spatial interconnectivity between sovereign markets.

Keywords Systemic risk · Financial contagion · Spatial regression · CDS returns

JEL Classification C21 · G12 · G18 · G21

Introduction

Sovereign CDS are ambivalent financial products. On the one hand, they are designed as hedging instruments and credit risk management. On the other hand, they were criticized for engendering financial instability and causing

systemic risk. This risk was particularly high among European countries. As regards spillover among Eurozone sovereign CDS, they are at least indirectly linked by the joint monetary policy transmission mechanism, the Eurosystem's collateral framework and by a shared default risk of Eurozone member countries.

The systemic effect of sovereign CDS markets is the result of their direct role in the reflection of credit market information. These spreads are widely viewed by market participants and analysts as a reflection of the market consensus on the solvency of the government in question. The implicit default probabilities derived directly from CDS spreads are also used for the valuation of credit derivatives. For example, in the context of the sovereign crisis in the euro area, CDS spreads were used as leading indicators of the potential default of banking institutions, affecting the valuation of their sovereign's obligations and feeding negative interactions between banking risk and sovereign risk.

Most previous researches have focused on Spillovers of corporate Credit Default Swap in Europe (Annaert et al. 2006; Alexander and Kaeck 2008; Castagnetti and Rossi 2008; Ericsson et al. 2009; Stulz 2010; Heise and Kühn 2012). Only few studies have attempted to examine the extent of systemic contingents across sovereign CDS markets in Europe. Augustin et al. (2014) examine the impact of the announcement of the first Greek bailout on April 11, 2010, on the spillover effects from sovereign to corporate credit risk in Europe. They show that a 10% increase in sovereign credit risk raises corporate credit risk on average by 1.1% after the bailout. These effects are more pronounced in countries that belong to the Eurozone and that are more financially distressed. Bank dependence, public ownership and the sovereign ceiling are channels that enhance the sovereign to corporate risk transfer.

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To attribute the movements in sovereign CDS spreads to the various contributing factors, Heinz and Sun (2014) use a generalized variance decomposition method on daily data to detect cross-country influences in the European CDS market, and a dynamic panel regression framework on monthly data to measure the impact of macroeconomic fundamentals on CDS spreads. They find that while spreads in Europe are primarily driven by changes in the global investor sentiment, country-specific macroeconomic fundamentals and CDS market liquidity conditions play an important role as well. In this paper, we contribute to this literature by studying systemic risk and spillover between sovereign CDS returns in Europe using a consistent spatial approach.

To model systemic risk in sovereign CDS markets, we use a spatial regression model that jointly includes local and global perspectives of financial markets. This approach allows as identifying systematically important countries in Europe. Specifically, our approach shows how an idiosyncratic crisis in one country is transmitted across the European credit market and impacts each European country. Our results show that CDS crisis in one country does not affect other countries in the same extent and the spillover effect depends mainly on the interdependency of sovereign credit markets.

We test systemic risk on sovereign CDS market in Europe using CDS returns. Using a spatial regression approach, we decompose CDS returns into systemic, systematic and idiosyncratic risk component. The idiosyncratic and systematic risks have been largely addressed by modern financial theories. Our contribution lies in the modeling of the systemic component of risk. We develop a model that links the credit risk of each country to the credit risk of other countries. To test the spillover effect across countries, a specific parameter that measures the degree of systemic risk should be estimated. Systemic spillover is measured by the correlations between CDS returns. These correlations reflect the economic dependencies between countries. A strong correlation between CDS returns implies high contagion risk and that all markets are highly sensitive to the same crisis.

The remainder of the paper is organized as follows: Second section presents the relevant literature on sovereign credit in Europe and discusses our main contributions. Third section presents our methodology. Fourth section analyzes the data used. Fifth section discusses main results of the spatial regressions. Sixth section presents Monte Carlo simulation of VaR analysis and stress testing results. Final section concludes.

A review of European sovereign CDS markets

Sovereign CDS are products originally created to protect investors against the failure of government bonds. It is comparable to an over-the-counter insurance in which the CDS buyer pays a periodic premium to guarantee the payment of the nominal value of the bond in case of government default. The premium is set according to the risk of default and the expected recovery rate in case of default of the sovereign issuer. Since the last financial crisis, sovereign CDSs have become widely used as indicators to assess the quality of credit issued by governments since they provide direct measures of default probabilities perceived by market participants.

Fontana and Scheicher (2010) suggest that like most CDS contracts, sovereign CDS are typically used as trading instruments rather than effective insurance instruments. Longstaff et al. (2011) argue that the substantial increase in sovereign debt in Europe has led to a financial contagion across sovereign CDS markets. After the Greece sovereign debt crisis, solvency of major European economies as Spain and Italy seriously worried international investors.

Sovereign CDS spreads in the Euro zone countries were marked by an increase over the period 2007–2009. This increase can be explained by the rapid increase in public sector debt due to the increase in social benefits and the importance of financial state commitments to support banks. The deterioration of public accounts resulted in an increase in sovereign risk premiums. Investors rationally should bought protection, which has led consequently to an increase in CDS premiums.

In light of rapid deterioration of the budgetary situation in Greece, financial markets and rating agencies turned their attention to the Greek fiscal imbalances. The premiums on Greek CDS were then increased rapidly to more than 400 basis points in early 2010, reflecting a significant increase in market expectations about a default or restructuring of Greek debt. The deterioration of the financial condition of Greece initiated a contagion effect across European economies and the crisis started to expand to other European countries. The main concern was the increase in systemic risk that can lead investors to lose confidence in other European countries having similar debt problems, such as Portugal and Ireland, and possibly even in larger countries like Italy or Spain. Furthermore, the sovereign debt crisis has been amplified by the degradation of most sovereign debt by international rating agencies. This destabilized the European interbank market because these debts were no longer accepted as collateral by the European Central Bank. In this context, sovereign CDSs drew particular attention because they estimate sovereign default credit probabilities irrespective of whether the

probabilities perceived by the market correspond to the evaluation carried out by official authorities. Several researchers in the literature (Alexander and Kaeck 2008; Castagnetti and Rossi 2008) have shown that the evolution of sovereign CDS in different European countries depends on a number of common external and internal factors. Others (Sandleris 2014; Xu et al. 2016) show the importance of systemic risk in explaining the joint movement of sovereign CDS in Europe. Reducing and controlling systemic risk has become an important issue. This paper is the first in-depth analysis of systemic risk spillover on sovereign CDS markets in Europe using spatial econometric techniques.

Methodology

Before describing the spatial econometrical approach to test sovereign CDS spillovers in Europe, we show how we calculate CDS returns.

Pricing CDS returns

Most previous studies focused on modeling CDS spreads and were conducted on the European market (Annaert et al. 2006; Alexander and Kaeck 2008; Castagnetti and Rossi 2008) and the US market (Collin-Dufresne et al. 2001; Ericsson et al. 2009). Most researchers have taken a keen interest in the determinants of the level of credit spreads (Kiesel et al. 2001; Blanco et al. 2005; Byström 2006; Karlson and Willebrand 2008).

Ericsson, Jacobs and Oviedo (2009) suggest that the use of CDS spreads in credit risk modeling excludes any misspecification problem from risk-free yield curve model. Blanco, Brennan and Marsh (2005) found that CDS spread reflect changes in credit risk more accurately than bond spreads. As any forward contracts, CDSs are designed so that their initial values are zero and there is no cash payment at the initiation of the contract which makes them easier to enter compared to bonds.

In this paper, we model CDS returns instead of modeling CDS spreads. The main difficulty in constructing CDS returns is that there are no time-series data on actual transaction prices for a specific default swap contract. Modeling CDS returns need valuing CDS contract first. Only few researchers conducted their works on CDS returns (Berndt and Obreja 2010).

Two main approaches are used in the literature to modeling credit risk. The first, called structural models approach, was initiated by Merton (1974) and is based on modeling the evolution of the company's balance sheet. The default occurs if the issuer of the debt is unable to honor its obligations and risky zero-coupons are calls on the value of the company issuing the debt. The second is called the reduced-form models. Unlike structural models, the default is considered as a random event governed by a stochastic process called hazard rate. This approach is used by Jarrow and Turnbull (1995), Jarrow et al. (1997) and Duffie and Singleton (1997) among others.

Our study refers to the second approach. We use the O'Kane and Turnbull (2003) market model to price CDS contracts. The CDS premium is a function of the credit risk of the reference entity. It is therefore perceived as an informational indicator of its solvency. When a market participant has protection and wants to estimate its present value, it must calculate the mark-to-market of the contract.

The CDS premium is the annually amount paid to the seller for providing protections against default risk. It is calculated in basis point of the notional amount and depends on two factors: the probability of default of the reference entity (PD) and the recovery rate (RR) (Amadei et al. 2011):

$$\text{CDS premium} = \text{DP} \times (1 - \text{RR}) \tag{1}$$

i.e., if the probability of default of the reference asset is 65% and the expected recovery rate is 70%, the premium will be: $0.65 * (1{-}0.70) = 195$ basis points (1.95% to pay on the notional). The risk of default increases with the probability of default. The deterioration in the underlying asset solvency increases the value of the premium. The recovery rate is the percentage of the notional expected to recover after the default. The premium will be higher if the RR is low because the loss given default (1-RR) will be higher (Matherat et al. 2012).

The price or mark-to-market (MtM) value of an existing CDS contract is computed using the following formula:

$$\begin{aligned}\text{CDS}_{\text{MTM}}(t_V, t_N) = &\pm [S(t_V, t_N) - S(t_0, t_N)] \\ &\times \text{RPV01}(t_V, t_N)\end{aligned} \tag{2}$$

The present value of a contract at time t_v with maturity t_N is the premium S observed at time t_V with maturity t_N minus the premium S negotiated at time t_0 with maturity t_N. The RPV01 is the risky present value at time t_V of one basis point that mature in t_N. To calculate the RPV01, it must be supported by a model that estimates the probability that the underlying will not default to each premium paid through arbitrations-free survival probabilities.

The model must also be adjustable to the term structure of the CDS premium (O'Kane and Turnbull 2003). There are two types of models for modeling credit risk: structural models and models in reduced form. When access to the information of the economic structure of the entity is not granted, the reduced-form models are preferred. Thus, instead of taking into account the entity's assets and liabilities to calculate credit risk as in structural models, only the default time will be modeled. It is considered

unpredictable and will be calibrated on historical market prices (Gourinchas and Rey 2007).

The most commonly used model for credit derivatives pricing is the reduced credit model of Jarrow and Turnbull (1995). It characterizes the credit event as the first event of a Poisson probability that is repeated at each premium payment. (The participant must survive with a given probability in each settlement period.) Therefore, O'Kane and Turnbull (2003) estimate the probability of survival Q (t_v, T) as a function of the probability λ that the underlying will survive between the valuation of the premium at the moment t_v and those paid up to maturity T:

$$Q(t_v, T) = \exp\left(-\int_{t_v}^{T} \lambda(s)\mathrm{d}s\right) \tag{3}$$

The parameter λ is the hazard rate of the Poisson process and is an approximate probability over a very short interval of time $= \mathrm{d}t$. Once the probability of survival has been estimated, it is possible to update the premium of a CDS (premium leg value) and find the RPV01. First, O'Kane and Turnbull (2003) write the following general formula:

$$\text{Premium Leg PV} = S(t_0, t_n) \times \text{RPV01} \tag{4}$$

Then, they present a formula for VPN01 to evaluate the present value of a CDS premium without arrears. The value of the premium is the set of payments $n = 1, \ldots, N$ paid on dates $t_1, \ldots, t_N$ until maturity t_N:

$$\text{Premium Leg PV} = S(t_0, t_n)$$
$$\sum_{n=1}^{N} \Delta(t_{n-1}, t_n, B) Z(t_V, t_N) Q(t_V, t_N) \tag{5}$$

where $\Delta(t_{n-1}, t_n, B)$ is a day count between two payment dates (t_{n-1} ett_n) according to convention B; $Z(t)$ is the discount factor for a payment received at time t, and $\Delta(t_{n-1}, t_n, B)$ is a day count between dates t_{n-1} and t_n corresponding to a basis B. $Q(t_V, t_n)$ is the probability that the underlying survives between the valuation of the premium at the moment t_v and its payment at the moment tn.

This equation does not take into account arrears. Indeed, when the underlying is missing between two coupon payments, the protection seller could ask to pay the premium according to the pro rata of the days between the last coupon paid and the credit event. O'Kane and Turnbull (2003) approximate the CDS premium by the following equation:

$$\text{Premium Leg PV} = S(t_0, t_n) \sum_{n=1}^{N} \Delta(t_{n-1}, t_n, B) Z(t_V, t_N)$$
$$\left[Q(t_V, t_N) + \frac{1_{\text{pa}}}{2}(Q(t_V, t_{n-1}) - Q(t_V, t_n))\right] \tag{6}$$

If a default occurs between two premiums, the average premium accrued is half the total premium. $1_{\text{pa}} = 1$ if the contract takes into account the premium accrued and $1_{\text{pa}} = 0$ if not (O'Kane and Turnbull 2003).

Spatial regression approach and construction of the weighting matrix

In this study, we model the returns of sovereign CDS across countries using the spatial regression approach. Anselin (1988) extends the traditional linear regression by incorporating spatial correlation within the econometric model. In most previous studies, CDS spreads or returns used traditional linear models of the form; $y = X\beta + \varepsilon$, where X is a vector of explanatory variables, $\varepsilon \sim N(0; \sigma^2 I_N)$ is an error vector, and $\sigma^2 I_N$ is the covariance matrix.

To capture dependencies across countries, we use a spatial autoregressive model and spatial error model. We suppose that CDS return of country i is a function of some independent factors of country I and the CDS returns of all other countries. Our specification allows for testing and measuring spillover effect across countries. We reinterpret spatial spillovers as financial contagion. We exploit the economic distances between countries, and we test their contribution to explain sovereign CDS returns.

Our two spatial models belong to this general specification:

$$Y = \underbrace{\rho W y}_{\text{systemic risk}} + \underbrace{X\beta}_{\text{systematic risk}} + \underbrace{\varepsilon}_{\text{idiosyncratic risk}} \tag{7}$$

where $\varepsilon = \lambda W\varepsilon + \upsilon$, with λ is the spatial autoregressive (SAR) parameter. $\upsilon \sim N(0; \sigma^2 I_N)$.

$W\varepsilon$ specifies the structure of spatial dependence between disturbances (ε). The interaction effects between error terms do not require a theoretical model for a spatial or economic interaction process, but we assume that the determinants of the dependent variable omitted from the model are locally autocorrelated, or follow a spatial model. The interaction effects between error terms can also be interpreted as reflecting a mechanism to governments to correct their debt policies in an effort to improve the quality of their sovereign CDSs.

The spatial error model (SEM) and the spatial autoregressive model (SAR) are found for $\rho = 0$ and $\lambda = 0$, respectively.

The model decomposes sovereign CDS returns into a systemic, a systematic and an idiosyncratic risk component. The systemic component reflects the effect of shocks transmission across sovereign credit markets between the different countries. The parameter ρ measures the magnitude of spillover and reflects economic dependencies across countries. Testing for the significance of ρ is a test

Table 1 Descriptive statistics

	CDS spreads			CDS returns		
	Mean	SD	Median	Mean	SD	Median
Germany	49.59	0.213	58.23	− 0.68	0.195	− 0.43
France	69.15	47.78	53.03	− 4.6	0.418	− 0.29
Italy	192.41	116.77	147.99	− 3.3	0.382	− 0.49
Portugal	372.82	328.71	273.70	− 9.78	0.530	− 1.42
Belgium	92.63	72.04	58.53	− 8.32	0.261	− 1.46
Greece	2139.60	5170.62	954.3	− 18.2	0.942	− 4.18
Spain	185.89	127.61	36.00	− 12.42	0.197	− 3.14
UK	50.716	27.68	16.5	− 7.21	0.729	− 1.95

for the presence of financial contagion between sovereign credit markets in Europe. A significant parameter ρ is an evidence of misspecification problems in traditional linear regression models. LeSage and Pace (2009) suggest that ignoring the systemic risk component in a regression may lead to biased results.

The systematic risk component reflects the sensitivity of Sovereign CDS returns to changes in macroeconomic risk factors (e.g., GDP, asset volatility and interest rate). The residual risk is the country idiosyncratic risk component.

The correlation matrix W measures the economic distances between sovereign credit markets in Europe. It is a determining factor of financial spillovers across CDS markets. Our data on CDS returns have a panel structure. For each country $i = 1,…, N$, we calculate returns on $t = 1,…, T$ years consisting of $s = 1,…, S$ months. In this matrix, we allow interconnectivity between CDS returns in the same month. But we do not allow interdependencies between months and years. The result will be a diagonal block matrix. To find monthly observations, we calculate correlations between daily CDS returns. Therefore, each element of the matrix W is a correlation coefficient of returns between two countries within the specific month. To guarantee the stationary of the model, we standardize the matrix obtained by dividing each element by the absolute value eigenvalue of W.

Data and descriptive statistics

Our empirical analysis focuses on the Eurozone sovereign CDS markets. Over the period June 2006 to April 2016, we collected weekly data for 5-year sovereign CDS spreads of eight European countries: France, Spain, Portugal, Greece, Germany, Belgium, UK and Italy. These countries have been chosen because of the particular role that they have played in the recent financial crisis and followed by the sovereign debt crisis that has severely affected the Greece. Also, these countries are often selected when studying the sovereign CDS spreads in the euro area.

Germany and France are the two core countries that have commonly sustaining other peripheral countries such as Italy, Spain and Portugal. We restrict our data to 5-year CDS since these are the most traded contracts and the most liquid on the markets. The data set is obtained from Thomson Reuters database.

Table 1 reports summary statistics of weekly sovereign CDS spreads and sovereign CDS returns.

CDS spreads are particularly high and very volatile in Spain, Portugal and Greece. These high spreads reflect a reassessment of sovereign credit risk in these European countries and coincide with bank failures and the strengthening of borrowing guarantees that have hampered public finances. This may be explained by the slowdown in the economy and the deterioration of the fiscal position of sovereign issuers. UK has the lowest CDS spreads. CDS returns appear negative for all countries ranging from 0.13 in France to − 18% in Greece. Berndt and Obreja (2010) argue that negative returns of CDS is due to the increase in default risk that has led investors to get rid of their securities and increased sovereign CDS supply in the markets.

Table 2 reports CDS returns correlation matrix across countries. The results indicate that there is a significant amount of commonality in sovereign CDS returns across European countries. The highest correlation is recorded between Germany and France (0.8340). However, the Greek CDS returns show a low correlation with most European countries.

Figure 1 depicts the CDS spread by country over the whole sample period along with expected returns. The impact of the market turmoil in 2008 and the turbulence in 2009 is evident. All curves show that sovereign CDSs started to increase from 2009 in response to the credit crunch begun to rebound by 2011. For example, the German CDS moved from a level below 5 basis points in June 2008 to a peak of 100 basis points in September 2011. The Greek sovereign CDS spread records a first peak in October 2008. However, the second peak in December 2010 by far exceeds the first peak as the CDS spread briefly surpassed 1000 basis points. The two peaks can also be observed for

Table 2 CDS returns correlation matrix across countries

	Germany	France	Italy	Portugal	Belgium	Greece	Spain	UK
Germany	–							
France	0.8340***	–						
Italy	0.6254**	0.7132	–					
Portugal	0.6123	0.4765	0.7264**	–				
Belgium	0.8136***	0.5641**	0.6841	0.4923	–			
Greece	0.5141	0.6134**	0.4363	0.4441	0.3216**	–		
Spain	0.6098	0.8233***	0.6711	0.8123***	0.2937	0.3132	–	
UK	0.7821***	0.6371	0.7923**	0.8120*	0.6423*	0.7820	0.6369***	–

other countries but at different amplitudes. These similar movements suggest that sovereign CDS markets in Europe are economically related. The extent of the impact of each market on the other will be examined through the application of a spatial approach.

Table 3 reports the descriptive statistics of the explanatory variables that we will use later in the spatial regression. The results show that the countries the most affected by the sovereign debt crisis (Greece, Portugal and Spain) show high levels of inflation as well as negative bond yields and stock returns.

Spatial regression results

Table 4 summarizes the results of spatial error dependence Anselin et al. (1996). These tests will be useful to select the preferred specification for spatial dependence. Results were obtained for the weight matrix measuring economic distances across countries.

We apply the Moran's I Cliff and Ord (1981) test adapted to the regression residual which is very powerful against all forms of spatial dependence, but it does not allow discriminating between them. In this purpose, we can use two Lagrange Multiplier tests (Anselin and Griffith 1988) as well as their robust counterparts (Anselin et al. 1996), which allow testing the presence of the two possible forms of autocorrelation: LM-Lag for an autoregressive spatial lag variable and LM-Error[1] for a spatial

autocorrelation of errors. Anselin et al. (1996) state the following rule to decide which specification is the more appropriate. If LM-Lag is more significant than LM-Error and RLM-Lag is significant but RLM-Error is not, then the appropriate model is the spatial autoregressive model. Conversely, if LM-Error is more significant than LM-Lag and RLM-Error is significant but RLM-Lag is not, then the appropriate specification is the spatial error model.

The results suggest strong spatial dependence and clearly point to the spatial error model as the proper specification in the sample of EU regions. Both LM-Lag and LM-Error are highly significant. The robust version of the Lagrange Multiplier Lag and error tests also rejects the null hypothesis of no spatial dependence.

Estimates of spillovers

Table 5 reports the results of OLS regression estimation without spatial effect, the SAR model and the SEM model, respectively. The analysis aims to examine the robustness of the results according to SEM and SAR spatial specifications and to highlight the possible sensitivity of the effects according to the structure of spatial interactions. The SAR model refers to a spatial multiplier effect that depends on the spatial autocorrelation parameter ρ on the growth of neighboring countries. For the SEM model, the effect is directly given by the estimate of the coefficient λ, without externalities or spatial propagation. Comparing the three specifications allows us, as an exercise, to decompose more and more finely the spatial process potentially present.

Before describing the results associated with the effects of spillovers, we discuss the effects of specific indicators for each country. The impact of economic growth and inflation on sovereign CDS returns appears to be positively positive and stable in the three regression models. Bond slope appears significantly positive only in the SEM model, while Stock index appears to affect significantly CDS returns only in SEM model.

Regarding spatial regression models, the spatial autocorrelation parameters ρ and λ appear significant and

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[1] LM-Lag and LM-Error statistics used in this paper are initially discussed by Anselin et al. (1996) and measured as follows:

$$\text{LM-Lag} = \frac{\left(\frac{\varepsilon' \mathbf{W} \mathbf{y}}{\hat{\sigma}_\varepsilon^2}\right)^2}{B} \sim \chi^2(1)$$

$$\mathbf{W} = \mathbf{I}_T \otimes W, \quad \hat{\sigma}_\varepsilon^2 = \varepsilon' \hat{\varepsilon}/NT, \quad \hat{\varepsilon} = \mathbf{y} - \mathbf{X}\hat{\boldsymbol{\beta}}$$

$$B = \left[(\mathbf{W}\hat{y})' \mathbf{M}(\mathbf{W}\hat{y})/\hat{\sigma}_\varepsilon^2\right] + T.trace(WW + W'W)$$

$$\text{LM-Error} = \frac{\left(\frac{\varepsilon'(\mathbf{I}_T \otimes W)\varepsilon}{\hat{\sigma}_\varepsilon^2}\right)^2}{T.trace(WW + W'W)} \sim \chi^2(1)$$

$$\hat{\boldsymbol{\varepsilon}} = \mathbf{y} - \mathbf{X}\hat{\boldsymbol{\beta}}, \quad \hat{\sigma}_\varepsilon^2 = \hat{\boldsymbol{\varepsilon}}' \hat{\boldsymbol{\varepsilon}}/NT.$

Fig. 1 CDS spreads and calculated returns
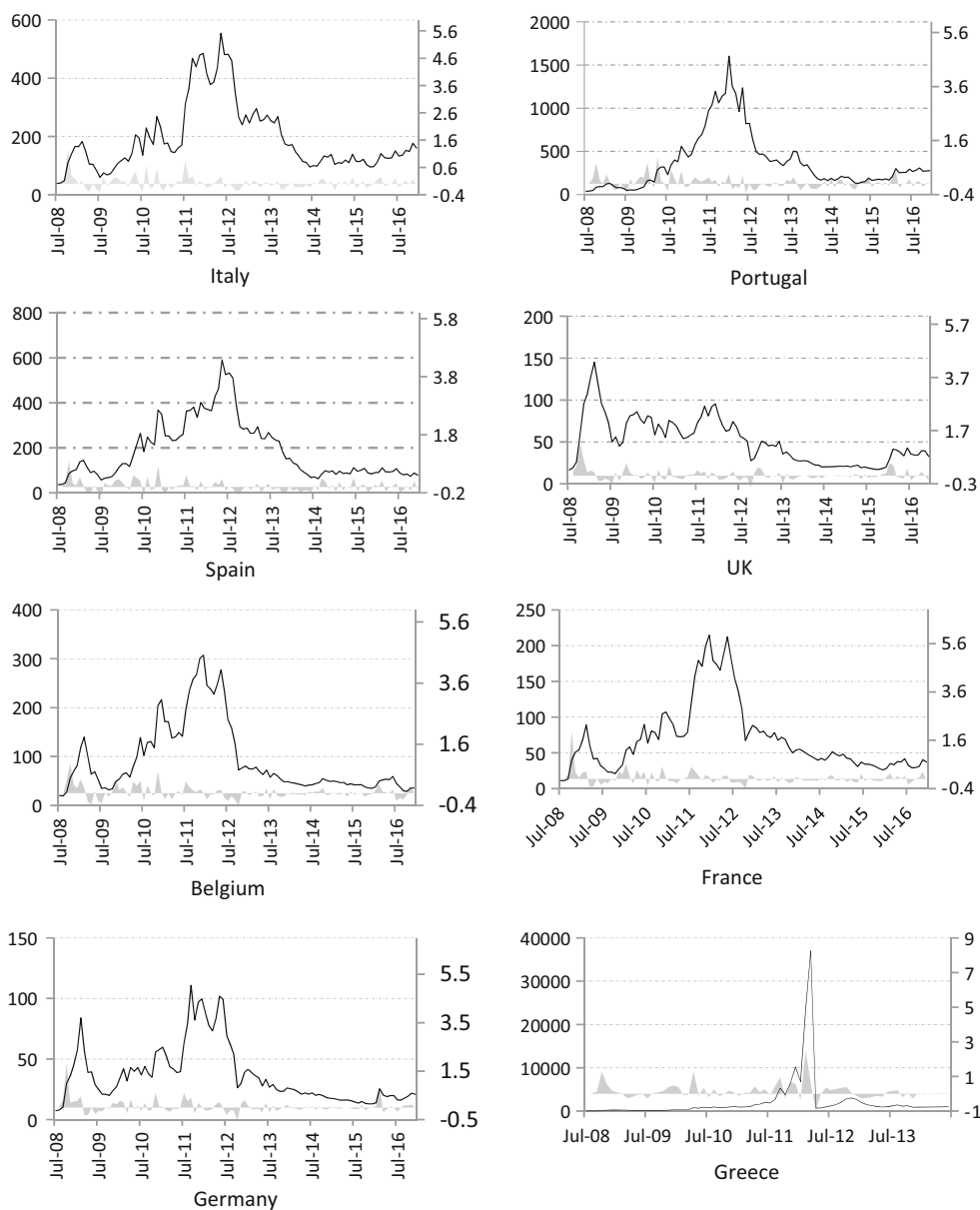
Table 3 Descriptive statistics of explanatory variables

	GDP		IPC		Bond		Stock_Index	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
UK	0.2864	0.7007	1.4635	1.3075	0.0047	0.0175	0.0021	0.0406
Spain	0.0838	0.7030	1.6508	1.7642	− 0.0043	0.0153	− 0.0001	0.0624
Portugal	− 0.0575	0.7872	1.4415	1.4983	− 0.0048	0.0305	− 0.0001	0.0546
Italy	− 0.1559	0.7780	1.7101	1.2877	0.0046	0.0169	− 0.0043	0.0614
Greece	− 0.6661	1.5015	1.9898	2.2892	− 0.0096	0.1562	− 0.0109	0.0963
Germany	0.3169	0.9973	1.4516	1.0117	0.0042	0.0136	0.0063	0.0560
France	0.1940	0.5140	1.3898	1.0746	0.0040	0.0117	0.0002	0.0504
Belgium	0.2711	0.5791	1.6838	1.4815	0.0044	0.0136	0.0005	0.0501

Table 4 Tests for spatial dependence

	Value	p value
Moran's I (error)	37.810	0.0000
LM-Lag	265.681	0.0000
Robust LM-Lag	34.262	0.0012
LM-Error	763.942	0.0001
Robust LM-Error	5.483	00.000

Table 5 Estimated results for returns and volatility over the entire sample period

	No spatial effects		
	$\rho = \lambda = 0$	SAR	SEM
GDP	1.9281***	2.1271***	1.9939***
	(6.367)	(5.621)	(11.091)
IPC	1.3279***	1.6273*	1.3501***
	(2.516)	(1.619)	(4.937)
Bond_Slope	2.2873	1.0241	2.6258***
	(0.133)	(0.327)	(2.332)
Stock_Index	0.4194	1.3628***	0.6205
	(0.132)	(2.132)	(0.345)
ρ		0.0182***	
		(3.074)	
λ			0.0173***
			(3.281)
Adj. R^2	0.1642	0.2678	0.2203
AIC	0.1235	0.7932	0.1127
BIC	0.6120	0.8331	0.5627

***, ** and * indicate significance at 1, 5 and 10%, respectively

T-statistics are reported between parentheses

positive in the SAR and SEM models, respectively, suggesting that the European CDS markets are not isolated from each other. In particular, the assumption of no dependence between sovereign CDS returns over the period 2006–2016 cannot be rejected. These results lead us to confirm the existence of global spillovers in European sovereign CDS markets.

The results of the SAR model imply that the CDS rate of returns in one European country increases by 1.82% when the returns on the sovereign CDSs of the neighboring countries increase on average by 1%. This impact is especially important since, except UK, all CDS returns in European countries exceeded 1%. However, to the extent that the spatial autocorrelation parameter ρ reflects a spatial propagation process, its impact on sovereign CDS returns is performed through the various explanatory factors selected.

The estimates of SEM model show a positive and significant λ coefficient, confirming a spatial autocorrelation of errors. This result implies that SEM model captures for spillover between sovereign CDS markets in Europe. The estimates of the model coefficient in SEM appear very close to those of OLS regression. Adjusted R^2 statistics show that both SEM and SLM have more explanatory power than OLS regression.

Figure 2 displays the estimated values of ρ obtained from an SAR(1) model (see Eq. 7) with varying numbers of neighbors for each market. For various numbers of neighbors (between 1 and 8), we use nine randomly generated neighborhood matrices. The figure also shows the range between the minimum and the maximum estimates for each case. The positive values of ρ indicate a common trend among markets. The average value of ρ increases, and the range between the minimum and the maximum estimates approaches zero when we increase the number of neighbors. More specifically, ρ reaches its maximum value when we use around six neighbors for each country. This indicates that by increasing the number of neighbors we capture the entire spatial dependence among CDS markets.

Sovereign credit risk management implications

In this section, we analyze more in depth the impact of systemic risk spillovers on CDS returns. We use Monte Carlo simulation to measure VaR of sovereign CDS portfolios. The robustness of our results will be checked by performing stress testing on CDS portfolios.

Monte Carlo simulations

In this section, we analyze the credit risk management consequences of assuming spatial interactions among sovereign CDS markets in Europe. We test how such interactions behave if the hold portfolio is adequately diversified across European countries. For this purpose, we built five alternative portfolio sizes under the spatial autoregressive and spatial error models. We simulate Monte Carlo value at risk for different portfolios by considering that our explanatory variables follow the two uniform distributions $U(0.5, 1)$ and $U(-0.5, 1)$, respectively. We consider different degrees of spatial dependency as captured by the parameters ρ and λ (0, 0.1, 0.5 and 0.8).

Our Monte Carlo simulation approach method for CDS portfolios consists of simulating the changes in the risk factors through the changes of generating thousands of hypothetical random risk factors. The changes are measured by the difference between the value of the portfolio at $T = 0$ and the expected value at $T + 1$. This method assumes that the statistical distribution of the simulation

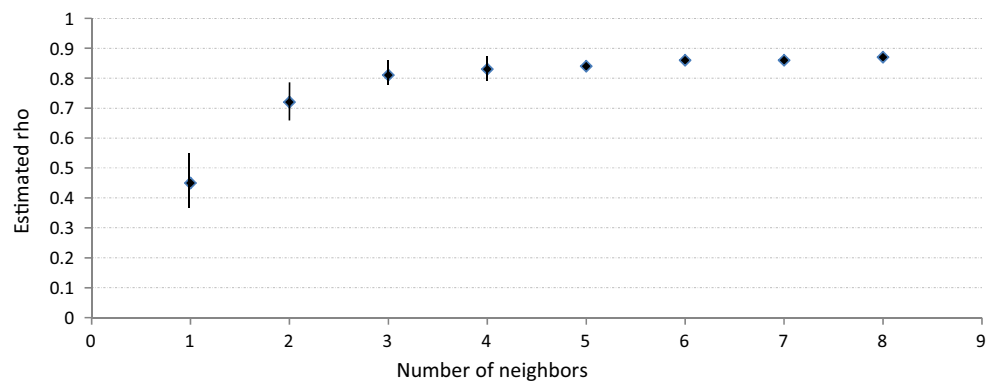**Fig. 2** Estimated spatial autocorrelation coefficients with randomly generated neighborhood matrices

Table 6 Simulations of spatial value at risk for different portfolio sizes

No. of assets	No spatial effects $\lambda = \rho = 0$	SAR $\rho = 0.1$	SEM $\lambda = 0.1$	SAR $\rho = 0.5$	SEM $\lambda = 0.5$	SAR $\rho = 0.8$	SEM $\lambda = 0.8$
Case 1: $E_i \sim U(0.5, 1)$							
N = 4	21.104	26.482	22.711	38.581	30.532	54.772	48.154
N = 5	20.716	24.528	22.528	35.633	26.745	47.236	46.207
N = 6	18.952	21.362	19.012	31.176	23.648	41.899	37.046
N = 7	16.331	19.501	18.217	30.316	21.641	39.321	31.621
N = 8	13.492	18.376	17.584	18.622	19.746	35.643	31.267
Case 2: $E_i \sim U(-0.5, 1)$							
N = 4	19.863	23.751	20.621	32.732	25.621	48.014	41.381
N = 5	17.956	22.140	19.785	30.425	21.342	43.841	37.756
N = 6	16.321	19.452	17.620	27.281	19.658	41.527	34.884
N = 7	14.027	18.396	14.983	25.049	17.902	38.643	31.112
N = 8	12.619	17.544	13.016	24.152	16.473	36.992	28.937

can fully reflect the trend of changes in market factors. This distribution is used to generate the profit/loss distribution of a portfolio and then find the VaR.

Simulation results are reported in Table 6. Regarding the low level of spatial dependency, the SAR and SEM models predict almost similar values of portfolio VaR, mainly for $E_i \sim U(0.5, 1)$. The differences between the estimated VaR increase as λ and ρ increase. For $\lambda = \rho = 0.5$, the VaR of SEM approach are higher than the VAR of SAR model when the portfolio includes less than 8 CDS. This difference increases with the number of CDSs included in the portfolios. This gap becomes more pronounced with the increase in spatial dependency between CDS markets ($\lambda = \rho = 0.8$). The table shows when portfolios include relatively risky CDS and spatial dependency is considerable, the values at risk generated by a SAR specification are much larger than those generated by the SEM specification. For $E_i \sim U(-0.5, 1)$, it can be observed that in the case of SAR model with $\rho = 0.8$ the effect of diversification is not very important. However, for $\lambda = 0.8$ the SEM model experiences high diversification effect, showed by the portfolio VaRs that range from 28 to 42%.

Stress testing

Because of assumptions on explanatory variables, distributions are very restrictive; VaR values calculated in the previous table do not capture the impact of extreme events on CDS portfolios. VaR analysis is usually completed by additional stress tests to estimate the losses resulting from extreme changes in market parameters (higher confidence levels) over time horizons that may be greater than those of VaR.

To provide an in-depth analysis of the results and to demonstrate the implications of sovereign market spillover, we implement the following stress test. Since the CDS returns fell strongly dropped in September 2008, we consider the fundamentals at this date as crisis values. The date of September 2008 will be our base scenario for assessing the outcome of an economic shock in December 2009. To test the impact of these values on CDS prices in September 2011 under stress conditions, we recalculate returns and VaRs in September 2011 using the fundamentals of 2008 but keeping the 2011 connection matrix. We compare the VaR in September 2011 with the predicted from our stress

Table 7 Value at risk stress testing

	Baseline	OLS linear model		SAR model		SEM model	
	VaR	VaR	% of change	VaR	% of change	VaR	% of change
Germany	21.42	29.30	36.79	35.78	67.04	39.76	85.63
France	26.63	46.24	73.62	56.34	111.58	57.41	115.59
Italy	27.97	45.31	61.98	55.21	97.40	64.29	129.86
Portugal	33.45	59.91	79.10	68.53	104.87	76.03	127.29
Belgium	29.24	46.98	60.68	56.30	92.56	60.73	107.70
Greece	45.27	83.26	83.91	94.43	108.60	107.31	137.04
Spain	26.93	48.47	79.99	57.54	113.68	63.65	136.35
UK	19.76	26.75	35.39	31.12	57.48	34.33	73.71

test. VaR will be calculated using the linear model, which does not take into account the spatial connections, the SAR model and SEM. The results are reported in Table 7.

Compared to the baseline, all models show higher value at risk for all countries showing the impact of stress test applied to explanatory variables. SAR and SEM models show higher spreads than the OLS models due to spillover contagion on sovereign CDS markets. This finding confirms the results found in Table 5, which shows significant interconnection between the sovereign CDS markets in Europe. It is also noticeable that the sensitivity of VaR to spatial dependency is twice as large for SEM model compared to SAR model.

The stress tests performed may not fully capture structural changes in European sovereign CDS markets. However, the results are robust to a number of checks and highlight some important relationships between sovereign CDS markets. SEM model shows higher VaR spreads than SAR model. While SAR model spreads do not exceed 113%, those of the SEM model attend 137%. Particularly, the SEM model shows that Greece and Spain suffer more than other countries from contagion with spreads of 137.04 and 136.35%, respectively. This result shows that the risk propagation mechanism for these two countries evolves mainly from systemic risk. Since this risk is not diversifiable, the returns of sovereign CDS do not depend on the risk of individual defaults of each country only but they depend also on systemic risk. The lowest spreads of SAR and SEM models are recorded for the UK, showing that it is less connected to other European CDS markets.

Conclusion

This paper explores systemic risk in sovereign European CDS markets. We use a spatial regression approach to model spillovers between CDS returns across countries during the period 2006–2016. Unlike most previous researches, our study is conducted on sovereign CDS returns and not CDS spreads. We find evidence that there exist spatial effects between sovereign CDS returns in Europe. This implies that systemic risk is a fundamental determinant of sovereign CDS market mainly in countries highly connected to other European markets.

To check the robustness of this finding, we calculate the VaR of a set of eight portfolios of sovereign CDS using Monte Carlo simulation. We show that spillovers between CDS markets increase the risk of CDS portfolios and the risk increases with the number of CDSs included in the portfolios. This gap becomes more pronounced for high spatial markets connection. We find that SAR model provides higher VaR than SEM model for high spatial dependency. In this paper, we perform also stress testing to capture the impact of extreme events on CDS portfolios. We show that SEM model shows higher VaR spreads than SAR model.

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