Structural Changes in the Transmission Mechanism between Banking and Sovereign CDS spreads: the Case of Spain

Joaquín López Pascual **Lidija Lovreta***

First version: August 2013

This version: January 2014

Abstract

In this paper we investigate structural changes in the mean and volatility transmission channel through which increased sovereign credit risk can spill over to the banking sector (and vice versa) for a sample of systematically important domestic banks in Spain. Our main results show that there is an evident change in the credit risk transmission mechanism, going from pronounced one-way bank to sovereign transmission until January 2010 to pronounced one-way sovereign to bank transmission since mid-May 2010. Endogenously identified transition break dates coincide with important events that severely affected investors' perception of the government implicit and explicit support to distressed banks.

JEL classification: G01, G12

Key words: Credit Default Swaps, BEKK GARCH

* Corresponding author: CUNEF (Colegio Universitario de Estudios Financieros), Complutense University of Madrid, address: Serrano Anguita 8, 28004 Madrid; Tel.: +34 914 480 892; Fax: +34 915 933 111; e-mail: lidija.lovreta@cunef.edu. The usual disclaimers apply.

Introduction

The global financial crisis that started in the US in mid-2007, and reached its critical point in September 2008 with the collapse of Lehman Brothers, rapidly spread to Europe strongly affecting a number of financial institutions. The financial sector turmoil was immediately followed by increased government interventions to avoid the collapse of the entire financial system, which, in turn, increased the interconnectedness between sovereign and banking credit risk. Government guarantees to the banking sector, and bank bailout programs, both increased sovereign credit risk. As a feedback effect, bank holdings of sovereign debt and bank's implicit and explicit guarantees induced the transmission of risk from the state to the banking sector. Since then, this vicious cycle relationship between the two sectors became the primary concern of supervisory authorities, and, in order to gauge the potential source of systemic financial instability, it became vital to fully understand the interrelationships within the system and the nature of the transmission mechanism.

The recent findings in the literature elucidate some aspects of the complex two-way relationship between sovereign risk and the risk of financial institutions. Attinasi et al., (2009) show that government announcements of substantial bank rescue packages led to an increase in the sovereign credit risk perceived by investors through a transfer of risk from the private financial sector to the government and that country's expected fiscal position has an effect on the investors' perception of its credit risk. Kallestrup et al., (2012) show that the perceived size of the implicit and explicit guarantees for the domestic banking system strongly impacts sovereign CDS premia. Dieckmann and Plank (2011) show that the magnitude of the private-to-public risk transfer depends on the relative importance of the country's financial system and that the sensitivity of the CDS spreads to the health of financial system is further magnified for EMU countries.

In a recent study, Alter and Schüler (2012) analyze credit spread interdependencies of the default risk of several Eurozone countries and their domestic banks from June 2007 to May 2010. Although they confirm the two-way feedback effect between bank and sovereign credit risk initially exposed in Acharya et al. (2011), they conclude that the bailout programs affected the linkage between the default risk of governments and their local banks. Their findings suggest a mean contagion from bank credit spreads to sovereign CDS spreads before the bank bailouts, whereas after the bailouts, government CDS spreads become an important determinant of banks' CDS series.

In this paper we further investigate the contagion channel and short-run dependence of sovereign and bank credit risk. In particular, we examine the mean and volatility transmission between sovereign CDS spreads and CDS spreads of systematically important domestic banks in Spain from November 2008 till July 2012. We contribute to the existing literature in two ways. First, unlike previous studies we do not impose *ex-ante* any specific break date but endogenously search for potential structural breaks in the transmission mechanism through which sovereign CDS spread returns influence banking sector CDS spread returns and vice versa. We show that there is considerable parameter instability over time that crucially affects the general conclusions about the transmission mechanism. Second, we account not only for the conditional mean but also for the conditional variance and provide preliminary evidence of the changes in the volatility transmission mechanism.

The focus on Spain is motivated by several reasons. First, Spain has received attention in recent years as one of the countries that has the most important impact on the European CDS market (Kalbaska and Gatkowski, 2012). Second, the Spanish financial system is dominated by banks that are large relative to the economy and thus the level of interconnectedness between the state and banking sector should be stronger.

As Gerlach et al. (2010) show, the size of the country's banking sector has an effect on the sovereign CDS spreads: the greater the size of the sector the higher the probability that the state will rescue banks in times of crisis. Third, the domestic banking sector is mostly exposed to the home sovereign: 30% of the Spanish sovereign debt is held by banks, out of which as much as 80.7% are domestic. Fourth, at the end of June 2009 the Spanish government had formed the bank bail-out fund, the Fund for Orderly Bank Restructuring (FROB; Fondo de Reestructuración Ordenada Bancaria) by a Royal Decree-Law 9/2009 which strengthens the state linkages with the banking sector and increases the probability of state intervention perceived by market participants. Finally, being the fourth largest economy in the Eurozone investors are highly concerned about the Spanish banking system.

Our main results could be summarized as follows. First, there is an evident change in the mean return transmission over the period examined: from pronounced one-way bank to sovereign transmission until January 2010, to pronounced one-way sovereign to bank transmission after May 2010. Endogenously identified transition break dates coincide with important events for the Spanish financial system: European Commission approval of the recapitalization scheme for credit institutions (January 2010) and government public announcement of the severe austerity measures (May 2010). These events severely affected investors' perception of the government implicit and explicit support to distressed banks and completely turned around credit risk transmission mechanism. Second, while banking and sovereign risk are highly correlated, correlations change over time. The period of almost perfect correlation coincides with the government announcement of the austerity measures in May 2010. Third, there is an evidence of two-way volatility transmission between sovereign and banking sector CDS returns, with stronger volatility transmission from the three largest banks in Spain (Banco Santander, BBVA, and La Caixa) to the sovereign CDS spreads. In addition, we provide preliminary evidence of the change in volatility transmission mechanism that from May 2010 seems to be one-way way directed from sovereign to banking sector.

The remainder of the paper is organized as follows. Section 1 presents some preliminary analysis of the data. Tests for structural change in the mean transmission are discussed in Section 2. Section 3 analyzes volatility transmission through the BEKK-GARCH framework. Section 4 concludes.

1. Data and preliminary analysis

The data on sovereign and bank CDS spreads is downloaded from Thomson Reuters and spans from January 2008 till July 2012. We use only the most liquid 5-year Euro denominated CDS contracts on senior unsecured debt and consider the following systematically important banks in Spain: Banco Santander, BBVA, La Caixa, Banco Popular, Banco Pastor, Banco Sabadell, and Bankinter.[1] Together, these financial institutions hold around 60% of the total assets of Spanish banks and had not yet been intervened by government through capital injections. All considered banks have exposures to home sovereign debt, and hold almost 70% of the total domestic exposure to sovereign debt.[2] Banco Santander and BBVA have the highest exposure levels holding as much as 8.51% and 8.09% of the total sovereign debt, respectively, as of July 2012.

In order to consider the longest time period possible given the data availability we use November 2008 as a starting point of the analysis provided that data is available for all banks from this point onward. In total, there are 969 daily observations for each

[1] In October 2011 Banco Pastor was acquired by Banco Popular but continued to run as a separate entity. The results of the paper remain unchanged when Banco Pastor is excluded from the analysis.

[2] Data on banks' sovereign exposures are taken from the CEBS EU-wide stress tests and are as of end-March 2010.

series. General descriptive statistics of the data set are presented in Table 1. Panel A depicts main summary statistics for the CDS spread levels. The mean level of sovereign CDS spreads was around 193 bp for the entire sample period whereas the mean level of CDS spreads for the banking sector was substantially higher, 329.51 bp, on average. Panel B depicts main summary statistics for the CDS returns calculated as log-differences (Alter and Schüler, 2012). The highest mean return of 0.191% was detected for the BBVA followed by the sovereign CDS mean return of 0.169% and Banco Santander CDS mean return of 0.153%. However, the sovereign CDS returns were characterized with the highest standard deviation. The Augmented Dickey Fuller Test (ADF) for the presence of unit roots shows that entity-specific CDS spreads are non-stationary at the 95% confidence level. On the contrary, the null hypothesis of non-stationarity for the log first-differences of CDS spread series is rejected for all entities considered.

<Table 1 about here>

In order to identify the commonality along CDS spreads and CDS returns in the banking sector we apply the principal components (PC) analysis. The results of the PC analysis, presented in Table 2, show that there is significant amount of commonality in the variation of banking sector CDS spread levels and banking sector CDS spread log-differences. The single common factor is able to explain around 86% of the individual variations in levels and around 50% of the individual variations in changes. The eigenvalues are not equally distributed along the banks, however. The loadings for CDS spread changes lie in the range 0.23-0.43, where BBVA, Banco Santander and Banco Sabadell have the highest loading coefficients of around 0.43, and Banco Pastor the lowest loading coefficient of 0.23.

<Table 2 about here>

A large systematic component extracted from the CDS returns of the major financial institutions in Spain serves as a risk indicator of the banking sector. We principally base our analysis on the extracted common banking sector component as it proxies for the risk inherent to the entire banking system in Spain, as opposed to risk associated with any individual entity. In this way, eventual changes in the risk transmission between sovereign and financial system could be revealed with more precision. Daily sovereign and banking sector CDS returns are presented in Figure 1. We can see that there are times of high and low volatility of returns. Therefore, we formally test for the presence of ARCH effects in the data using the Lagrange Multiplier (LM) test. First, we estimate OLS regression of squared returns on a constant term and then test the null hypothesis of the homoscedasticity of residuals. In all of the cases the null hypothesis is rejected in favor of the ARCH alternative. Additionally, we perform the Ljung-Box Q statistics for up to 12 and 24 lags for the squared residuals. The null hypothesis of no serial correlation is rejected.

<Figure 1 about here>

Following the common approach adopted in the literature, we proceed first by running a pairwise Granger Causality test in a benchmark VAR model of the following form:

$$y_{1,t} = \alpha_1 + \sum_{j=1}^{p} \gamma_{11,j}\, y_{1,t-p} + \sum_{j=1}^{p} \gamma_{12,j}\, y_{2,t-p} + \varepsilon_{1,t} \,, \tag{1}$$

$$y_{2,t} = \alpha_2 + \sum_{j=1}^{p} \gamma_{21,j}\, y_{1,t-p} + \sum_{j=1}^{p} \gamma_{22,j}\, y_{2,t-p} + \varepsilon_{2,t} \,. \tag{2}$$

where $y_{1,t}$ are daily log-changes of sovereign CDS spreads ($y_{SOV,t}$) and $y_{2,t}$ are daily log-changes of banking sector CDS spreads ($y_{BK,t}$), ε_1 and ε_2 are i.i.d. error terms, and p is the number of lags determined according to the Schwarz Information Criterion. The optimal number of lags resulted in one lag in all of the cases considered. The Granger Causality Test shows whether coefficients of the lagged changes in banking sector CDS spreads are statistically significant, and help in the explanation of the current changes in sovereign CDS spreads (and vice versa). The results of the pairwise Granger Causality test, presented in Table 3, do not provide expected two-way feedback effect, i.e. a bi-directional relationship between sovereign and bank CDS spreads during the time period considered. On the contrary, when the overall sample period is considered the strong one-way relationship (the changes in the sovereign CDS spreads Granger Cause the changes in the banking sector CDS spreads, but not the other way around) is evident for the common banking sector component, as well as for Banco Santander, BBVA, La Caixa, Banco Pastor and Banco Popular. The two-way feedback effect seems to be present only for two entities, Banco Sabadell and Bankinter.

<Table 3 about here>

2. Tests for structural change

In order to check for a possible break in the VAR system described in (1) and (2) we start with preliminary break-point tests on single time-series and on individual equations of the benchmark VAR. In line with the current literature we consider the Quandt-Andrews $SupF$ test (Quandt, 1960; Andrews, 1993) defined as the largest test statistics of the individual Chow breakpoint tests performed over all possible break dates between τ_1 and τ_2, i.e. $SupF = max_{\tau_1 \leq \tau \leq \tau_2}\left(F(\tau)\right)$. For that purpose we use the Wald F version of the Chow test with 15% trimming. In addition, we also use exponentially weighted Wald test suggested by Andrews and Ploberger (1994), $ExpF = ln\left(\frac{1}{\tau_2-\tau_1+1}\sum_{\tau=\tau_1}^{\tau_2} exp\left(\frac{1}{2}F(\tau)\right)\right)$, which summarizes all single breakpoint tests performed at every observation into one test statistics for a test against the null hypothesis of no breaks between τ_1 and τ_2. The *p*-values are calculated as asymptotic *p*-values using the approximation of Hansen (1997), as well as using the fixed-regressor bootstrap developed in Hansen (2000), replacement bootstrap developed in Candelon and Lütkepohl (2001), and robust "wild" bootstrap that accounts for heteroskedasticity in residuals.

Applying these standard tests for structural breaks on individual series of sovereign ($y_{1,t} = y_{SOV,t}$) and banking sector ($y_{2,t} = y_{BK,t}$) CDS log-returns, we do not find evidence of any discrete shift in neither of the series during the time period considered (see Table 4, Panel A). However, it is evident that the null hypothesis of no structural breaks is rejected in most of the cases when individual equations of the VAR model are considered. These results are reported in Table 4, Panel B. The maximum sup-Wald statistic for the first equation refers to the January 22, 2010, and for the second equation to January 28, 2010, suggesting that the VAR system is likely to have a common break. Interestingly, these break dates coincide with the European Commission approval of the Spanish recapitalization scheme for credit institutions on January 28, 2010, that allowed the bank bail-out fund – FROB to acquire convertible preference shares to be issued by credit institutions. In addition, the breakpoint tests performed on the constant coefficient and slope coefficients separately reveal that instability of the system comes in fact from the changes in the return transmission mechanism, even after the eventual changes in the variance are accounted for.

To detect eventual shifts in the variance we work with VAR residuals before and after accounting for breaks in the mean equation. Test for the break in variance is the same as a test for a break in a regression of squared residuals on a constant. We do not find evidence of the shift in variance for the banking sector component return equation whereas the variance of residuals of the sovereign CDS return equation indicates the presence of structural break on December 13, 2011. However, once we apply GARCH filtering on the data and consider GARCH filtered residuals the evidence of the break disappears. These results indicate that the GARCH model is able to capture observed heterogeneity in the volatility and that there is no firm evidence of the abrupt structural change in the level of residual variance.

<Table 4 about here>

The equation-by-equation procedure clearly rejects the null hypothesis of no structural breaks in the data. However, Bai, Lumsadaine and Stock (1998) show that the estimate of the change point is more precise when series with a common break are analyzed jointly.[3] Building on the preliminary evidence that the underlying process of the mean transmission has changed over time and without imposing any specific date *ex-ante*, we start the endogenous search for the possible break dates in the transmission channel using three bootstrapped versions of the Chow test: sample-split, break-point and forecast test as defined in Candelon and Lütkepohl (2001) and Lütkepohl and Kratzig (2004).[4] We set sequential break-even dates starting from November 2008, and recursively divide the overall sample into two sub-samples, before and after the potential break point. The bootstrapped *p*-values, calculated as defined in Candelon and Lütkepohl (2001), for the recursive sample-split Chow test are presented in Figure 2.

<Figure 2 about here>

All three recursive tests for structural breaks clearly indicate that there is a structural change in the system. The null hypothesis of no breaks is rejected, at least at 5% level, by all three measures for all days during the period that spans from the beginning of November 2009 (November 3, 2009) to the beginning of February 2010 (February 5, 2010). The absolute maximum of all three measures (i.e. the largest test statistic over all possible break dates) corresponds to the January 6, 2010, which is

[3] The breaks specific to each equation do not necessarily reflect the breaks in the system that is approximated by the VAR as the system approach makes an assumption that the change in the transmission mechanism occurs at the same point in time for both equations.

[4] Candelon and Lütkepohl (2001) show that the distributions of the test statistics under the stability hypothesis may be different from assumed χ^2 and F distributions in dynamic models, and that bootstrapped p-values are more reliable.

formally confirmed with the "supremum" test of Andrews (1993). The $ExpF$ test for a structural break with unknown break point verifies the existence of the statistically significant structural break in the VAR system (see Table 5, Panel A). Finally, for a partial structural change model in which only a subset of coefficients is subject to change, as before, constant coefficients seem to be stable over time while it is precisely the slope coefficients that exhibit structural breaks.

<Table 5 about here>

The previous tests clearly provide evidence of at least one structural break in the initial benchmark VAR model. To check for the possibility of more structural breaks we continue in line with Bai (1997) and Bai and Perron (1998) sequential tests for multiple structural changes. We start by splitting the sample in two, using as a starting break date point the January 6, 2010 suggested previously by all three versions of the Chow test, and reapply the test on the spitted subsamples. We fail to find the evidence of an additional break in the first sub-period (see Table 5, Panel B), but find a statistically significant break point in the second sub-period that corresponds to May 12, 2010 (see Table 5, Panel C).[5] The bootstrapped p-values, calculated as defined in Candelon and Lütkepohl (2001), for the sample-split Chow test sequence in the two sub-periods are presented in Figure 3.

<Figure 3 about here>

In order to reinforce the structural break analysis we perform recursive Granger Causality tests by adding consecutively one observation to the sample. Figure 4 plots p-values of recursive Granger Causality tests for the sovereign and banking sector

[5] Similar results are obtained if we follow the procedure of global minimization of the sum of squared residuals developed in Bai and Perron (2003). In our case, we set as the objective function to maximize the value of the likelihood ratio, and simultaneously estimate break dates T_1 and T_2 using the grid search algorithm.

component. Interestingly, we can observe similar patterns as before. Namely, we can observe a clear one-way influence of the banking sector CDS spreads on the sovereign CDS spreads until January 2010. This initial period is followed by the short transition period that ends with the large structural change in the mean transmission mechanism between government and banking sector in May 2010. The large breakpoint in the data is confirmed on an individual bank level as well. From May 2010 and onward the null hypothesis that changes in sovereign CDS spreads do not Granger-cause changes in banks CDS spreads is rejected at 1% significance level for all banks considered on an individual basis.

<Figure 4 about here>

Taken together, all conducted tests show strong evidence in favor of the presence of the structural changes in the system. Thus, in reference to the previous analysis and several patterns revealed, we divide data into three sub-periods: November 2008 to December 2009, January 2010 to May 2010 and June 2010 to July 2012, and conduct Granger Causality tests for the three periods separately. Results are reported in Table 6. The first sub-period (November 2008 to December 2009) is characterized with the one-way influence of the banking sector on the sovereign CDS spreads. The second-sub period (January 2010 – May 2010) is characterized with a two-way feedback mean transmission mechanism between banking sector and the government. This interim period coincides with the consolidation of the Spanish banking system and major restructuring of the saving banks; the European Commission approval of the Spanish recapitalization scheme for credit institutions that sharply increased investors' expectation of government support to distressed banks; and substantial increase in the CDS spread levels across Eurozone countries following the announcement of the newly appointed Greek government of much larger than expected budget deficit (from originally stated 6% to 12.7% of GDP) in October 2009. This event raised uncertainty about the quality of banks' assets and led to reassessment, from part of investors, of the sovereigns' perceived creditworthiness across Eurozone. As a feedback effect increased sovereign credit risk directly negatively affected the quality of the bank's assets through their holdings of sovereign debt, and the value of collateral that can be used for funding. Moreover, Spain's debt rating was downgraded (from AAA to AA+ on May 28 by Fitch, and from AA+ to AA by S&P in April), leading to a cascade of downgrades of Spanish domestic banks. The third-sub period (June 2010 to July 2012) is characterized with a clear one-way influence from sovereign CDS spreads to banking sector CDS spreads. The third sub-period starts with the pronounced break in the mean transmission between sovereign and banking sector CDS spreads that occurred in the mid-May 2010 which coincides with the government public announcement of the severe austerity measures on the May 12, 2010. This event severely raised investors concerns about Spanish government deficit, negatively affecting investors' perception about the value of implicit and explicit government guarantees to banks. Moreover, it followed the first EU-IMF bailout of Greece at the May 2, 2010 when Greece received a 110 billion rescue package conditional on a series of severe austerity measures. These results of the sub-period Granger causality tests are substantially different from the results for the complete data set suggesting that without controlling for relevant structural breaks wrong conclusions about the transmission mechanism could be made.

<Table 6 about here>

In light of the previous findings we augment each equation of the baseline VAR system with the interaction break dummy variables, allowing interactions with intercept and slope coefficients (i.e. lags of the endogenous variables) preserving in this way the symmetry in the VAR system. The mean return generating process is defined as follows:

$$y_t = \alpha + \Gamma y_{t-1} + d_t^1(\delta^1 + \mathrm{D}^1 y_{t-1}) + d_t^2(\delta^2 + \mathrm{D}^2 y_{t-1}) + \varepsilon_t, \tag{3}$$

where y_t is a 2×1 vector of daily CDS spread log-changes at time *t* of sovereign ($y_{1,t} = y_{SOV,t}$) and banking sector ($y_{2,t} = y_{BK,t}$); d_t^1 is a dummy variable that takes the value 1 if the observation belongs to the first sub-period (November 2008 – December 2009) and 0 otherwise and d_t^2 is transition period dummy variable that takes the value 1 if the observation belongs to the second sub-period (January 2010 – May 2010) and 0 otherwise. In this way we consider a VAR model with the three structural regime shifts that reflect the change in the dynamics of the mean transmission. The own market segment mean spillovers and cross market segment mean spillovers are measured by the estimates of the matrix Γ, D_1 and D_2. The diagonal elements of the corresponding matrix measure the effect of the own lagged returns, and the off-diagonal elements the effect of the cross-market lagged returns. Thus, the off-diagonal elements detect the return spillover.

3. Volatility transmission

The traditional VAR model applied in recent papers is based on the assumption of homoscedasticity of residuals. Given that the time series of CDS returns resembles a GARCH process we estimate a bivariate VAR-BEKK-GARCH model proposed by Engle and Kroner (1995). We consider the full BEKK representation of Baba, Engle, Kraft, and Kroner (1990) that allows for the time-varying variance-covariance matrix and, by construction, guarantees that the estimated conditional covariance matrix is positive definite. Specifically, in order to capture conditional heteroskedasticity and estimate volatility transmission throughout the financial system we estimate the regime-switching VAR(1)-GARCH(1,1) model within the BEKK framework of the following form:

$$\varepsilon_t|\Omega_{t-1} \sim N(0, H_t) \tag{4a}$$

where

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \tag{4b}$$

$$H_t = \begin{bmatrix} \sigma_{11,t} & \sigma_{12,t} \\ \sigma_{21,t} & \sigma_{22,t} \end{bmatrix};\ C = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix};\ A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix};\ B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$$

$$\varepsilon_t = \begin{pmatrix} \varepsilon_{1,t} & \varepsilon_{2,t} \end{pmatrix}'$$

The ε_t is a 2×1 vector of residuals, i.e. vector of innovations for each market segment at time *t,* with its corresponding conditional covariance matrix, H_t. The market information available at time *t-1* is represented by the information set Ω_{t-1}.

Equation (4) defines the variance generating process. The H_t is the 2×2 conditional variance-covariance matrix of residuals, that, in the bivariate case of the model, requires 11 parameters to be estimated. The matrix C is an upper triangular matrix containing the constants for the variance equation. The ARCH coefficients are derived from the A matrix and the GARCH coefficients are derived from B matrix. We choose the GARCH(1,1) as this specification is showed to be sufficient to provide parsimonious results. The model is estimated using the maximum likelihood estimation procedure. The log-likelihood function is given by:

$$L = \sum_{t=1}^{T} L_t(\theta) = \sum_{t=1}^{T} \left(-ln(2\pi) - \frac{1}{2} ln|H_t| - \frac{1}{2} \varepsilon'_t H_t^{-1} \varepsilon_t \right)$$

The BHHH (Berndt, Hall, Hall, and Hausman (1974)) algorithm is used to maximize the log-likelihood function. The starting values for the constants in the conditional variance-covariance equations are obtained from univariate GARCH. The convergence criterion is 1e-5.

3.1. Main Results

The results from estimating bivariate VAR-BEKK-GARCH model described with equations (3) and (4) are provided in Table 7.[6] The mean spillovers are measured with the parameters of Γ matrix. Specifically, the parameters of Γ matrix measure the effects of innovation in one segment of the market to its own lagged return (diagonal elements) and that of the other segment (off-diagonal elements). For example, γ_{12}, measures the effect that the a change in banking sector CDS return has on the sovereign sector CDS return in one day time. Given that we consider a regime-switching model these coefficients have to be interpreted together with the elements provided in matrix D_1 and D_2. Considering the common banking sector component, as well as individual banks we can observe the same pattern: the mean transmission from the banking sector to the government was the strongest in the first period, decreased in the second, and completely turned around in the third sub-period in which we observe a highly pronounced mean transmission from government to the banking sector. Specifically, γ_{21} coefficient is positive and statistically significant at 1% level not only for the common banking sector component but also for all of the banks considered on an individual basis.

<Table 7 about here>

The ARCH parameters are represented by matrix A whereas the coefficients of matrix B measure the influence of lagged conditional variances and covariances on the conditional variance today. These coefficients measure the volatility clustering and the larger the coefficient the longer is the effect of shocks.

---

[6] The covariance stationarity in the BEKK model is ensured if eigenvalues of $(A \otimes A) + (B \otimes B)$, are less than one in modulus. The biggest of eignevalues is around 0.98 in modules which means that time varying volatility is highly persistent. We check the adequacy of the VAR-BEKK-GARCH specification using the Ljung-Box Q-statistic and Lagrange Multiplier (LM). We report Ljung-Box statistics for standardized squared residuals up to lag 12 and 24. The results show no serial dependence in the standardized squared residuals which indicates that the model is appropriate and that is able to capture the dynamics of the conditional volatility well.

The diagonal elements of A and B matrices measure the effect of the own past shocks (a_{ii}) and past volatility (b_{ii}). The a_{11} measures the dependence of conditional sovereign CDS return volatility on its own lagged past shocks, and a_{22} the dependence of conditional banking sector CDS return volatility on its own lagged past shocks. The a_{11} and a_{22} coefficients are statistically significant at 1% level in all of the cases, indicating that there were strong ARCH effects. The b_{11} measures the dependence of conditional sovereign CDS return volatility on its own lagged volatility, and b_{22} the dependence of conditional banking sector CDS return volatility on its own lagged volatility. The b_{11} and b_{22} coefficients are statistically significant at 1% level in all of the cases, indicating that there were strong GARCH effects.

We are here particularly interested in the off-diagonal elements as these will reveal the volatility spillovers across the market segments considered. The coefficient a_{ij} measures the spillover of the squared values of shocks in the previous period from the i^{th} to the current volatility of j^{th} market. The a_{21} measures the dependence of conditional sovereign CDS return volatility on the lagged shocks of bank CDS returns. The a_{21} coefficient is statistically significant at 1% level for the banking sector credit risk component, and individually for Banco Santander, BBVA, La Caixa and Bankinter. The opposite effect, the dependence of conditional banking sector CDS return volatility on the lagged shocks of sovereign CDS returns is measured with the a_{12} coefficient. This coefficient is statistically significant at least at 5% level in the case of BBVA, Banco Popular, Banco Sabadell and Bankinter. Nevertheless, the common banking sector component is not statistically significant.

On the other hand, b_{ij} measures the spillover of the conditional volatility of the i^{th} market in the previous period to the j^{th} market in the current period. The b_{21} measures the dependence of conditional sovereign CDS return volatility on the lagged volatility of bank CDS returns. The b_{21} coefficient is statistically significant at 1% for the common banking sector component, Banco Santander, BBVA and La Caixa. The b_{12} measures the dependence of conditional banking sector CDS return volatility on the lagged volatility of sovereign CDS returns. The common banking sector component as well as the volatility of CDS returns of BBVA, Banco Pastor, Banco Popular and Bankinter are affected by lagged volatility of sovereign CDS returns.

Figure 6 presents conditional variances and covariances for sovereign CDS returns and first principal component of the banking sector CDS returns. The peak in conditional variances and covariances refers to 11th of May 2010, which coincides with the abrupt break detected in the mean transmission. The time-varying conditional correlations between sovereign returns and common factor in banks' returns, presented in Figure 7 are positive throughout the sample period, ranging from minimum of 0.21 and maximum of 0.95, with the mean of 0.56. The positive correlations for the overall sample period considered suggest that the two variables are interconnected.

<Figure 6 about here>

<Figure 7 about here>

In conclusion, although there is an evidence of the two-way volatility transmission between sovereign and banking sector CDS returns the results of the variance equation show that volatility transmission from banking sector to sovereign sector is particularly evident in the case of the 3 largest Spanish banks: Banco Santander, BBVA and La Caixa, whereas the opposite doesn't hold. Namely, the volatility transmission from sovereign to banking sector seems to be less pronounced for these financial institutions and, specifically, we do not find any evidence of the volatility transmission from sovereign level to CDS spread returns of Banco Santander and La Caixa.

3.2. Structural changes in the volatility transmission

In order to detect eventual changes in the volatility transmission it is possible to apply Granger Causality test directly on time-varying variances in a VAR framework of the following form:

$$\sigma_{11,t} = \alpha_1 + \sum_{j=1}^{p} \gamma_{11,j}\, \sigma_{11,t-p} + \sum_{j=1}^{p} \gamma_{12,j}\, \sigma_{22,t-p} + \varepsilon_{1,t} \ , \qquad (5)$$

$$\sigma_{22,t} = \alpha_2 + \sum_{j=1}^{p} \gamma_{21,j}\, \sigma_{11,t-p} + \sum_{j=1}^{p} \gamma_{22,j}\, \sigma_{22,t-p} + \varepsilon_{2,t} \ . \qquad (6)$$

where $\sigma_{11,t}$ is the time-varying sovereign CDS return volatility and $\sigma_{22,t}$ is the time-varying banking sector CDS return volatility , ε_1 and ε_2 are i.i.d. error terms, and p is the number of lags determined according to the Schwarz Information Criterion. The optimal number of lags is 3. In line with previous analysis we test for the structural breaks in the VAR system and find a significant break point that again coincides with the May 12, 2010. Once the overall sample is divided in two subsamples, and the structural break point tests reapplied on the two subsamples, additional break point can be detected only in the first sub-period, and coincides with January 28, 2010. These results, presented in Table 8, are quite in line with the breaks detected in the mean transmission and independent of whether sovereign and banking sector volatility is calculated before or after accounting the changes in the mean transmission. Finally, the results of the pairwise Granger Causality tests are presented in Table 9.

<Table 8 about here>

<Table 9 about here>

4. Conclusions

The mechanism of shock transmissions between sovereign and banking sector default risk has important implications for financial stability, but is not well understood. This paper shed light upon this issue by empirically investigating the mean and volatility transmission channel through which increased sovereign credit risk can spill over to the banking sector by increasing the financing costs of banks (and vice versa), using the sample of systematically important banks in Spain during the period 2008-2012. We contribute to the existing literature in two ways. First, unlike previous studies, we endogenously search for potential structural breaks in the mean and volatility transmission mechanism. Our main results show that there is an evident change in the mean return transmission over the period examined: from a pronounced one-way bank to sovereign transmission at the beginning of the period, to a pronounced one-way sovereign to bank transmission since mid-May 2010. Endogenously identified break dates coincide with important events for the Spanish financial system that severely affected investors' perception of the government implicit and explicit support to distressed banks. Second, we account not only for the conditional mean but also for the conditional variance using the VAR-BEKK-GARCH framework. We find evidence of two-way volatility transmission between sovereign and banking sector CDS returns, with strong volatility transmission from the three largest banks in Spain to the sovereign level. Moreover, we provide preliminary evidence of the changes in the volatility transmission from two-way transmission to one-way sovereign to bank transmission since mid-May 2010.

References

Acharya, V.V., Drechsler, I., and Schnabl, P., 2011, “A Pyrrhic Victory? - Bank Bailouts and Sovereign Credit Risk”, NBER Working Paper No. 17136;

Alter, A., and Schüler Y.S., 2012, “Credit spread interdependencies of European states and Banks during the financial crisis”, *Journal of Banking and Finance*, 36, 3444-3468;

Andrews, D.W.K., 1993, “Tests for parameter instability and structural change with unknown change point”, *Econometrica*, 61, 821-856;

Andrews, D.W.K., and Ploberger, W., 1994, “Optimal tests when a nuisance parameter is present only under the alternative”, *Econometrica*, 62, 1383-1414;

Attinasi, M.G., Checherita, C., and Nickel, C., 2009, “What explains the surge in Euro Area sovereign spreads during the financial crisis of 2007-09?”, EBC Working paper 1131;

Baba, Y., R.F. Engle, D. Kraft, and K. Kroner, 1990, Multivariate simultaneous generalized ARCH, unpublished manuscript, University of California, San Diego;

Bai, J., 1997, “Estimating multiple breaks one at a time”, *Economic Theory*, 13(3), 315-352;

Bai, J., Lumsadine, R.L., and Stock, J.H., 1998, “Testing for and dating common breaks in multivariate time series”, *Review of Economic Studies*, 65, 395-432;

Bai, J., and Perron, P., 1998, “Estimating and testing linear models with multiple structural changes”, *Econometrica*, 66, 47-78;

Bai, J., and Perron, P., 2003, “Computation and analysis of multiple structural change models”, *Journal of Applied Econometrics*, 18, 1-22;

Candelon, B., and Lütkepohl, H., 2001, “On the reliability of Chow-type tests for parameter constancy in multivariate dynamic models”, *Economics Letters*, 73, 155-160;

Dieckmann, S., and Plank, T., 2011, “Default Risk of Advanced Economies: An Empirical Analysis of Credit Default Swaps during the Financial Crisis”, Working paper;

Engle, R.F., and Kroner, K.F., 1995, “Multivariate Simultaneous Generalized ARCH”, *Econometric Theory*, 11(5), 122-150;

Gerlach, S., Schulz, A., and Wolff, G., 2010, “Banking and Sovereign Risk in the Euro Area”, Deutsche Bundesbank Discussion Paper No. 09;

Hansen, B., 1997, “Approximate asymptotic *p* values for structural change tests”, *Journal of Business and Economic Statistics*, 1, 60-67;

Hansen,B., 2000, “Testing for structural change in conditional models”, *Journal of Econometrics*, 97(1), 93-115;

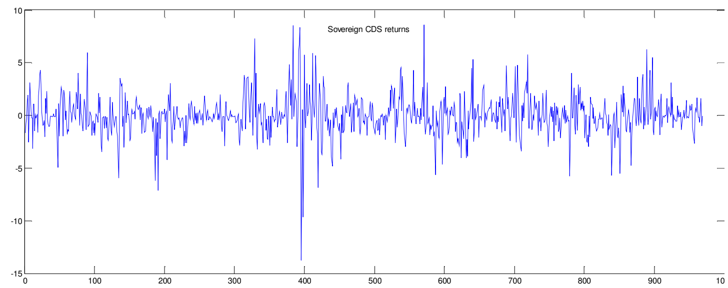
Kalbaska, A., and Gatkowski, M., 2012, “Eurozone sovereign contagion: Evidence from the CDS market (2005-2010)”, *Journal of Economic Behavior & Organization* (forthcoming);

Kallestrup, R., Lando, D., and Murgoci, A., 2012, “Financial sector linkages and the dynamics of bank and sovereign credit spreads”, Working paper;

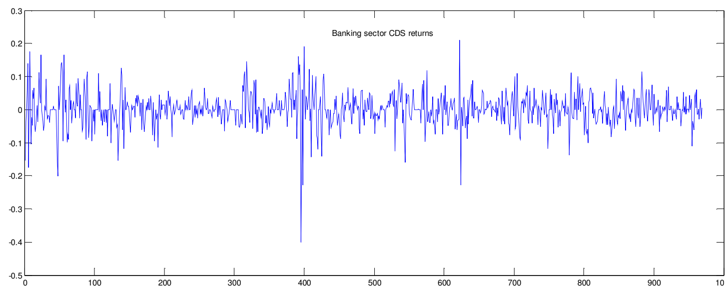
Lütkepohl, H, and M. Kratzig, 2004, “Applied Time Series Econometrics”, Cambridge University Press;

Quandt, R., 1960, “Tests of the hypothesis that a linear regression system obeys two separate regimes”, *Journal of the American Statistical Association*, 55, 324-330;

Figure 1. Daily sovereign and banking CDS returns



Q^2 *(12)*	187,35
p-val	0,00
Q^2 *(24)*	206,86
p-val	0,00
LM^2 *(12)*	136,04
p-val	0,00
LM^2 *(24)*	140,96
p-val	0,00



Q^2 *(12)*	278,76
p-val	0,00
Q^2 *(24)*	329,98
p-val	0,00
LM^2 *(12)*	197,25
p-val	0,00
LM^2 *(24)*	202,47
p-val	0,00

Figure 2. Bootstrapped p-values from the sample-split test

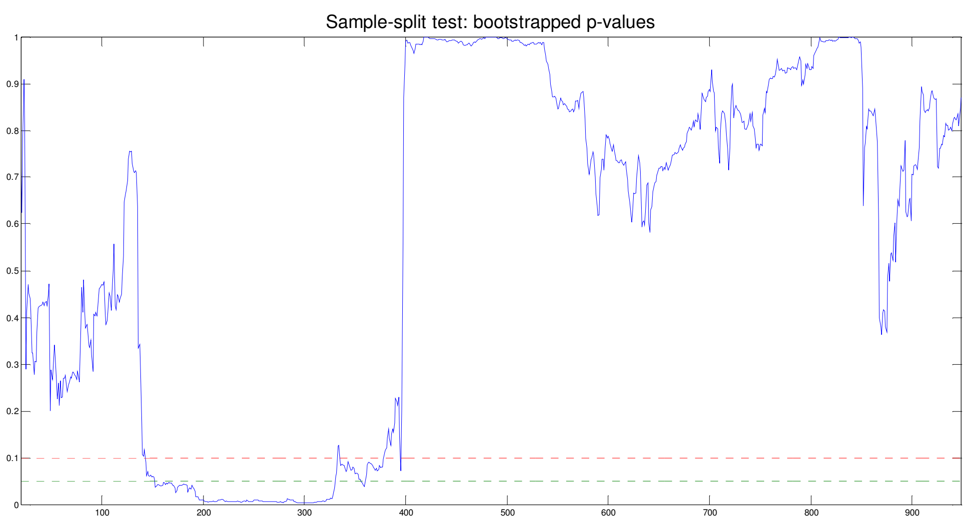
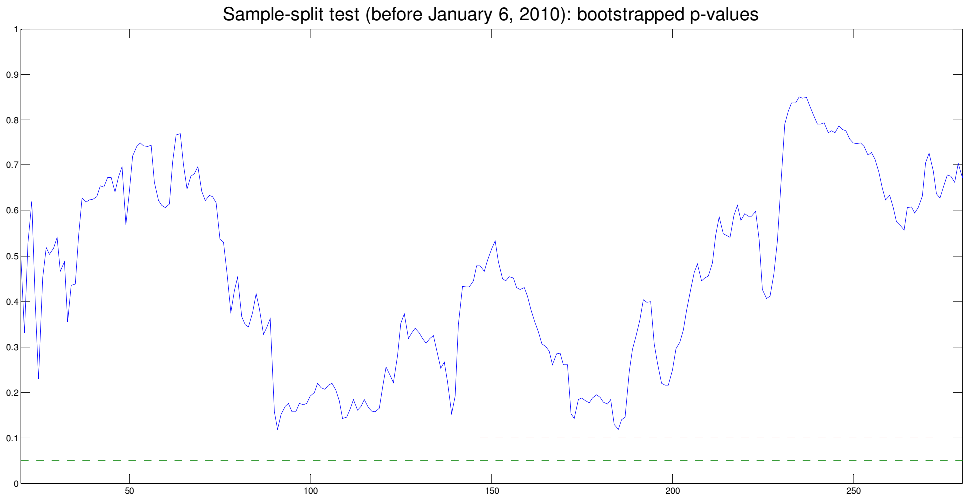


Figure 3. Bootstrapped p-values before and after January 6th 2010



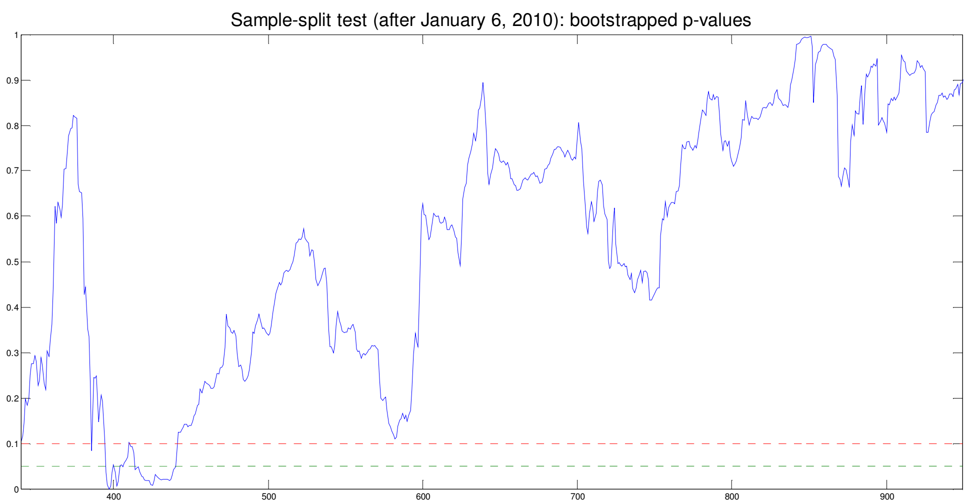
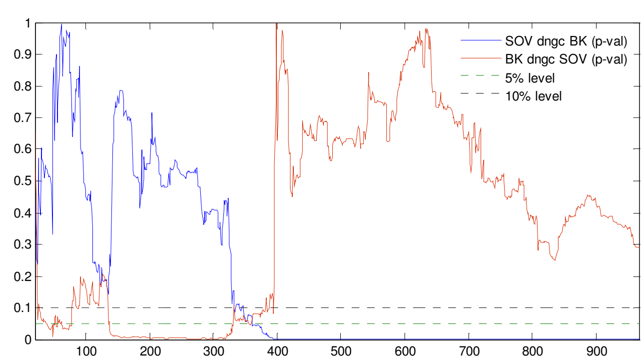


Figure 4. Recursive Granger causality tests (*p*-values) – banking sector component



The graph represents p-values of recursive Granger Causality tests estimated by adding consecutively one observation to the sample.

Figure 6. Conditional variances for sovereign and banks CDS returns

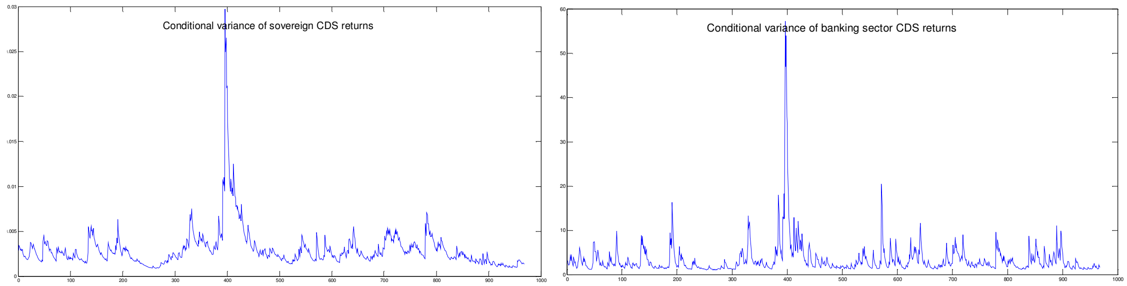


Figure 7. Conditional correlations between sovereign and banks CDS returns

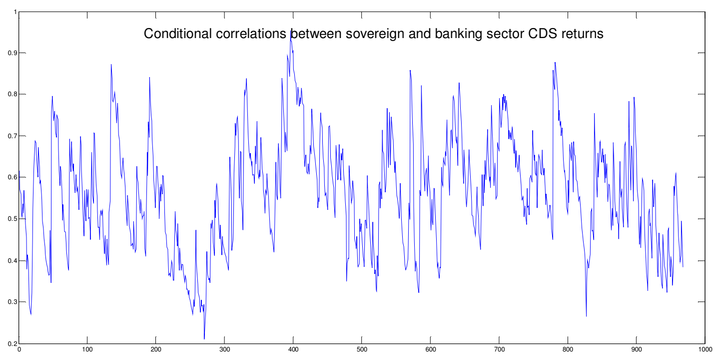


Table 1. Summary statistics of sovereign and banking sector CDS spreads

Panel A

Entity	Mean	Max	Min	SD	Skew	Kurt	Jarq-B	*p*-value	ADF test	
									t-stat	*p*-val
Spain	193.31	472.62	47.00	106.82	0.63	2.41	78.32	0.00	-2.90	0.16
Banco Santander	211.57	487.76	63.00	112.10	0.62	2.53	72.13	0.00	-3.21	0.08
BBVA	205.60	487.59	66.16	109.65	0.69	2.46	89.51	0.00	0.67	0.86
La Caixa	238.30	446.42	82.75	81.64	-0.19	2.45	18.09	0.00	0.02	0.69
Banco Pastor	510.92	1387.23	165.00	253.43	1.23	4.27	311.45	0.00	-0.01	0.68
Banco Popular	387.96	872.33	133.00	221.03	0.87	2.44	135.72	0.00	0.47	0.82
Banco Sabadell	388.15	837.91	133.71	204.69	0.88	2.49	135.31	0.00	0.46	0.81
Bankinter	364.06	820.09	137.50	184.95	0.93	2.69	144.63	0.00	0.10	0.71

Panel B

Entity	Mean	Max	Min	SD	Skew	Kurt	Jarq-B	*p*-value	ADF test	
									t-stat	*p*-val
Spain	0.1689	28.26	-41.75	5.45	-0.35	8.63	1,298.74	0.00	-18.22	0.00
Banco Santander	0.1533	20.97	-40.06	4.91	-0.62	9.87	1,966.51	0.00	-17.64	0.00
BBVA	0.1914	17.04	-37.33	4.58	-0.77	10.88	2,600.43	0.00	-16.73	0.00
La Caixa	0.0481	23.61	-27.50	3.80	-0.09	14.14	5,008.51	0.00	-29.25	0.00
Banco Pastor	0.0922	39.33	-43.53	4.27	-1.05	34.19	39,454.27	0.00	-32.17	0.00
Banco Popular	0.1497	18.64	-21.15	3.18	-0.43	14.69	5,546.80	0.00	-26.00	0.00
Banco Sabadell	0.1316	15.83	-17.22	2.97	-0.04	10.22	2,105.86	0.00	-15.09	0.00
Bankinter	0.1317	22.31	-32.61	3.61	-0.24	19.61	11,148.33	0.00	-16.66	0.00

This table provides main summary statistics for Spanish sovereign CDS spreads and CDS spreads of seven major financial institutions in Spain. ADF unit root tests are performed for three possible alternatives: without constant and trend in the series, with constant and without trend, and with constant and trend. Reported ADF test statistics correspond to the model with the lowest Schwartz Information Criterion, where the number of lags is determined according to the Akaike Information Criterion. Panel A depicts main descriptive statistics in CDS spread levels and Panel B main descriptive statistics of CDS spread returns expressed in %. CDS returns are calculated as log differences.

Table 2. Principal component analysis

Bank	CDS levles		CDS changes	
	loadings	corr(bank, FC1)	loadings	corr(bank, FC1)
Banco Santander	0.387	0.94	0.422	0.79
BBVA	0.383	0.95	0.432	0.81
La Caixa	0.284	0.70	0.388	0.73
Banco Pastor	0.379	0.93	0.234	0.44
Banco Popular	0.402	0.99	0.364	0.68
Banco Sabadell	0.401	0.98	0.426	0.80
Bankinter	0.395	0.97	0.339	0.64
First component	85.9%		50.1%	

This table provides results from principal component analysis conducted on CDS spread levels and CDS spread changes.

Table 3. Granger Causality Test

Bank	ΔCDS_{sov} does not GC ΔCDS_{bk}		ΔCDS_{bk} does not GC ΔCDS_{sov}		Correlation
	F-Statistics	Prob.	F-Statistics	Prob.	
First component	**32.53**	**0.00 *****	**1.36**	**0.24**	**0.62**
Banco Santander	24.53	0.00 ***	1.83	0.18	0.66
BBVA	38.54	0.00 ***	1.49	0.22	0.65
La Caixa	46.99	0.00 ***	1.14	0.29	0.44
Banco Pastor	30.69	0.00 ***	2.00	0.16	0.20
Banco Popular	24.33	0.00 ***	0.71	0.40	0.33
Banco Sabadell	43.89	0.00 ***	4.25	0.04 **	0.41
Bankinter	35.82	0.00 ***	5.20	0.02 **	0.28

The table reports pairwise Granger Causality Test statistics for the common systematic component of the banking sector and the individual banks when overall sample period is considered (November 2008 – July 2012). The number of lags is selected according to the Schwarz Information Criterion. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 4. Tests for structural breaks – individual equations

Panel A

	Test statistic	Approximate p-value	Bootstrap p-value(1)	Bootstrap p-value(2)	Bootstrap p-value(3)		Test statistic	Approximate p-value	Bootstrap p-value(1)	Bootstrap p-value(2)	Bootstrap p-value(3)
First series: y_{SOV}						**Second series: y_{BK}**					
SupF	1.88	0.815	0.816	0.807	0.781	SupF	4.72	0.278	0.280	0.290	0.232
ExpF	0.15	0.898	0.871	0.882	0.872	ExpF	0.64	0.344	0.346	0.350	0.334

Panel B

	Test statistic	Approximate p-value	Bootstrap p-value(1)	Bootstrap p-value(2)	Bootstrap p-value(3)		Test statistic	Approximate p-value	Bootstrap p-value(1)	Bootstrap p-value(2)	Bootstrap p-value(3)
VAR equation (1): y_{SOV}						**VAR equation (2): y_{BK}**					
H_0: Stability of all coefficients						H_0: Stability of all coefficients					
Ha: There is a structural break						Ha: There is a structural break					
SupF	15.37	0.027	0.032	0.035	0.050	SupF	13.21	0.065	0.054	0.067	0.101
ExpF	5.52	0.017	0.017	0.020	0.031	ExpF	3.57	0.095	0.081	0.078	0.142
H_0: Stability of the constant coefficient						H_0: Stability of the constant coefficient					
SupF	1.40	0.930	0.918	0.918	0.916	SupF	3.27	0.501	0.494	0.511	0.490
ExpF	0.11	1.000	0.936	0.938	0.942	ExpF	0.33	0.605	0.599	0.610	0.603
H_0: Stability of the slope coefficients						H_0: Stability of the slope coefficients					
SupF	14.72	0.013	0.011	0.014	0.030	SupF	12.35	0.036	0.030	0.037	0.051
ExpF	5.38	0.006	0.004	0.007	0.017	ExpF	3.01	0.061	0.064	0.057	0.070
H_0: Stability of the variance						H_0: Stability of the variance					
SupF	11.83	0.011	0.008	0.015	0.010	SupF	5.14	0.233	0.238	0.187	0.199
ExpF	2.96	0.016	0.017	0.015	0.012	ExpF	1.31	0.127	0.138	0.110	0.128
GARCH filtered residuals						GARCH filtered residuals					
SupF	4.45	0.312	0.333	0.294	0.269	SupF	2.50	0.664	0.665	0.656	0.626
ExpF	0.52	0.422	0.443	0.438	0.423	ExpF	0.29	0.658	0.656	0.667	0.676

This table reports $SupF$ and $ExpF$ break-point tests. Panel A reports results for individual CDS return series, and Panel B results for individual equations of the benchmark VAR described in (1) and (2). The p-values are calculated as: a) asymptotic p-values using the approximation of Hansen (1997) – *Approximate p-value*, b) fixed-regressor bootstrap values developed in Hansen (2000) – *Bootstrap p-value(1)*, c) replacement bootstrap values developed in Candelon and Lütkepohl (2001) – *Bootstrap p-value(2)*, and d) robust "wild" bootstrap values – *Bootstrap p-value(3)*. The number of bootstrap replications is set to 1,000.

Table 5. Tests for structural break in VAR system

	Panel A: Whole sample				
	Test statistic	Approximate p-value	Bootstrap p-value(1)	Bootstrap p-value(2)	Bootstrap p-value(3)
VAR system					
H_0: Stability of all coefficients Ha: There is a structural break					
Sup	20.32	0.045	0.043	0.040	0.090
Exp	7.68	0.028	0.025	0.035	0.065
H_0: Stability of the constant coefficient					
Sup	3.95	0.735	0.736	0.734	0.727
Exp	0.39	0.939	0.925	0.917	0.937
H_0: Stability of the slope coefficients					
Sup	17.83	0.027	0.030	0.022	0.070
Exp	6.89	0.010	0.012	0.012	0.043

	Panel B: First sub-period				
	Test statistic	Approximate p-value	Bootstrap p-value(1)	Bootstrap p-value(2)	Bootstrap p-value(3)
VAR system					
H_0: Stability of all coefficients Ha: There is a structural break					
Sup	10.99	0.598	0.592	0.584	0.574
Exp	3.33	0.570	0.574	0.596	0.591
H_0: Stability of the constant coefficient					
Sup	8.97	0.142	0.152	0.145	0.129
Exp	2.51	0.104	0.118	0.111	0.110
H_0: Stability of the slope coefficients					
Sup	3.95	0.985	0.982	0.972	0.956
Exp	0.83	0.989	0.984	0.980	0.966

	Panel C: Second sub-period				
	Test statistic	Approximate p-value	Bootstrap p-value(1)	Bootstrap p-value(2)	Bootstrap p-value(3)
VAR system					
H_0: Stability of all coefficients Ha: There is a structural break					
Sup	19.78	0.054	0.055	0.052	0.096
Exp	5.72	0.127	0.134	0.120	0.206
H_0: Stability of the constant coefficient					
Sup	9.90	0.099	0.089	0.113	0.099
Exp	1.52	0.303	0.301	0.312	0.305
H_0: Stability of the slope coefficients					
Sup	15.99	0.055	0.050	0.064	0.093
Exp	3.60	0.192	0.214	0.197	0.256

This table reports $SupF$ and $ExpF$ break-point tests in VAR system described in (1) and (2). Panel A reports results for the overall sample period, Panel B results for the first sub-period, from November 2008 to December 2009, and Panel C results for the second sub-period, from January 2010 to July 2012. The p-values are calculated as: a) asymptotic p-values using the approximation of Hansen (1997) – *Approximate p-value*, b) fixed-regressor bootstrap values developed in Hansen (2000) – *Bootstrap p-value*(1), c) replacement bootstrap values developed in Candelon and Lütkepohl (2001) – *Bootstrap p-value*(2), and d) robust "wild" bootstrap values – *Bootstrap p-value*(3). The number of bootstrap replications is set to 1,000.

Table 6. Granger Causality Test

Period	Observations	ΔCDS_{sov} does not GC ΔCDS_{bk}		ΔCDS_{bk} does not GC ΔCDS_{sov}		Correlation
		F-Statistics	Prob.	F-Statistics	Prob.	
Whole sample	**969**	**32.53**	**0.00 *****	**1.36**	**0.24**	**0.62**
One break						
November 2008 - December 2009	304	0.68	0.41	9.06	0.00 ***	0.53
January 2010 - July 2012	665	35.86	0.00 ***	7.18	0.01 ***	0.65
Two breaks						
November 2008 - December 2009	304	0.68	0.41	9.06	0.00 ***	0.53
January 2010 - May 2010	107	13.02	0.00 ***	4.35	0.04 **	0.72
June 2010 - July 2012	558	18.87	0.00 ***	2.04	0.15	0.61

The table reports pairwise Granger Causality Test statistics for the sovereign level and common systematic component of the banking sector considering the overall sample, and assuming one and two breaks in the system. The number of lags is selected according to the Schwarz Information Criterion. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 7. The regime-switching VAR-BEKK-GARCH(1,1)

Parameter	First component	Banco Santander	BBVA	La Caixa	Banco Pastor	Banco Popular	Banco Sabadell	Bankinter
γ_{11}	0.218 ***	0.122 **	0.182 ***	0.193 ***	0.193 ***	0.190 ***	0.188 ***	0.203 ***
γ_{12}	-0.002	0.088	-0.018	-0.061	-0.139 **	-0.088	-0.065	-0.143 **
γ_{21}	7.829 ***	0.194 ***	0.296 ***	0.172 ***	0.139 ***	0.056 **	0.104 ***	0.137 ***
γ_{22}	0.143 ***	0.060	-0.051	-0.035	-0.023	0.177 ***	0.107 **	-0.079 *
d_{11}^1	-0.179 *	-0.093	-0.170	-0.048	-0.035	-0.051	-0.039	-0.048
d_{12}^1	0.009 ***	0.122	0.254 **	0.159	0.156 *	0.196	0.163	0.244 *
d_{21}^1	-6.325 *	-0.118	-0.246 ***	-0.113 *	-0.029	0.021	-0.005	-0.086
d_{22}^1	0.155	0.091	0.250 ***	-0.087	-0.086	-0.064	-0.086	0.050
d_{11}^2	0.119	0.179 *	0.036	0.093	0.021	0.029	0.139 *	0.026
d_{12}^2	-0.005 *	-0.300 **	-0.064	-0.251 *	-0.103	-0.172	-0.508 ***	-0.113
d_{21}^2	5.165	0.149	-0.049	0.053	0.011	0.108 **	0.062	0.049
d_{22}^2	-0.170 *	-0.337 ***	-0.022	-0.004	-0.045	-0.162 *	-0.047	-0.081
c_{11}	0.006 *	0.009 ***	0.007 ***	0.007 ***	0.016 ***	0.006 ***	0.007 ***	0.004
c_{12}	0.398 **	0.014 ***	0.006 *	0.006	0.005 ***	-0.001	0.002	-0.028
c_{22}	0.509 ***	0.004 ***	0.012 ***	0.013 ***	0.008 ***	0.007 ***	0.006 ***	0.000
a_{11}	0.179 ***	0.186 ***	0.160 ***	0.210 ***	0.342 ***	0.235 ***	0.235 ***	0.202 ***
a_{12}	0.805	0.010	-0.061 ***	0.023	0.010	-0.032 **	0.031 **	-0.252 ***
a_{21}	0.005 ***	0.158 ***	0.214 ***	0.140 ***	0.018	0.063	0.039	0.221 ***
a_{22}	0.468 ***	0.411 ***	0.446 ***	0.564 ***	0.232 ***	0.223 ***	0.287 ***	0.400 ***
b_{11}	0.996 ***	0.989 ***	0.981 ***	0.975 ***	0.888 ***	0.966 ***	0.965 ***	0.984 ***
b_{12}	2.044 **	0.010	0.040 *	0.019	-0.034 ***	0.017 ***	-0.002	0.215 ***
b_{21}	-0.002 ***	-0.089 ***	-0.068 ***	-0.067 ***	0.009	-0.012	-0.015	-0.266 *
b_{22}	0.766 ***	0.850 ***	0.832 ***	0.752 ***	0.956 ***	0.944 ***	0.928 ***	0.322 ***
Log likelihood	-106.607	3,450.88	3,515.23	3,548.58	3,282.82	3,598.80	3,741.41	3,448.33
AIC	0.25	-7.11	-7.24	-7.31	-6.76	-7.42	-7.71	-7.11
SC	0.31	-7.04	-7.18	-7.25	-6.70	-7.35	-7.65	-7.05
LR(χ^2)	387.27	475.65	452.50	137.62	57.65	97.83	122.24	76.16
LR(*p*-val)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$Q^2(12)$	9.61	10.80	7.08	4.47	14.46	5.01	4.61	3.26
p-val	0.65	0.55	0.85	0.97	0.27	0.96	0.97	0.99
$Q^2(24)$	31.24	15.61	15.60	9.53	21.39	17.87	20.80	8.92
p-val	0.15	0.90	0.90	1.00	0.62	0.81	0.65	1.00
$LM^2(12)$	8.92	10.77	6.59	4.76	13.34	5.82	5.28	3.20
p-val	0.71	0.55	0.88	0.97	0.34	0.93	0.95	0.99
$LM^2(24)$	31.09	14.88	15.29	10.68	20.91	22.64	22.02	8.65
p-val	0.15	0.92	0.91	0.99	0.64	0.54	0.58	1.00

This table presents the regression estimation results allowing for three shifts. d^1 is a dummy variable that takes the value 1 if the observation belongs to the first sub-period (November 2008 – December 2009) and 0 otherwise and d^2 is a dummy variable that takes the value 1 if the observation belongs to the second sub-period (January 2010 – May 2010) and 0 otherwise. Constant terms are not are not reported to save space. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 8. Tests for structural break in volatility transmission

	Panel A: Whole sample						Panel B: First sub-period						Panel C: Second sub-period				
	Test statistic	Approximate p-value	Bootstrap p-value(1)	Bootstrap p-value(2)	Bootstrap p-value(3)		Test statistic	Approximate p-value	Bootstrap p-value(1)	Bootstrap p-value(2)	Bootstrap p-value(3)		Test statistic	Approximate p-value	Bootstrap p-value(1)	Bootstrap p-value(2)	Bootstrap p-value(3)
VAR system - before accounting for changes in the mean																	
H_0: Stability of all coefficients Ha: There is a structural break						H_0: Stability of all coefficients Ha: There is a structural break						H_0: Stability of all coefficients Ha: There is a structural break					
Sup	98.93	0.000	0.000	0.021	0.020	Supl	45.19	0.001	0.002	0.121	0.067	Supl	27.58	0.211	0.243	0.476	0.767
Exp	42.95	0.000	0.000	0.021	0.021	Exp	18.66	0.001	0.004	0.102	0.067	Exp	10.92	0.175	0.199	0.393	0.736
Ave	30.16	0.000	0.000	0.017	0.084	Ave	25.88	0.004	0.008	0.025	0.053	Ave	16.25	0.236	0.246	0.320	0.631
VAR system - after accounting for changes in the mean																	
H_0: Stability of all coefficients Ha: There is a structural break						H_0: Stability of all coefficients Ha: There is a structural break						H_0: Stability of all coefficients Ha: There is a structural break					
Sup	108.41	0.000	0.000	0.006	0.005	Supl	41.68	0.004	0.006	0.160	0.075	Supl	27.24	0.227	0.232	0.520	0.761
Exp	47.69	0.000	0.000	0.007	0.006	Exp	16.76	0.005	0.008	0.157	0.080	Exp	10.76	0.190	0.212	0.442	0.731
Ave	31.36	0.000	0.000	0.011	0.067	Ave	23.45	0.013	0.020	0.049	0.068	Ave	16.08	0.250	0.242	0.330	0.634

This table reports $SupF$ and $ExpF$ break-point tests in VAR system described in (5) and (6). Panel A reports results for the overall sample period, Panel B results for the first sub-period, from November 2008 to May 2010, and Panel C results for the second sub-period, from June 2010 to July 2012. The p-values are calculated as: a) asymptotic p-values using the approximation of Hansen (1997) – *Approximate p-value*, b) fixed-regressor bootstrap values developed in Hansen (2000) – *Bootstrap p-value(1)*, c) replacement bootstrap values developed in Candelon and Lütkepohl (2001) – *Bootstrap p-value(2)*, and d) robust "wild" bootstrap values – *Bootstrap p-value(3)*. The number of bootstrap replications is set to 1,000.

Table 9. Granger Causality Test

Period	Observations	σ_{sov} does not GC σ_{bk}		σ_{bk} does not GC σ_{sov}	
		F-Statistics	Prob.	F-Statistics	Prob.
Whole sample	**969**	**6.12**	**0.00 *****	**8.26**	**0.00 *****
One break					
November 2008 -May 2010	411	5.19	0.00 ***	13.85	0.00 ***
June 2010 - July 2012	558	4.09	0.04 **	2.05	0.15
Two breaks					
November 2008 - January 2009	321	1.13	0.34	3.95	0.01 ***
February 2010 - May 2010	90	0.64	0.59	1.65	0.18
June 2010 - July 2012	558	4.09	0.04 **	2.05	0.15

The table reports pairwise Granger Causality Test statistics for the variance of the sovereign CDS returns and variance of the banking sector CDS returns considering the overall sample, and assuming one and two breaks in the system. The number of lags is selected according to the Schwarz Information Criterion. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.