VOLATILITY SPILLOVERS IN THE EUROPEAN BANK CDS MARKET

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Abstract

From the 2007 subprime crisis to the recent Eurozone debt crisis, the banking industry has experienced terrible financial instability with increasing volatility levels of bank default probability. Using European CDS spreads data from January 2006 to March 2013, this paper sheds light on the impact of three recent significant events of credit risk volatility transmission between, firstly, Eurozone and non-Eurozone banks, and then between distressed peripheral and core countries inside the Eurozone. We employ an asymmetric multivariate BEKK model to measure cross-market volatility spillovers. We find that both recent crises are distinct episodes. The global financial crisis that originated outside Europe is characterized by unidirectional volatility spillovers in credit risk from inside to outside the Eurozone. By contrast, the Eurozone debt crisis is revealed to be local in nature with the euro as the key element, suggesting a financial market fragmentation within the Eurozone between distressed peripheral and non-distressed core Eurozone countries, whereas retaining the local currency has acted as a firewall.

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1. Introduction

The serious tensions that emerged in the international financial markets in 2007 and 2008 broke the stability that had characterized the first ten years of the Eurozone, affecting the real estate sector and causing a rapid deterioration in the major European economies, and to a greater extent in the distressed peripheral economies inside the Eurozone. It led to the Eurozone sovereign debt crisis, which for the first time severely tested the robustness of the Eurozone since its inception in 1999 and resulted in the divergence of financial conditions for debt issuers across countries within the Eurozone. This area has become the heart of the world's financial stress with the break-up of the euro continuing to be a possibility. As a consequence, the European banking industry has witnessed a terrible credit and liquidity crisis from 2007 to the present. The vulnerability of the banking sector has become evident, to a great extent due to globalization, increasing the perception of its credit risk to unprecedented levels, playing a key role in the global financial crisis and causing damage, especially to the banking sector and, consequently, to financial stability.

Extraordinary measures have been taken by central banks and governments to prevent a collapse of the sector that threatened the entire economy. This situation has caused bank supervisors and regulators to rethink banking regulations. Evidence suggests that stability in the banking system, given the role of banks as financial intermediaries as providers of liquidity transformation and monitoring services, is crucial for economic growth and the global financial sector. In this line, the Basel III agreements have improved the capital requirements of credit institutions and the regulatory requirements in Solvency II did the same in the field of insurance companies. The goal was to eliminate credit risk as far as possible, which was, until the onset of the global financial crisis, hardly considered a threat to the developed financial economics.

Volatility in credit spreads has significantly increased in Europe, and even more so within the Eurozone, since 2007. The market perception of default risk has increased and, as a consequence, we are in a new scenario in which a bank credit event is considered a real possibility. Given this background, it becomes crucial to understand the linkages over time between the volatility of European bank credit spreads inside and outside the Eurozone. More concretely, this article fills this gap using the information content in the banking Credit Default Swaps (CDS) spreads, which we employ, following the most recent literature, as an indicator of bank credit risk[2]. In this sense, despite the importance of bank credit risk in financial markets, relatively little is known about the impact of credit risk volatility transmission in European banking credit markets before and during this turbulent period. This paper aims to shed some light on how volatility spillovers work, as this is crucial for understanding how financial crises spread.

More concretely, the main objective of this study is to analyse whether volatility transmission patterns in European banking markets have changed after three significant events during the period January 2006 to

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[2] CDS spreads are considered a good proxy for bank riskiness and default probability (see *Longstaff et al., 2011, Kalbaska and Gatkowski, 2012*). They reflect market perceptions about the financial health of banks, signalling regarding financial stability.

March 2013: the subprime crisis which became manifest in Europe on August 9, 2007 (hereafter SC), the bankruptcy of Lehman Brothers on September 15, 2008 (hereafter LB), and the first bailout of Greece on May 8, 2010 (hereafter GB)[3]. These three events are characterized by all having caused a volatility increase in European bank CDS data, with a different impact depending on the location of the bank in the Eurozone.

We make the following contributions. To the best of our knowledge, this is the first study of volatility credit risk transmission using CDS exclusively for the European banking sector. Moreover, we try to assess whether the volatility spillovers have changed after the three significant events selected, in order to learn the impact of the different recent crises on credit risk transmission among banks of different European zones. Finally, we contrast if CDSs have asymmetric responses regarding volatility.

2. Literature Review

The extensive literature on volatility transmission has mainly focused on international shock transmission between stock market indices, stocks, exchange rates, interest rates and spot and futures markets (see for instance *Engle et al., 1990* and *Susmel and Engle*, *1994*). In fact, it seems that some markets have even more interdependence in volatility than in returns. However, as far as we know, there are few studies that focus on volatility transmission using the CDS market. Therefore, relationships, results and ideas about volatility spillovers in CDS are still not clear. *Groba et al. (2013)* is the only other paper that tests the existence of cross-border volatility effects between the central and the peripheral European Union (EU) countries. They show a significant volatility spillover from distressed to central Eurozone economies leading to a significant impact on the default swap risk premia. However, they use sovereign CDS data instead of bank CDS.

Overall, the existing CDS literature has explored the connections between the CDS market and the bond and/or stock markets (*Blanco et al., 2005, Forte and Peña, 2009, Delatte et al., 2012, Guo et al., 2011*). Most recent articles have identified a number of contagious relationships in the sovereign credit risk markets. Using CDS spread changes, *Caporin et al. (2013)* show that the propagation of shocks in the major euro area countries has been remarkably constant during 2008-2011 even though, in a significant part of the sample, periphery countries have been greatly affected by their sovereign debt and fiscal situations. Using the Granger-causality test *Kalbaska and Gatkowski (2012)* reveal that sovereign risk is mainly concentrated in the EU countries. Another strand of the literature focuses on the contagious relationships between the sovereign and bank CDS markets (*Alter and Schüler, 2012, Dieckmann and Plank, 2012).* However, little attention has been paid to the banking sector itself. As far as we know, *Ballester et al. (2014)* is the only other paper that studies contagion in the US and European CDS banking sector. They show return spillovers in banking markets from 2007 onwards, finding remarkable differences in vulnerability to contagion within Europe and the Eurozone, with the main peripheral banks inside the Eurozone being the most exposed.

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[3] We establish the event's dates following *Drudi et al. (2012*), which analyzes the crises effects in the case of the Eurozone.

To sum up, the existing literature on the CDS market has identified a number of contagious relationships mainly focused on sovereign CDS, but little attention has been paid to the banking sector. As well, volatility transmission has barely been studied. We cover this gap by analyzing volatility spillovers only for the banking industry using a large sample of European commercial banks.

3. Data

The sample consists of daily five year CDS spreads for the main European banks collected from the Thomson Datastream-CMA database. The decision to focus on banks is due to the special nature of the banking business in their role as financial intermediaries as providers of liquidity transformation and monitoring services, and even more importantly because of their key role in the recent crises. Moreover, banks are major users of derivative instruments that provide a relatively important channel to alter bank risk. Firms are selected by considering the availability of CDS trading entities included in the database. This criterion results in 90,809 (unbalanced) panel observations with 50 banks in 14 countries in 1,885 days[4].

Next, we build Eurozone and non-Eurozone equally-weighted bank portfolios using average CDS data[5] from each country[6]. This way we capture the average bank credit risk of each monetary area. The Euro portfolio consists of all the available banks inside the Eurozone, Austria, Belgium, France, Germany, Netherlands, Greece, Italy, Portugal and Spain, whereas the Non-Euro portfolio is constructed using data from Denmark, Norway, Sweden, Switzerland and UK, the available European countries outside the Eurozone. As pointed out by *Groba et al. (2013)*'s sovereign CDS results, the recent financial crisis has shown the fragmentation of financial markets within the Eurozone. Following this idea, we also build Euro-Peripheral and Euro-Core portfolios distinguishing between banks inside peripheral countries with sovereign debt problems (Greece, Italy, Portugal and Spain) and the rest (Austria, Belgium, France, Germany and Netherlands).

The sample period spans January, 2006 to March, 2013. This period of study allows us to investigate three recent critical financial events that may have had different impacts on CDS markets: SC, LB, and GB. In order to analyse separately the volatility transmission patterns before and after the events, the sample has been divided into four sub-samples, covering pre- and post-event periods.

Figure 1 displays the daily time evolution of bank CDS spreads for the four portfolios, while their summary statistics are reported in Table 1. In the Pre-SC period, the CDS spreads exhibit stable volatility levels for the four portfolios. However, after SC there is an abrupt increase in the standard deviation of CDS spreads. Specifically, the Eurozone portfolio rises at over 500%, while the Non-Euro shows the largest increase,

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[4] Thus, our sample comprises more than the 90% of the European banks that trade CDS. Some banks are not included due to their infrequent trading.

[5] Instead of using daily CDS spread data we use the investor's actual CDS returns calculated following the novel approach of *Berndt and Obreja (2010)*. This strategy replicates the payoff of the contract.

[6] The portfolios are sorted first by country, then by zone in order to circumvent the unbalanced problem that will arise due to the variability of the number of available banks across countries.

887%. The upward trend is continued after the LB event but in a smoother way, with Euro-Peripheral being the most volatile of the portfolios (131%). After the GB event, significant differences could be observed between Euro and Non-Euro bank portfolios and moreover, inside the Eurozone, between Euro-Core and Euro-Peripheral. Eurozone CDS volatility rises up to 360% increasing the cost of market funding due to the sovereign debt problems that some of its countries suffer from, whereas there is a relatively volatility stability in the Non-Euro portfolio (22%). Within the Eurozone, Euro-Peripheral CDS volatility has an increase of 400% while Euro-Core banks are affected in a much smoother way (70%). These results reflect the fragmentation of the Eurozone financial market since LB.

Additionally, we perform some descriptive tests[7]. We reject normality for all the portfolios and periods, and we find significant autocorrelation both in level and squared returns, so that there is persistence in mean as well as in variance. The returns exhibit conditional heteroskedasticity which justifies the use of multivariate ARCH/GARCH volatility models. Additionally, we observe differences in variance between periods, indicating a change over time in the pattern of volatility transmission in the different portfolios and thus differences in sensitivity to the risk factors that affect the bank CDS. Finally, returns are stationary so we will consider a VAR specification for the mean.

4. Methodology Approach

Motivated by the preliminary data analysis we first model the conditional mean using a VAR(p) model. Next, innovations are orthogonalized following a structural decomposition approach, dubbed SVARS[8]. These new innovations will be used as input in the variance-covariance equation and have the convenient property that they are uncorrelated across both time and equations. To this second equation we use an asymmetric version of the BEKK model. It allows us to study whether data exhibit asymmetrical conditional behaviour, that is, that positive values of the residuals have a different effect than negative ones[9].

Finally, as a robustness test of the model results, we calculate the Asymmetric Volatility Impulse-Response Functions (AVIRF). The AVIRF are computed in order to measure the impact of an unexpected shock on the predicted volatility with the advantage that it can change, with the sign of the shock[10]. This methodology examines how fast CDS series incorporate new information, which enables us to test for the speed of adjustment, analyse the dependence of volatilities across the variables and moreover, it allows us to distinguish between negative and positive return shocks.

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[7] The results are not shown but are available upon request.

[8] It was proposed by *Bernanke (1986)* and *Sims (1986)* independently. In contrast with those based on the Choleski factorization, this procedure does not suffer from the problem of imposing a semi-structural interpretation on a mechanical procedure.

[9] Note that in that case conclusions obtained from volatility transmission models could be erroneous when asymmetries are not modelled (*Susmel and Engle, 1994*). We introduce the asymmetric effect into the model following *Glosten et al. (1993).* See Appendix A for a detailed exposition of the well-known model and estimation procedure.

[10] See Appendix B for a detailed exposition of the AVIRF equations.

5. Empirical results

Table 2 shows VAR-BEKK model estimation results[11], while Figure 2 presents the outcomes for the AVIRF. In both, Panel A shows the results regarding Euro and Non-Euro bank portfolios, while Panel B displays the results inside the Eurozone, that is between Euro-Peripheral and Euro-Core.

Panel A (Table 2) highlights the different behaviour of volatility spillovers depending on the studied event. We observe that credit risk conditional volatility in each portfolio is never explained by the past volatility of the other portfolio. The impact is observed in terms of past shocks. Our findings show significant volatility shock spillovers from inside to outside the Eurozone during the relatively stable period (before SC) and the whole global financial distress period (before GB). It seems that this unidirectional historical behaviour in shocks is maintained while the financial critical events originate outside of Europe, which is the case for the SC and LB events, where the shocks in credit risk caused in the Eurozone banking firms are determinant in explaining the volatility in the credit risk of the Non-Euro portfolio. However, this effect disappears after GB, an event produced in Europe, and more specifically, within the Eurozone. We observe that GB broke the historical credit risk volatility transmission between both monetary areas. Shocks in Euro banks are no longer transmitted to Non-Euro banks, suggesting, as pointed out by *Groba et al. (2013)* in the case of sovereign CDS, that retaining the local currency in Europe acted as a firewall during the Eurozone debt crisis period. However, given this result and as this was a period of great market tensions in the Eurozone financial sector[12], we expect to find in our second analysis a significant credit risk volatility transmission inside the Eurozone portfolios, when analysing Euro-Peripheral and Euro-Core portfolios.

Looking at the AVIRF results (Panel A in Figure 2), we observe that both positive and negative credit risk shocks in Euro bank portfolio have an important immediate effect (for $s = 1$) on the Non-Euro volatility during the Post-SC period (about 33% (38%) of the positive (negative) shock) and to a lesser extent during the Post-LB period (about 12% (15%) of the positive (negative) shock), but again the effect disappears after GB. The values obtained for $s = 10$ show that positive shocks take less than 10 days to be absorbed, while negative ones take longer to die out. For instance, about 3% (30%) of an unexpected decrease (increase) in credit risk volatility inside the Eurozone is spilled outside the Eurozone after 10 days during Post-SC.

Inside the Eurozone (Panel B in Table 2) we first observe how SC causes a highly significant bidirectional volatility transmission that is maintained only during the Post-SC period. Secondly, we observe how after GB the effect only goes from Euro-Core to Euro-Peripheral banks, which stand out as being more fragile

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[11] Both the estimated parameters for the VAR-BEKK model and the non-linear functions of the BEKK parameters are not shown. Moreover, the standardized residuals are free of conditional heteroskedasticity and autocorrelation both in level and squared returns (revealed by the tenth order ARCH and Ljung-Box tests (not shown)). All these results are available upon request.

[12] At GB leaders of the Eurozone countries resolved to take drastic action to protect the euro and constrain the European financial contagion from further market turmoil, after approving the $110bn European Central Bank bailout plan for Greece. The eruption of the Eurozone debt crisis was already a fact.

than banks in non-distressed Eurozone core economies during the Eurozone debt crisis. They not only have to deal with sovereign debt troubles of their own economies, but they are also volatility spillover recipients from the Euro-Core bank[13]. In terms of shocks, the relationship is bidirectional. Concretely, both unexpected increases and decreases in a bank portfolio's credit risk have a positive effect on the other portfolio's credit risk volatility, but the increasing ones have a bigger impact (asymmetric effect). These results indicate that the European sovereign debt crisis appears to be local in nature, with the euro as the key element. In particular, it seems that it has caused financial sector fragmentation within the Eurozone.

The AVIRF results (Panel B, Figure 2) confirm previous results. After SC, Euro-Peripheral negative (and to a lesser extent positive) shocks spill into Euro-Core banking firms volatility with an impressive immediate value of 67% (12%), with an impact of 16% (1%) after 10 days. On the other hand, about 30% (20%) of a negative (positive) shock in the Euro-Core volatility is spilled into the Euro-Peripheral volatility, taking more (less) than 10 days to die out. From LB to GB it can be observed that only negative shocks in the Euro-Peripheral have a significant effect in the Euro-Core (about 8%), but the reverse is not detected. Finally, a similar pattern can be observed in the last period.

6. Conclusions

Volatility in European banks' credit risk expectations has significantly increased since SC, and even more if possible from GB onwards in the case of banks in the Eurozone. A credit event of a major bank is no longer perceived as a rare event. Using CDS data this article investigates volatility spillovers patterns between different pairs of European zone portfolios. The current study also provides additional insights into the changes in magnitude and the nature of credit risk transmission due to three important events selected from the long sample period, SC, LB and GB. In this way, and using an asymmetric VAR-BEKK model, we are able to shed light on the impact of the different crises on the European banking credit risk dynamics

Overall we see both recent crises as distinct episodes. The global financial crisis that originated outside Europe (from SC to GB) is characterized by a unidirectional volatility shock spillover effect in credit risk from inside to outside the Eurozone with a greater impact of negative shocks (increases in credit risk) that take a long time to die out. On the other hand, portfolios inside the Eurozone only experienced a highly significant and bidirectional volatility transfer from SC to LB.

In contrast, the Eurozone debt crisis (from GB onwards) appears to be local in nature with the euro being the key element. Shocks in the Eurozone are no longer transmitted outside the Eurozone after GB, suggesting that retaining the local currency has acted as a firewall during the Eurozone debt crisis period. In fact, after

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[13] These findings differ from those of *Groba et al. (2013)* who report, using sovereign CDS, a unidirectional volatility spillover from distressed peripheral to core Eurozone countries from January 2008 to July 2012. We attribute the discrepancy to differences in bank and sovereign CDS and to the distinct sample period.

GB, there has been a noticeable increase in the volatility transmission between the two Eurozone portfolios, indicating that GB has occasioned a European financial sector fragmentation inside the Eurozone between core and peripheral Eurozone countries, with the latter standing out as being more fragile since they receive volatility spillovers from the former. In terms of shocks both Eurozone bank portfolios are significantly affected by the other's past shocks, with a stronger impact of unexpected increases in credit risk.

This information is undoubtedly of interest to regulators and policy makers who need to understand the channels of the cross-market credit risk transmission among banks in Europe and even more so within the Eurozone. Monetary policies need to control credit conditions in order to reduce the intensity of future crises. This is crucial for the stability of the euro which requires policy measures intended to alleviate the fragmentation observed between peripheral and core economies that share the euro as the common currency.

Appendix A. The model

We first consider the following Vector Autoregressive VAR(p) model for the conditional mean equation,

$$\begin{bmatrix} R_{1,t} \\ R_{2,t} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \beta_{11,1} & \beta_{12,1} \\ \beta_{21,1} & \beta_{22,1} \end{bmatrix} \begin{bmatrix} R_{1,t-1} \\ R_{2,t-1} \end{bmatrix} + \cdots + \begin{bmatrix} \beta_{11,p} & \beta_{12,p} \\ \beta_{21,p} & \beta_{22,p} \end{bmatrix} \begin{bmatrix} R_{1,t-p} \\ R_{2,t-p} \end{bmatrix} + \begin{bmatrix} u_{1,t} \\ u_{2,t} \end{bmatrix} \tag{1}$$

where $R_{1,t}$ and $R_{2,t}$ are the CDS returns of the selected portfolios. μ is the vector of constants, $\beta_{ij,k}$ for $i,j = 1{,}2$ and $k = 1,\ldots,p$ are the parameters that measure the own and cross-effects of past returns and u is the vector of non-orthogonal innovations. In the next step, the conditional variance-covariance matrix in t, (H_t), is modelled using the asymmetric version of the BEKK model[14]. The compacted form of this model is:

$$H_t = C'C + B'H_{t-1}B + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + D'\eta_{t-1}\eta'_{t-1}D \tag{2}$$

where C is a lower-triangular and positive definite matrix, with $C'C$ representing the unconditional part of H_t; A and B are parameters matrices dictating the multivariate ARCH and GARCH evolution, where the ortogonalized error term, ε_t, coming from the conditional mean equation (1) shows the asymmetric effects in volatility, with $\eta_{1,t} = \max(0, -\varepsilon_{1,t})$ and $\eta_{2,t} = \max(0, -\varepsilon_{2,t})$, and thereby, a positive and significant value of D means that the negative residuals tend to increase the variance more than positive ones. To estimate (2), normally distributed innovations in the estimation process are assumed, which implies that the parameters of the BEKK system are estimated by maximizing the conditional log-likelihood function. Numerical maximization techniques were used to this end based on the BFGS algorithm (see *Press et al., 1988).* Quasi-

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[14] The main advantage of the popular BEKK specification of *Engle and Kroner (1995)* is that it directly imposes positive definiteness on the variance-covariance matrix. Moreover, it significantly reduces the number of parameters to be estimated compared with other specifications and without imposing strong constraints on the shape of the interaction between variables. This model enables us to analyse the volatility spillovers between both markets, since it allows for both own market and cross-market influences in the conditional variance.

maximum likelihood method estimation is applied since *Bollerslev and Wooldridge (1992)* show that the standard errors calculated using this method are robust even when the normality assumption is violated.

However, estimated parameters from *C*, *B*, *A* and *D* matrices in (2), cannot be interpreted individually. Instead, we have to interpret the non-linear functions of the parameters which form the intercept terms and the coefficients of the lagged variances, covariances and error terms that appear in the following expanded equations for each portfolio conditional variance:

$$\begin{aligned} h_{11,t} &= c_{11}^2 + c_{21}^2 + b_{11}^2 h_{11,t-1} + b_{21}^2 h_{22,t-1} + 2b_{11}b_{21}h_{12,t-1} + a_{11}^2\varepsilon_{1,t-1}^2 + a_{21}^2\varepsilon_{2,t-1}^2 \\ &\quad +2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + d_{11}^2\eta_{1,t-1}^2 + d_{21}^2\eta_{2,t-1}^2 + 2d_{11}d_{21}\eta_{1,t-1}\eta_{2,t-1} \\ h_{22,t} &= c_{22}^2 + b_{12}^2 h_{11,t-1} + b_{22}^2 h_{22,t-1} + 2b_{12}b_{22}h_{12,t-1} + a_{12}^2\varepsilon_{1,t-1}^2 + a_{22}^2\varepsilon_{2,t-1}^2 \\ &\quad +2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + d_{12}^2\eta_{1,t-1}^2 + d_{22}^2\eta_{2,t-1}^2 + 2d_{12}d_{22}\eta_{1,t-1}\eta_{2,t-1} \end{aligned} \tag{3}$$

To that end, we follow *Kearney and Patton (2000)* and calculate the expected value and the standard errors of these non-linear functions that form the intercept terms and the coefficients of the lagged variance, covariance and error terms. This is called the delta method and enables us to conduct significance tests.

Appendix B. The Asymmetric Volatility Impulse-Response Functions (AVIRF)

The AVIRF for the asymmetric BEKK model is taken by *Meneu and Torró (2003)* and *Chuliá et al. (2009)* by applying the volatility symmetric structure proposed by *Lin (1997)* to (2):

$$R_{s,3}^{+} = \begin{cases} a & s = 1 \\ \left(a + b + \frac{1}{2}d\right) R_{s-1,3}^{+} & s > 1 \end{cases} \qquad R_{s,3}^{-} = \begin{cases} a + d & s = 1 \\ \left(a + b + \frac{1}{2}d\right) R_{s-1,3}^{-} & s > 1 \end{cases}$$

where $R_{s,3}^{+}$ and $R_{s,3}^{-}$ represent the impulse-response function for conditional volatility for positive and negative initial shocks, respectively, with *s* being the lead indicator. The 3 × 3 parameter matrices a, b and d are computed by: $a = D_N^{+}(A' \otimes A')D_N$, $b = D_N^{+}(B' \otimes B')D_N$ and $d = D_N^{+}(D' \otimes D')D_N$, where D_N is a duplication matrix, D_N^{+} is its Moore-Penrose inverse and ⊗ denotes the Kronecker product, that is:

$$D_N = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \qquad D_N^{+} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1/2 & 1/2 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

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Table 1

Descriptive statistics of bank CDS spreads

This table presents the summary statistics for the daily 5-year CDS spreads in basis points for the full period, from January 2006 to March 2013, and four sub-periods identified by three significant events: the eruption of the subprime crisis (August 9, 2007), SC, Lehman Brothers default (September 15, 2008), LB, and Greece's bailout (May 8, 2010), GB, respectively. The banks of the sample are summarized in equally weighted portfolios sorted first by country, then by geographic zone.

	CDS Spreads														
	Full Period Jan06 – Mar13			**Pre-SC Jan06 – Aug07**			**Post-SC / Pre-LB Aug07 – Sep08**			**Post-LB / Pre-GB Sep08 – May10**			**Post-GB May10 – Mar13**		
	Max	Mean	Std. Dev.	Max	Mean	Std. Dev.	Max	Mean	Std. Dev.	Max	Mean	Std. Dev.	Max	Mean	Std. Dev.
Euro	903.02	230.97	214.04	37.58	17.15	3.96	132.81	70.35	23.86	338.54	158.18	35.24	903.02	453.32	162.35
Non-Euro	245.59	92.30	62.65	23.77	10.91	2.54	117.60	55.70	25.06	227.82	116.72	38.37	245.59	137.66	46.64
Euro-Peripheral	1625.25	348.71	374.99	34.24	16.31	2.92	124.92	63.69	23.48	537.09	163.45	55.09	1625.25	749.25	280.38
Euro-Core	384.92	136.77	94.22	40.24	17.82	6.03	153.84	75.68	25.12	274.42	153.96	42.04	384.92	216.58	71.98

Table 2

Volatility spillovers between bank CDS returns portfolios

This table presents volatility spillovers results between portfolios of the linearized asymmetric BEKK model for the full period, from January 2006 to March 2013, and four sub-periods identified by three significant events: the eruption of the subprime crisis (August 9, 2007), SC, Lehman Brothers default (September 15, 2008), LB, and Greece's bailout (May 8, 2010), GB, respectively. * Significance at the 10% level; ** Significance at the 5% level; *** Significance at the 1% level.

Panel A:

	Non-Euro			
Euro	**Pre-SC Jan06–Aug07**	**Post-SC / Pre-LB Aug07–Sep08**	**Post-LB / Pre-GB Sep08–May10**	**Post-GB May10–Mar13**
$h_{ii,t-1}$				
$\varepsilon_{i,t-1}^{2}$	$\overset{*}{\rightarrow}$	$\overset{*}{\rightarrow}$	$\overset{**}{\rightarrow}$	
$\eta_{i,t-1}^{2}$	$\overset{*}{\leftarrow}$			

Panel B:

	Euro-Core			
Euro-Peripheral	**Pre-SC Jan06–Aug07**	**Post-SC / Pre-LB Aug07–Sep08**	**Post-LB / Pre-GB Sep08–May10**	**Post-GB May10–Mar13**
$h_{ii,t-1}$		$\overset{***}{\leftrightarrow}$		$\overset{***}{\leftarrow}$
$\varepsilon_{i,t-1}^{2}$				$\overset{***}{\leftarrow} / \overset{*}{\rightarrow}$
$\eta_{i,t-1}^{2}$				$\overset{***}{\leftrightarrow}$

Figure 1

Time evolution of bank CDS spreads and returns portfolios

Daily bank CDS spreads in basis points for the four equally weighted portfolios, sorted by the geographical area where banks are headquartered. The sample period is January 2006 to March 2013. The vertical black solid lines identify the eruption of the subprime crisis (August 9, 2007), SC, the Lehman Brothers default (September 15, 2008), LB, and Greece’s bailout (May 8, 2010), GB, respectively. The scaling in Euro is from 0 to 1,000; in Euro-Peripheral it is from 0 to 1,800; in the others it is from 0 to 400.

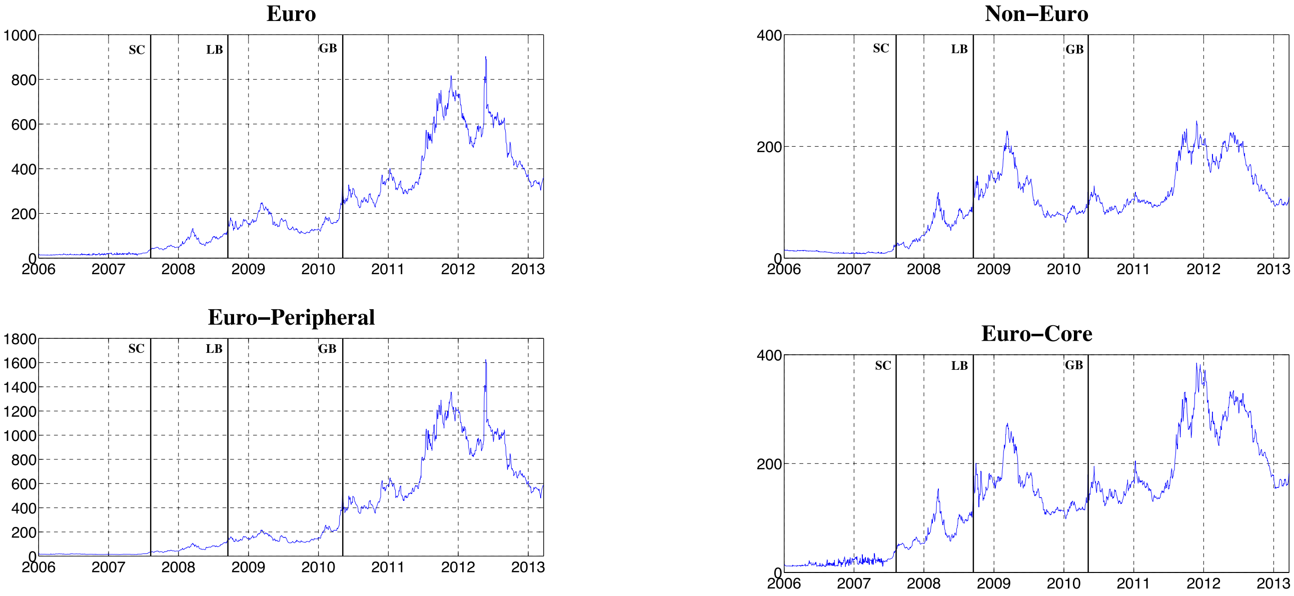
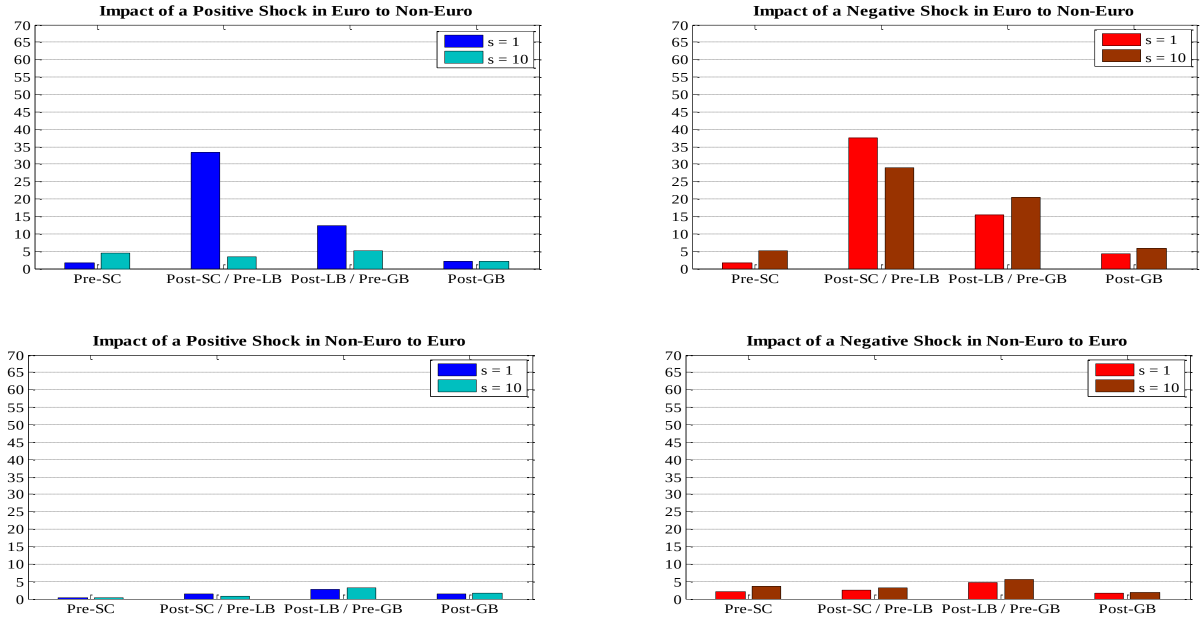


Figure 2
AVIRF to unexpected shocks from the VAR-Asymmetric BEKK

This figure reports the Asymmetric Volatility Impulse Response Functions (in percentage terms) for two significant values of the lead indicator *s* (that is, for *s* equals 1 and 10), and where positive and negative shocks (decreases and increases of credit risk) are in blue and red, respectively. Results are shown for the full period, from January 2006 to March 2013, and four sub-periods identified by three significant events: the eruption of the subprime crisis (August 9, 2007), SC, the Lehman Brothers default (September 15, 2008), LB, and Greece's bailout (May 8, 2010), GB, respectively. Panel A shows the case of Euro and Non-Euro portfolios. Panel B presents the case of Euro-Peripheral and Euro-Core portfolios.

Panel A: Euro and Non-Euro portfolios



Panel B: Euro-Peripheral and Euro-Core portfolios