Credit Spread Interdependencies of European States and Banks during the Financial Crisis

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Abstract

This study proposes a setup for measuring the interdependence of the default risk of several European countries (France, Germany, Italy, Ireland, Netherlands, Portugal, Spain) and their domestic banks during the period June 2007 - May 2010. Using daily credit default swap (CDS) spreads, we investigate how bank bailout programs affected the link between the default risk of governments and their local banks. Our main findings suggest that in the period before bank bailouts the contagion disperses from bank credit spreads into the sovereign CDS market. After bailouts, a financial sector shock affects more strongly sovereign CDS spreads in the short-run, however the impact becomes insignificant at a long horizon. Furthermore, government CDS spreads become an important determinant of banks' CDS series. The interdependence of government and bank credit risk is heterogeneous across countries, but homogeneous within the same country.

JEL-Classification: C58, G01, G18, G21.
Keywords: credit default swaps, private-to-public risk transfer, bank bailout, cointegration, generalized impulse responses.

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"The scope and magnitude of the bank rescue packages also meant that significant risks had been transferred onto government balance sheets. This was particularly apparent in the market for CDS referencing sovereigns involved either in large individual bank rescues or in broad-based support packages for the financial sector."

(BIS, December 2008, p. 20)

1 Introduction

During the recent financial crisis extraordinary measures were taken by central banks and governments to prevent a potential collapse of the financial sector that threatened the entire economy. However, the effects on the interdependence of the financial and the sovereign sector were widely unknown. Gray (2009, p. 128) argues that "regulators, governments, and central banks have not focused enough on the interconnectedness between financial sector risk exposures and sovereign risk exposures and their potential interactions and spillovers to other sectors in the economy or internationally". The lack of theoretical macroeconomic models that are able to incorporate contagion mechanisms between government and financial sector amplified the uncertainty related to implications of government interventions. Nevertheless, regulators and policy makers need to understand the complex dynamics of the risk transmission in order to be able to formulate effective policies and to be aware of the risk transferred from the financial sector to governments.

As pointed out by Gray et al. (2008), using arguments from the contingent claims analysis (CCA)[1], there are several channels linking the banking and sovereign sector, which are impacted on by implicit as well as explicit guarantees. A systemic banking crisis can induce a contraction of the entire economy, which weakens public finances and transfers the distress to the government. This contagion effect is amplified when state guarantees exist for the financial sector. As a feedback effect, risk is further transmitted to holders of sovereign debt. An increase in sovereign debt costs leads to the devaluation of the government debt that impairs banks' balance sheets that hold these assets. Acharya et al. (2011) have recently used the term "two-way feedback" to describe these interdependencies. The authors construct a novel theoretical framework to model the link between bank bailouts and sovereign credit risk, emphasizing the role of a country's legacy of debt in formulating an effective rescue scheme for the financial sector.

Empirically, this interconnectedness has been described in the context of the recent financial crisis as well. For instance, Gerlach et al. (2010) find that as a consequence of macroeconomic imbalances, especially for peripheral European countries (e.g. Greece, Ireland), a jump in bond and credit default swap (CDS) spreads for sovereigns is transmitted to the banking sector. The authors claim that systemic and sovereign risk became more interwoven after governments issued guarantees for banks' liabilities. This result is supported by Ejsing and Lemke (2011) who argue

[1] This approach is based on Merton's and Black-Scholes'(1973) option pricing work. It can also be employed for measuring the sovereign-banks interaction, taking into account the implicit and explicit contingent liability for the financial system.

that the sensitivity of sovereign CDS spreads to the intensifying financial crisis increases after the bailout of the financial sector. Dieckmann and Plank (2010) present evidence for a private-to-public risk transfer in the countries where governments stabilized the financial system after the Lehman Brothers' event as well. Banks' and sovereign CDS became closely linked: financial institutions hold important amounts of government debt and states bearing vital contingent liabilities for the financial system. Furthermore, Acharya et al. (2011) provide empirical evidence for the interconnection of the financial and sovereign sector credit risk implied by bailout programs.

This paper proposes a new way to investigate changes in the interdependence of bank and sovereign credit risk in the euro area. We study the lead-lag relation between government's and bank's default risk with a focus on the effect of bank bailouts in the midst of the recent financial crisis. First, we research whether prior to government interventions an increase in default risk of banks and states originates mainly from the financial sector. Second, we assess if public contingent liabilities to the financial sector affected government's default risk. In tandem, this study examines whether default risk of the banking sector is influenced by the sovereign default risk. Finally, we investigate the following two questions: i) Does the perceived degree of a bank's participation in a national rescue scheme influence its dependency on the development of the sovereign spread? ii) Are country-specific bailout characteristics reflected in the impact of government bailout programs?

Methodologically, we consider the relationship between government and banks' CDS spreads, as they provide a proxy for the risk of default.[2] We conduct this analysis by applying the theory of cointegration, Granger-causality, and impulse responses to daily CDS series, which are able to capture changes in the dynamic relation between government and bank credit risk. We consider sovereign CDS from seven EU member states (France, Germany, Italy, Ireland, Netherlands, Portugal, and Spain) together with a selection of bank CDS from these states. We divide the analyzed period, i.e. June 2007 until May 2010, into before and after bank bailout programs.

Our main findings suggest: in the period *preceding* government interventions the contagion from bank credit spreads disperses into the sovereign CDS market. This finding can be interpreted as evidence for the systemic feature of the recent financial crisis. The default risk spills over from the financial system to the entire economy and questions the government's capacity to repay its liabilities. *After* government interventions, due to changes in the composition of both banks' and sovereign balance sheets, we find augmented importance of the government CDS spreads in the price discovery mechanism of banks' CDS series. Furthermore, a financial sector shock affects more strongly the sovereign CDS spreads in the short-run, however the impact becomes insignificant at a long horizon. Differences in the perceived risk transferred from banks to the government leads to inconsistent results within the same country. Lastly, our cross-country analysis reveals noticeable differences in the outcomes of state interventions.

The paper is organized as follows. In section 2 we discuss studies related to our research. Section 3 presents our hypotheses, the data, our sub-sample selection procedure, and the method-

[2] The objective of this paper is not to investigate the accuracy of this proxy. Our research design takes this link as given, even though there might have been distortions in this proxy during the last turmoil.

ology. In Section 4 we present our results and Section 5 concludes.

2 Related Literature

A few papers analyze the effect of the financial crisis and the emerging government policies on the risk of default of financial or sovereign entities. Relying on a structural model,[3] Schweikhard and Tsesmelidakis (2009) conclude that credit and equity markets decoupled during the financial turmoil. They find support for the "too-big-to-fail" hypothesis, as some companies' debt holders benefited from government interventions and a shift of wealth from taxpayers to the creditors took place after the bailout programs. During the crisis some other factors might have influenced CDS prices (e.g. counterparty or liquidity risk). Researching on the determinants of CDS changes Collin-Dufresne et al. (2001) find that credit spreads are mostly driven by a systematic factor; however they are not able to identify it. Berndt and Obreja (2010) study determinant factors for European corporate CDS and identify the common factor, that explains around 50% of the variation, as the super-senior tranche of the iTraxx Europe index, referred as *"the economic catastrophe risk"*.[4]

Similar to our study, Dieckmann and Plank (2010) find evidence for a private-to-public risk transfer for the countries with government interventions in the financial system. By employing panel regressions the authors analyze the determinants of changes in sovereign CDS spreads and find that both domestic and international financial systems bear an important role in explaining the dynamics of the CDS spreads. They also argue that countries in the EMU[5] are more sensitive to the health of the financial system than non-EMU countries. Ejsing and Lemke (2011) use a seemingly unrelated regressions framework with time-varying coefficients in order to investigate the co-movement between the CDS spreads of Euro area countries and banks. Before October 2008 the common risk factor that explains much of the variation of these spreads is the iTraxx CDS index of non-financial corporations. The authors find that government bailout and guarantee programs for the financial sector induced a drop in the credit spreads for banks but a jump in governments' CDS spreads. Both papers identify as a structural break mid-October 2008, when first massive bank rescue packages were set up after the default of Lehman Brothers. Our study extends their analyses by providing details on the risk-transfer mechanism in several European countries via joining the cointegration and generalized impulse responses framework. Our research is one of the first studies to emphasize important changes in these linkages. We argue that our findings are mainly a consequence of the bank bailout programs and the heterogeneity in effects across European states is a result of the relative differences between the rescue schemes.

Using the contingent claims analysis for financial institutions, Castren and Kavonius (2009)

[3] We use the term structural model to indicate a framework for pricing CDS spreads. In more detail, researchers try to replicate market prices by employing structural models or reduced-form ones. In this context, the well known Merton model can be regarded as a benchmark.

[4] The economic catastrophe risk can be interpreted as a total disfunction of the economy or as a sequence of sovereign defaults.

[5] European Monetary Union

identify the main channels that propagate risk within the euro area, by constructing a risk-based network from bilateral sector-level exposures. They claim that the financial sector plays an important role in transmitting shocks to the other sectors. Their paper reveals the mechanism that interconnects governments and financial institutions through the credit risk channel.

Furthermore, there are studies that solely investigate the sovereign bond market. Using a GARCH-in-mean model, Dötz and Fischer (2010) analyze the EMU sovereign bond spreads and find that the implied probability of default reached unprecedented values and the increased expected loss component made some sovereign bonds to loose their status of "safe haven" investment. Gerlach et al. (2010) analyze the determinants of Euro area sovereign bond spreads. They show that the size of the banking sector has an important explanatory value for the changes in bond spreads, suggesting that markets perceive countries with an important stake of this sector at higher risk of stepping up and rescuing the banks. Employing a dynamic panel Attinasi et al. (2009) highlight the main factors that explain the widened sovereign bond spreads in some Euro area countries for the period that covers the core part of the financial crisis in Europe.

Our study is also related to the literature that analyzes contributions to the price discovery of bond and CDS markets. For example Hull et al. (2004) or Norden and Weber (2004) analyze the impact of credit rating announcements on stocks, CDS spreads and bond yields. They find that markets anticipate both news and reviews for downgrade and that credit rating announcements contain important information and have a significant effect especially in the CDS market. Dötz (2007) studies European corporate entities listed in the iTraxx Europe index in a time-varying setup and finds support for a relatively equal contribution to the price discovery of both markets. During the credit turmoil in 2005, CDS markets' contribution fell dramatically, leaving space for the interpretation that CDS and bond markets are decoupling during turbulent times and that CDS prices might lag behind bond markets in price discovery for corporations. Since then, CDS markets consistently developed in terms of volume and market participants. Focusing on Euro area sovereigns, Fontana and Scheiche (2010) identify the main determinants of the bond and CDS spreads. They include in the set of explanatory factors proxies for market liquidity and global risk appetite and these are found to be significant. Furthermore, they employ a lead-lag analysis for bond and CDS markets and find that for France, Germany, Netherlands, Austria, and Belgium the cash market dominates, while for Greece, Italy, Ireland, Spain, and Portugal the CDS market is more important in terms of price discovery.

3 Hypotheses, Data, and Econometric Methodology

3.1 Hypotheses

In this subsection we develop the hypotheses to be tested in our study. We firstly describe the main transmission channels that emerge when either a (systemic) banking crisis develops or sovereign distress appears. Based on Acharya et al. (2011), Gray (2009) and IMF (2010), we present both directions of the contagion mechanism.

If a financial institution faces funding and/or liquidity issues, this can trigger a sharp rise in its default risk and may have specific contagion effects: *(I)* the bank cannot pay its obligations to another financial counterparty which in turn can set off funding/liquidity difficulties for the latter and increases its perceived default risk; *(II)* the state might intervene in order to prevent bankruptcy of banks. This private-to-public risk transfer augments the probability of default for the state and lowers the default risk of the financial institution. If *(I)* occurs, difficulties within the entire financial system (e.g. systemic banking crisis) might arise and translate into a contraction of the economy, which also weakens public finances (e.g. a decrease in the present value of taxes) and, thus, the sovereign default risk increases.

In the case of a country's distress, in the first wave, the contagion to other entities can be triggered via three direct channels (Chapter 1. of IMF (2010)): *(i)* from the affected state to other countries that are highly interconnected through bilateral trade, or share similar problems (e.g. public deficit, funding needs, etc.); *(ii)* from the distressed country to domestic banks as the market value of government bonds held by these banks decreases, and government support loses credibility;*(iii)* from the impaired state to foreign banks, that hold important government (or banks) bonds (or other assets) from the affected country.

Before government interventions, we argue that financial sector issues had a systemic component, leading to contagion mechanism *(I)*. Thus, the rising default risk of banks had an indirect effect on governments' credit risk. Additionally, state interventions in response to financial sector problems were possibly expected by market participants. Thus, the perceived sovereign default risk augmented but was considered of limited importance for heaving a visible impact on banks' default risk.

Hypothesis 1. *Prior to state interventions, changes in the default risk of banks impact on the default risk of European governments, but not vice-versa.*

After government interventions, states do not only bear an asset exposure to the banking sector but their balance sheets contain contingent liabilities (e.g. government guarantees) as well. Thus, the sensitivity of government default risk to the banking sector risk is expected to increase. Furthermore, through the *credibility* of government contingent liabilities, changes in government default risk directly impact on the perceived risk of financial institutions.

Hypothesis 2 (a). *Changes in the default risk of banks impact on the default risk of states stronger in the period after government interventions than before.*

Hypothesis 2 (b). *After bailout programs, an increase/decrease in government's default risk affects the default risk of the domestic banks in the same direction.*

The following hypothesis links the sensitivity of the banks's default risk to the extent of government support.

Hypothesis 3. *The sensitivity of the bank to the government risk of default increases with the perceived risk transferred from the bank to the government.*

Our last hypothesis compares the outcome of bailout programs in different countries.

Hypothesis 4. *Heterogeneity of bailout programs across European countries translates into asymmetric interdependence between states' and banks' default risk.*

The model introduced by **?** describes in detail this feedback mechanism, i.e. how financial sector and government default risk are linked. The authors present a three period model, in which a financial and corporate sector produce jointly the aggregate output. There exists a potential underinvestment problem. Bank bailouts are used to better this problem in the financial sector. The framework predicts that bank bailouts increase sovereign credit risk. The latter impacts the financial sector as the value of guarantees and bond holdings decreases. This linkage implies a post-bailout increase in the co-movement of government and financial sector risk of default.

3.2 Bailout Specific Characteristics

In order to compare the selected countries, we relate our analysis to the specific bailout schemes provided in each country. Hence, we look at the magnitude of different support measures utilized by each country, while additionally considering the particular aid for each bank. Following Stolz and Wedow (2010), we categorize the general set of measures emphasizing the differences and similarities across countries. Even though there is a discrepancy in the number and types of institutions involved in the banking crisis management, there is less variation across countries in what types of support measures were applied. The financial aid programs can be classified into four broad categories: capital injections, guarantees for bank liabilities, asset support programs, and deposit insurance (see Table 1).

Table 1: Government Support Measures to Financial Institutions (October 2008 - May 2010)

Country	Capital injection		Liability guarantees		Asset support		Total commitment	Deposit insurance
	Within Schemes	Outside Schemes	Guaranteed issuance of bonds	Other guarantees, loans	Within Schemes	Outside Schemes	as % 2008 GDP	in EUR
France	8.3 (21)	3	134.2 (320)	0	- (-)	-	18%	70,000
Germany	29.4 (40)	24.8	110.8 (400)	75	17 (40)	39.3	25%	Unlimited
Ireland	12.3 (10)	7	72.5 (485)	0	8 (90)	-	319%	Unlimited
Italy	4.1 (12)	-	- (-)	0	- (50)	-	4%	103,291
Netherlands	10.2 (20)	16.8	54.2 (200)	50	- (-)	21.4	52%	100,000
Portugal	- (4)	-	5.4 (16)	0	- (-)	-	12%	100,000
Spain	11 (99)	1.3	56.4 (100)	9	19.3 (50)	2.5	24%	100,000

Note: All amounts are in billions of EUR, except for the last two columns. Figures (in brackets) denote totally committed funds and figures (outside brackets) are utilized amounts up to May 2010. "Within schemes" refer to a collective bailout program that can be accessed by any bank that fulfills the requirements for that particular aid scheme. "Outside schemes" refer to individually tailored aid measures (ad-hoc schemes). *Source*: Stolz and Wedow (2010)

Based on the ratios of total commitment to GDP, the selected countries can be ranked (from high to low): Ireland, Netherlands, Germany, Spain, France, Portugal, and Italy. Furthermore, the set of countries can be clustered into three groups: Ireland (high commitment); Netherlands, Germany, Spain, France (medium commitment); Portugal and Italy (low commitment).

3.3 Data and Sub-Sample Selection

We use daily CDS spreads collected from Datastream[6], for seven European countries together with two banks from each country, i.e. in total 21 institutions: **France (FR)**, BNP Paribas (BNP), Société Générale (SG), **Germany (DE)**, Commerzbank (COM), Deutsche Bank (DB), **Italy (IT)**, Intesa Sanpaolo (ISP), Unicredito (UCR), **Ireland (IR)**, Allied Irish Banks (AIB), Bank of Ireland (BOI), **Netherlands (NL)**, ABN Amro Bank (ABN), ING Group (ING), **Portugal (PT)**, Banco Comercial Portugues (BCP), Banco Espirito Santo (BES), and **Spain (SP)**, Banco Santander (BS), Banco Bilbao Vizcaya Argentaria (BBVA).[7] All banks are important financial institutions, with most of them belonging to the iTraxx Europe index (8 out of 14). The selection of bank and sovereign CDS series was restricted by data availability. In terms of CDS spreads we decided to use contracts on senior unsecured debt with 5 years maturity, as they are the most liquid ones.

Briefly, a CDS is a bilateral agreement that transfers the credit risk of a reference entity[8] from the "protection buyer" to the "protection seller". The former party pays a periodic fee to the latter party (the credit-risk taker), and in return is compensated in case of default (or similar credit event) of the underlying entity, with a payoff[9]. The CDS spread represents the insurance premium and is paid quarterly until either the contract ends or at the arrival of a credit event (e.g. default). CDS markets are intensively used as a proxy for credit risk.

Our sample covers the time span from 1 June 2007 until 31 May 2010 and includes 772 observations of daily data for each of the selected series.[10] Prior to the econometric analysis, we log-transform the CDS levels as suggested by Forte and Pena (2009). We further motivate this step by relatively low levels of the CDS for the sovereigns in the first stages as compared to the last stages (wide data range).

Our aim is to analyze the linkages between bank's and sovereign CDS spreads in a two sub-period setup: 1.)before and 2.)during and after bank aid schemes. In order to capture other structural breaks, we follow BIS (2009) and divide the entire time span into six stages[11]. We group the first two stages (i.e. Stage 1+2) to form the sub-period before government interventions and the last three stages (i.e. Stage 4+5+6) to constitute the sub-period during and after bank aid schemes. Stage 3 is regarded as a period of market adjustments and it is neglected. When issues concerning structural breaks appear in our stability analysis (see Section 3.4), we analyze stages in combinations (i.e Stage 4+5, Stage 5+6) or individually.

The first stage runs from June 2007 until mid-March 2008 and contains 203 observations. This

[6]We downloaded CDS data from Datastream, which in turn is provided by Credit Market Analysis (CMA).

[7]In parentheses are defined the abbreviations for later use.

[8]The reference entity can be a corporation, a sovereign, an index, or a basket of assets that bears credit risk.

[9]In the case of cash settlement only the difference between the par value of the bond (notional amount of the loan) and its recovery value when the credit event occurs is paid in cash by the protection seller. In the case of physical settlement the par value is paid in exchange for the physical underlying bond.

[10]In the case of Ireland the sample starts on 4 October 2007 because of inconsistencies with the data obtained from Datastream.

[11]BIS (2009) covers only our first five stages, starting with 1 June 2007 until 31 March 2009 when Stage 5 emerges. For the time span that was not included in the latter study we define a sixth stage. The last stage is selected to start based on developments in the sovereign CDS market at the end of 2009.

period is characterized by financial stress which has been triggered by fears on losses due to US subprime mortgage loans and the spillover to European banks (e.g. IKB Deutsche Industriebank, BNP Paribas). Second stage emerges in March 2008, with the liquidity shortage of Bear Stearns. This time span consists of 126 observations and ends in mid-September 2008, with the collapse of Lehman Brothers. BIS (2009) defines the third stage from mid-September until late October 2008. As this stage includes only 30 observations we exclude it from our analysis. In this period, first government policy measures are taken.[12] Additionally, coordinated actions of major central banks try to control the situation. The fourth stage is defined from late October 2008 to mid-March 2009 and contains 98 observations. This period is marked by concerns about deepening global recession. By issuing the guidelines[13] for European states, the European Commission gives green light for government bailout programs. Stage 5 starts in mid-March 2009 when the first signs of recovery appear. Announcements of central banks concerning balance sheet expansions, the range and the amount of assets to be purchased lead to a significant relief of financial markets. The fifth stage ends on 30 November 2009, right before the inception of sovereign debt crisis in Europe. This stage includes 143 observations. Stage 6, the last one in our sample, begins in December 2009 and ends in May 2010. It consists of 172 observations. This period is driven by concerns about European sovereign debt. In May 2010, European governments set up a rescue fund for aiding states in trouble.

3.4 Econometric Methodology

In order to analyze the dynamics of the short- and long-run interdependency between the selected CDS series, this study employs a bivariate vector error correction (VEC)[14] and bivariate vector autoregressive (VAR) framework. Besides interpreting the cointegration relations, we additionally conduct tests on Granger-causality and consider impulse responses in order to describe the entire dynamics between the CDS spreads.

We conduct our analysis by considering two main sub-periods: before and during/after government bailouts. Results from the Granger-causality and impulse response analysis are reported for these two periods. Only the study of the long-run relations, i.e. using the VEC framework, makes use of further sub-samples if required.[15] Impulse responses are obtained using the VEC framework if available for the two main periods. If not, we obtain the impulse responses from a VAR, in which variables are modeled in $\log$-levels. Granger-causality tests in this paper refer to Wald tests on lag augmented VARs as proposed by Dolado and Lütkepohl (1996). This test is chosen as it guarantees the validity of the asymptotic distribution of the test statistic even when there is uncertainty about the cointegration properties and stationarity of the variables.

[12]E.g. UK authorities intervene in an attempt to relief the "pressure on financial stocks through a suspension of short selling" (BIS, 2009, p.27) on some financial products.

[13]IP/08/1495

[14]During tranquil times we believe that the CDS series of the financial as well as government sector are stationary. However, during times of market turmoil we argue that both CDS series (i.e. bank and sovereign CDS) are impacted by the same stochastic trend, because both are linked by channels as expressed in Subsection 3.1.

[15]See Appendix B for further information

For a global view on the interrelations of the series we employ *generalized impulse responses* (GIR) as proposed by Pesaran and Shin (1998). Routinely the analysis of impulse responses is carried out via the application of the Cholesky decomposition. However, the researcher has to specify some causal ordering of the variables. In our case, a theory which defines such ordering is hard to justify, especially in the context of daily data. Based on this argument, we decide to use GIR because no ordering is necessary and contemporaneous relations are allowed for. One can regard GIR as the effects of a shock in the structural error of the variable that is ordered first in the system of orthogonalized impulse responses. To model the uncertainty around our point estimates of impulse responses we apply the recursive-design wild bootstrap as described in Gonçalves and Kilian (2004). This bootstrap technique delivers valid confidence bands in the case of conditional heteroskedasticity. We simulate the 95% confidence intervals using 2000 replications. The generalized impulse response function can be written in our bivariate setup as follows:

$$\begin{pmatrix} \psi_{Sov}^{Sov}(n) \\ \psi_{Sov}^{Bk}(n) \end{pmatrix} = \sigma_{(Sov,Sov)}^{-1/2} \Phi_n \Sigma_u \begin{pmatrix} 1 \\ 0 \end{pmatrix}, \qquad \begin{pmatrix} \psi_{Bk}^{Sov}(n) \\ \psi_{Bk}^{Bk}(n) \end{pmatrix} = \sigma_{(Bk,Bk)}^{-1/2} \Phi_n \Sigma_u \begin{pmatrix} 0 \\ 1 \end{pmatrix},$$

where $\sigma_{(j,k)}$ is the variance related to the error of variable j, k (again $j, k \in (Sov, Bk)$) and n denotes the period after which the impulse has occurred. Φ_n represents the matrix of the vector moving average coefficients at lag n, which can be calculated in a recursive way from the VAR coefficient matrices. It is worth emphasizing that, as we deal with possibly cointegrated VAR models, the effects of shocks may not die out asymptotically (Lütkepohl, 2007, pp. 18-23, 263). $\psi_{Bk}^{Sov}(n)$ denotes for example the response of the sovereign $\log CDS$ to a shock in Bk n periods ago. The exact interpretation of the impulse responses follows the usual reading for semi-elasticities. E.g. taking into account that $\Phi_0 = I_K$, an impulse in variable j in period 0 means a unit increase in the structural error that leads to an increase of the respective CDS series by $\sigma_{(j,j)}^{1/2}$%. In order to enable more easily a comparison of the results across banks and countries, we standardize each series of impulse responses, i.e. the responses caused by the same shock are divided by the standard deviation of the impulse variable. In the example above, our responses would be divided by $\sigma_{(j,j)}^{1/2}$, so that the initial response of the j-th variable to its own shock is equal to 1 or 100% of the initial shock of size one standard deviation. Responses can, thus, be interpreted as percentages of the initial shock in the impulse variable.

In the following the VEC and VAR model setup is discussed. In our setup, i.e. with a sovereign CDS spread (in short 'Sov') and a selected domestic bank CDS spread (in short 'Bk'), a VECM with $p-1$ lags can be written as follows:[16]

[16]We use the notion of $p-1$ lags, to remind of the fact that a VECM($p-1$) has a VAR(p) representation.

$$\begin{pmatrix} \Delta cds_{Sov,t} \\ \Delta cds_{Bk,t} \end{pmatrix} = \begin{pmatrix} \alpha_{Sov} \\ \alpha_{Bk} \end{pmatrix} (\beta_{Sov} cds_{Sov,t-1} + \beta_{Bk} cds_{Bk,t-1} + \beta_0) + \sum_{i=1}^{p-1} \begin{bmatrix} \gamma_{SovSov,i} & \gamma_{SovBk,i} \\ \gamma_{BkSov,i} & \gamma_{BkBk,i} \end{bmatrix} \begin{pmatrix} \Delta cds_{Sov,t-i} \\ \Delta cds_{Bk,t-i} \end{pmatrix} + u_t, \quad (1)$$

where $cds_{j,t}$ with $j \in (Sov, Bk)$ refers to $\log CDS_{j,t}$, i.e. the logarithmized CDS series of the country or bank. $\Delta cds_{j,t}$ denotes the first differences of $cds_{j,s}$. β_0 is a (restricted) constant, and u_t is assumed to be $wn(0, \Sigma_u)$[17]. γ coefficients portray the short-run dynamics. In contrast, the β coefficients describe the long-run relationship between banks and sovereign $\log$-CDS spreads. β_{Sov} is normalized (i.e. $\beta_{Sov} = 1$) and only β_{Bk} is estimated. The loading coefficients, α, measure *the speed of adjustment* with which a particular CDS adjusts to the long-run relationship.[18]

The bivariate VAR setup with p-lags can be written as in the following:

$$\begin{pmatrix} cds_{Sov,t} \\ cds_{Bk,t} \end{pmatrix} = \nu + \sum_{i=1}^{p} \begin{bmatrix} \alpha_{SovSov,i} & \alpha_{SovBk,i} \\ \alpha_{BkSov,i} & \alpha_{BkBk,i} \end{bmatrix} \begin{pmatrix} cds_{Sov,t-i} \\ cds_{Bk,t-i} \end{pmatrix} + u_t, \quad (2)$$

where ν is a vector of intercepts and the αs refer to the respective VAR coefficients.[19]

4 Results

This section presents the results for long-run and short-run relationships and, in addition, considers the generalized impulse responses. First, the cross country analysis is presented and second we report the specific results for three countries. In the appendix, Table 3 shows the results of all countries for Granger causality tests, Table 4 outlines the results from our cointegration analysis and Table 5 summarizes the generalized impulse responses for all countries.

4.1 Cross-Country Analysis

The results of the impulse response analysis underline the change in the interdependence of European sovereign CDS spreads and bank CDS spreads. As we are analyzing CDS spreads in levels, our responses in the long horizon (after 22 days) report whether a long term change in the respective CDS series occurs due to a shock in either the sovereign or financial sector. Table 2 shows the percentage of the long-run responses that are reported to be significantly/insignificantly different from zero after 22 days.

[17] wn stands for "white noise" and refers to a discrete time stochastic process of serially uncorrelated random variables with the above mentioned first two moments.

[18] For further details on the interpretation of the long-run relations in a VEC framework, please see Appendix B.

[19] The Granger-causality test (e.g. the bank does not Granger-cause the government CDS series if and only if the hypothesis $H_0 : \alpha_{SovBk,i} = 0$ for $i = 0, \ldots, p$ cannot be rejected) in this paper is carried out on a VAR with $p + 1$ lags.

Table 2: Percentage of Significant/Insignificant Responses in the Long-Run (After 22 days)

	Bank → Country		Country → Bank	
	Before	During/After	Before	During/After
Significant	100%	21.43%	14.29%	100%
Insignificant	0%	78.57%	85.71%	0%

Note: Significant/Insignificant refers to evaluating a 95% confidence interval estimated using a recursive-design wild bootstrap with 2000 replications. The left side of the table concerns the country responses to a banking sector CDS shock. The right side refers to banks responses to a sovereign CDS shock. "Before" concerns the period preceding banking sector bailouts and "During/After" the period during and after government interventions.

Comparing the periods before and after, one can observe the pronounced effects of the risk transfer mechanism. The ratio of significant bank-responses to a sovereign shock increases from 14.29% before to 100% after interventions. In contrast, the percentage of significant country-responses to a banking sector shock decreases from 100% before to 21.43% after bank bailouts. The banks, for which we still find significant responses after bailouts are the Portuguese banks and one Italian bank (ISP). In the period before, there is a stark contrast between the result that all banks are found to impact its sovereign CDS series and only a very small fraction of the countries affect bank CDS spreads. We argue that the roots of this finding are in the systemic component of the crisis that originated from financial institutions and spilled over to the sovereign CDS market. In the period after, the picture changes completely: the effects of a sovereign shock becomes permanent to bank CDS spreads, while banking sector shocks are less important than before. As emphasized in other recent papers, these findings are the effect of the private-to-public risk transfer.

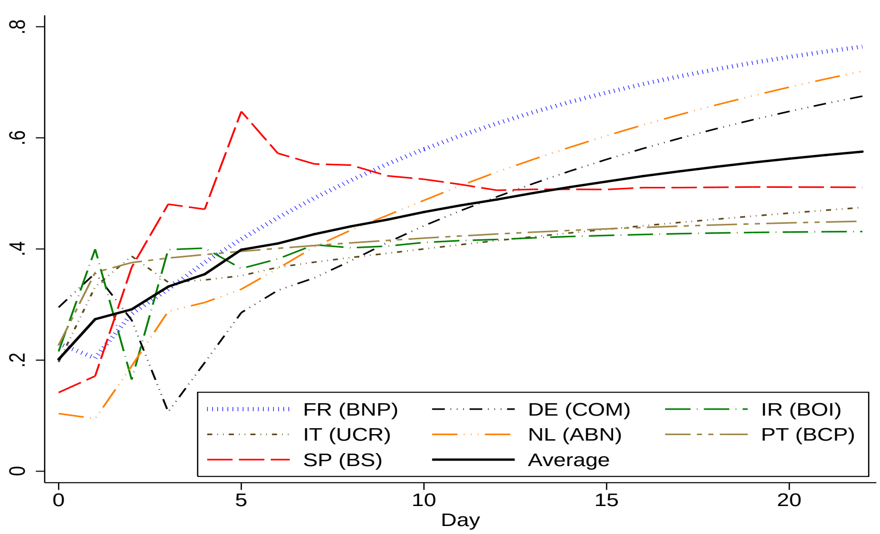
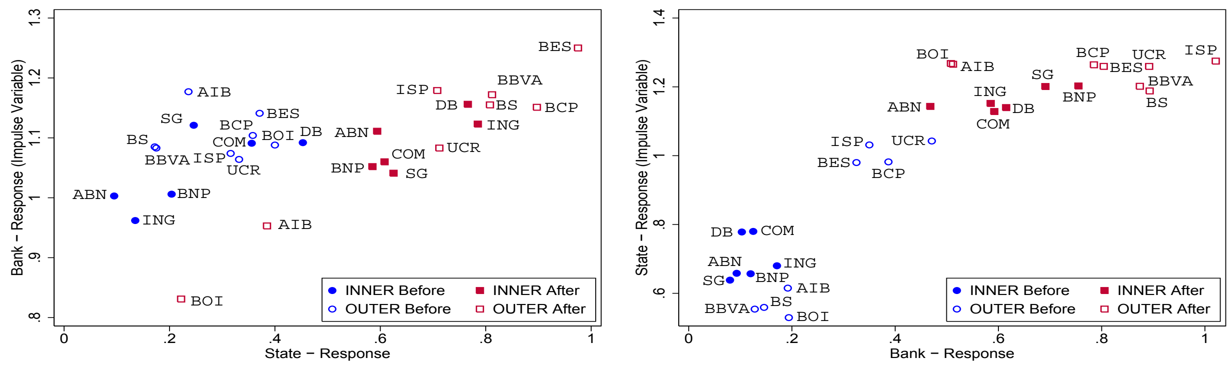


Figure 1: Effects of a Banking Sector Shock on Government Spreads: Before Government Interventions
Note: Sources of the banking shock are written in parentheses. Shocks in banks spreads within the same country have very similar impact on the sovereign spread in the period before government interventions. One of the two bank responses per country are depicted as results are similar. The "Average" line represents the mean of the sovereign responses from a shock in the seven bank CDS spreads.

Figure 1 depicts the state-responses to banking sector shocks. Considering in this graph the



(a) Bank Shock

(b) Country Shock

Figure 2: Responses at Day 1 after the Shock

Note: Responses of both variables of the bivariate systems are plotted (i.e. bank response (y-axis) vs. country response (x-axis) and country response (y-axis) vs. bank response (x-axis)). For example, ∘ ABN is located at (1,.1) indicating that a shock (at day 0, before government interventions) in the CDS series of ABN, that leads to a 1% increase of the ABN spread, impacts the Dutch CDS spread by 0.1% at day 1.

long-run effects (after 22 days), which are all estimated to be significant, countries can be separated into two groups: INNER composed by FR, DE, IR, NL (with responses above the "Average", after 22 days) and OUTER that consists of IT, SP, PT (with responses below the "Average", after 22 days). The results for the INNER group can be argued by a weak interest (i.e. low liquidity of the CDS contracts) in insuring against the default of these countries in the period before Lehman Brothers' collapse. This could have led first to mispricing and then followed by a strong repricing effect, as the volume increased. On the other hand, in this period, OUTER countries were already at levels closely linked to their domestic banks' CDS spreads, i.e. public imbalances and high debt burdens were priced in for the latter group.

Concentrating on the point estimates of the responses at day 1, i.e. Figure 2 (a) and (b), two important results can be emphasized. Firstly, one can see how bank bailouts impact the risk transfer mechanism and secondly that INNER and OUTER groups can be distinguished in the short run as well. Related to the change in the risk transfer mechanism, Figure 2 (a) reveals that the sovereign CDS series are more sensitive to a banking sector shock, while the sensitivity of the banks to its own shock remains of similar magnitude. Only the responses of AIB and BOI on the dimension of the state-responses seem to stay on approximately the same level, while their impacts on themselves decreases. Thus, Ireland seems to be most successful in limiting the risk of default stemming from the banking sector in the short-run. In the case of a country shock we find an increase of the sensitivity in both dimensions. Countries as well as banks suffer stronger from a government shock. In the period during/after bank bailouts, responses after one day, of which almost all are significantly different from zero, can be clustered into INNER and OUTER.

As noted above, the importance of a sovereign shock augments dramatically in the post intervention era. Figure 3 depicts the entire impulse response series of the selected banks to a shock in the government sector. Sorting banks by the effect in the long-run, which were shown to be sig-

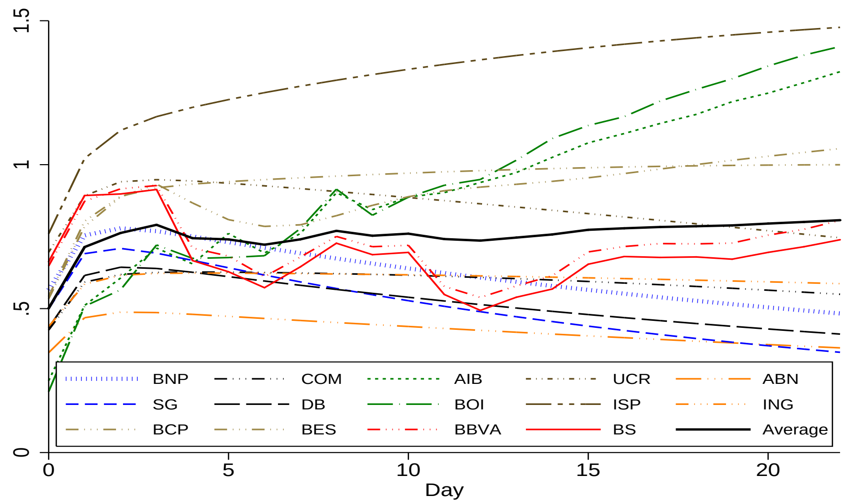


Figure 3: Effects of a Sovereign Shock on Bank spreads: After Government Interventions.
Note: The "Average" line represents the mean of the bank responses from a shock in the seven sovereign CDS spreads.

nificant in all cases, we obtain the following ranking (from lowest effect to the highest): SG, ABN, DB, BNP, COM, ING, BS, UCR, BBVA, BCP, BES, AIB, BOI, ISP. Long-run responses of the banks from the same country are clustered. The only exception are the Italian banks, in which case ISP is more sensitive to a sovereign shock than UCR (148% compared to 75%). While SG is impacted only by 35% of the initial shock, the top three banks' impacts range from 128% to 148%. ISP and Irish banks respond the most to a sovereign shock. They are followed by the Portuguese and then the Spanish banks, where UCR ranks between BBVA and BS. At the bottom of this ranking are the Dutch, German, and French banks.

4.2 Specific Country Analysis

In this subsection the results for three countries are presented, i.e. Germany, Ireland, and Italy. These have been selected out of the group of countries considered as they differ strongly in their total commitment to the financial sector relative to their 2008 GDP. Ireland represents the country with the highest engagement and Italy with the lowest. Germany can be argued to range in the middle of these measures.

4.2.1 Germany

In the case of Germany we analyze the bivariate setups of the German (DE) sovereign CDS spread in relation to the CDS spread of Commerzbank (COM) and the CDS spread of Deutsche Bank (DB) respectively. The results for the tests on Granger-causality are depicted in Table 3, cointegration relations in Table 4, and impulse responses in Table 5 which are presented in Appendix A.[20]

[20]Test results and the graph of the German sovereign CDS together with the German banks' CDS time series are presented in Appendix C.2.

Cointegration and Granger-Causality Analysis

For the entire period before government interventions (i.e. Stage 1+2) we find evidence for a stable long-run equilibrium relationship between the German CDS spread and both bank CDS series. The hypothesis that both estimated β coefficients for the banks are equal to -1 cannot be rejected using a standard t-test. The error correction equation, e.g. for the relation with DB can be written as:

$$cds_{DE,t} = \underset{(0.118)}{0.930} \times cds_{DB,t} - \underset{(0.471)}{2.087} - ec_t,^{21}$$

where ec_t refers to the value of the long-run relation at time t and standard errors are provided in parentheses. As variables are measured in $\log$s, the β coefficients may be interpreted as elasticities, yielding to a bank-sovereign CDS equation. This relation implies, neglecting the rest of the estimated dynamics in the model, that a 1% increase in the CDS spread of DB leads to a 1% increase in the CDS spread of DE. For COM the same interpretation applies.

The α-coefficients in the relations of DB and COM with DE suggest that the bank spreads do not adjust to any deviations from the long-run equilibrium, while the German CDS spread adjusts with a rate of $\hat{\alpha}_{DE} = -0.122$ and $\hat{\alpha}_{DE} = -0.108$ in the relation with DB and COM respectively. A formal test confirms this result as $cds_{DB,t}$ and $cds_{COM,t}$ are tested to be weakly exogenous, which leads to the argument that DB and COM provide the stochastic trend in the cointegration relations. Tests for Granger-causality indicate that only COM Granger-causes DE on a 1% significance level in the period before state interventions.

After bank aid schemes the long-run relations change. Firstly we do not find a stable long-run relation for DE-COM for the entire post-intervention period, but only in Stage 5. Compared with the pre-intervention results, we find equal values for the β-coefficients, implying the same elasticities as mentioned above. However the constant changes from 1.24 (before) to insignificant (after) yielding the interpretation that the gap between the two CDS series vanished. In contrast we do find a cointegration relation for DE and DB for the entire post-intervention period.

The relation for COM and DE in Stage 5 yields the conclusion that COM is weakly exogenous and DE adjusts with a rate of $\hat{\alpha}_{DE} = -0.045$, which is close to the α-value from the period before interventions. In the second cointegration relation, that takes together all three stages after the bailout scheme, we find DE to move the equilibrium in the direction of its development (as DE's α and β coefficients are both positive). Granger-causality tests indicate further for the period during and after the state interventions that all variables Granger-cause each other on the 1% level.

Impulse Response Analysis

The results from the impulse response are depicted in Figure 4. The analysis before government interventions refers to the VECM setup; only in the period after we use a VAR framework for examining the relationship between DE and COM. In all graphs the three solid lines represent

[21] The cointegration graph is provided in Appendix C.2, Figure **??**.

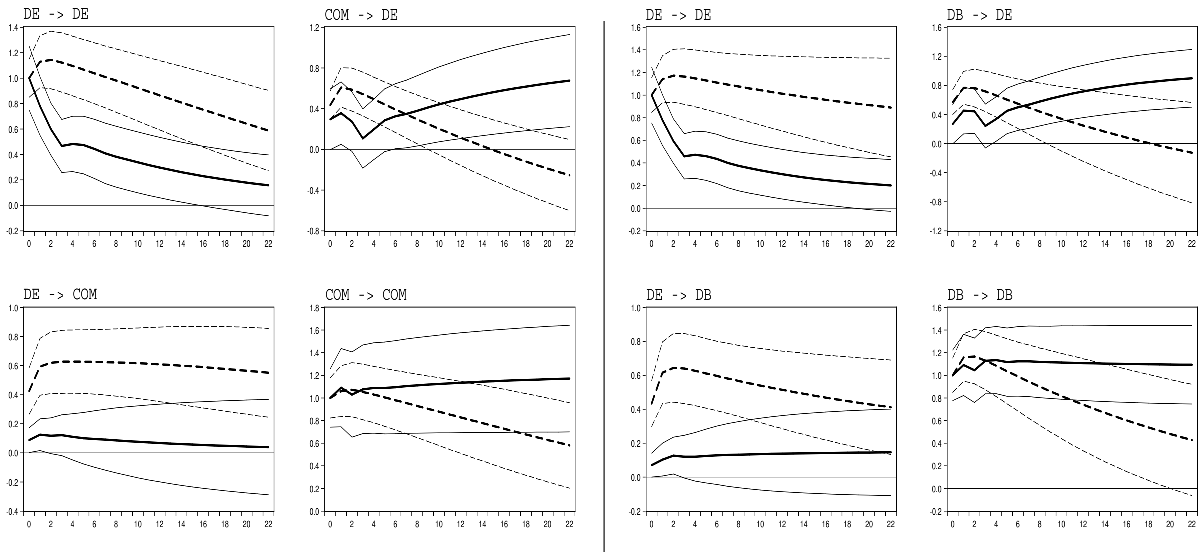


Figure 4: Generalized Impulse Responses for Germany: (Solid) Before, (Dotted) During & After Gvt. Interv.
Note: Solid lines: responses before government interventions (bold) and the 95% bootstrapped confidence interval (thin). Dotted lines: responses during and after government interventions (bold) and the 95% bootstrapped confidence interval (thin). X-axis: number of days (after the shock). Y-axis: impact relative to one standard deviation shock of the impulse variable. ***[Left Panel]*** Upper-Left: DE (impulse variable) - DE (response variable). Lower-Left: DE (impulse var.) - COM (response var.). Upper-Right: COM (impulse var.) - DE (response var.). Lower-Right: COM (impulse var.) - COM (response var.). ***[Right Panel]*** Upper-Left: DE (impulse var.) - DE (response var.). Lower-Left: DE (impulse var.) - DB (response var.). Upper-Right: DB (impulse var.) - DE (response var.). Lower-Right: DB (impulse var.) - DB (response var.).

the impulse responses before interventions, where the light ones refer to the 95% bootstrapped confidence interval. The bold dotted line describes the responses during and after rescue schemes and the light dotted lines the bootstrapped confidence bands. Firstly, we observe that the pattern of the left panel resembles strongly the pattern depicted in the right panel. In the upper-right corner of each panel the effects of a shock from the bank CDS spread to German CDS are plotted. Before interventions (solid) a banking sector shock impacts permanently the government CDS series, while in the period after (dotted) there is only a temporary effect.

In the case of a government shock to the banking sector we notice that DB (right panel) and COM (left panel) are only affected in the very short-run ($t \leq 3$) before interventions. In the period after the bank bailouts, we find that both series react permanently to a shock stemming from the sovereign.

Additionally, the graphs show that the effects of a banking sector shock on itself are stronger in the pre-interventions period, as they are estimated to have a permanent effect. The responses after state interventions suggest a decrease of the impact of the latter in both cases. The shocks from the government CDS spread on itself have a stronger impact in both bivariate setups after interventions.

Discussion

From October 2008 until the end of May 2010, Germany provided a total support to the local financial sector of EUR 619.1bn or of 25% of total 2008 GDP. From a total committed amount of

EUR 64.8bn for capital injections, EUR 54.5bn were demanded by German banks until the end of May 2010. Germany pledged EUR 475bn in form of liability guarantees, from which local banks utilized EUR 185.8bn until the end of our time frame.

SoFFin[22] granted COM an individual guarantee for issuing EUR 15bn of debt securities.[23] Furthermore, SoFFin participated with EUR 8.2bn in form of a silent equity holding ("silent participation") and COM's recapitalization by government amounted EUR 10bn.[24]. Although DB, the biggest German bank, resisted to state capital injections, we do not find strong differences in the dynamics of both CDS series in relation with the German sovereign CDS spread. Nonetheless, our results suggest that investors anticipated the direct support for COM as Granger-causality tests underpin that the CDS spreads of COM contain important information for determining the German spreads. Furthermore, a shock to the sovereign spread drives the CDS spread of COM permanently. Thus, before interventions we have evidence that the dynamics of the series differ, suggesting that the link between the CDS series of COM and DE is more sensitive than the link between DB and DE.

The research design of our analysis enables us to draw inference only on outcomes. COM is known to have had severe difficulties during the last crisis, which led, SoFFin to provide extra support to this bank. The results of our empirical analysis, however, underline that the dynamics of the two banks do not substantially differ in the post-intervention period. Assuming that this similarity is a consequence of the extra support provided, we conclude that the rescue schemes in the case of Germany were successful. The extra funding for COM was necessary in order to induce a credible perception that the tail risk of the latter was absorbed by the state. We find that shocks of both banks have a weaker effect on themselves after the bailout schemes. However, the result is stronger for DB. The cost for this positive aspect is a higher sensitivity of both banks to developments in the government CDS spreads. Interestingly, the German spread is not influenced at a long horizon by a banking sector shock after bailout measures are provided.

Altogether, the results highlight that the contagion emerged from the banking sector and spilled-over to German sovereign CDS spread in the period before rescue schemes. Thus, we find evidence for H1. The dependence in the other direction is weaker or only existent in the very short-run. Afterwards, future developments of the perceived default risk of all series are strongly interwoven as suggested by cointegration analysis and the results of the Granger-causality tests. Furthermore, impulse responses highlight a stronger interdependency of all series, while an unexpected change in the bank CDS series has only a temporary effect on the sovereign CDS spread (H2a, H2b). Moreover, we find no strong differences in the dynamics of COM and DB in relation to changes in German CDS spreads (contradicting our H3). Our results suggest that the extra support for COM credibly transfered the default risk on the government's balance sheet.

[22]The German Special Fund for Financial Market Stabilization (SoFFin) is in charge for managing the German financial support programs.

[23]https://www.commerzbank.de/en/hauptnavigation/aktionaere/service/archive/ir-nachrichten_1/2008_5/ir_nachrichten_detail_08_2203.html

[24]These capital injections became public on 3 November 2009.

4.2.2 Ireland

Within the set of analyzed countries, the results for Ireland reveal most clearly the impact of government interventions. As the dynamics for both setups, i.e. Ireland (IR) - Allied Irish Banks (AIB) and Ireland (IR) - Bank of Ireland (BOI), resemble strongly we report only one of them. Tests on Granger-causality are depicted in Table 3, cointegration relations in Table 4, and impulse responses in Table 5 which are presented in the Appendix.[25]

Cointegration and Granger-Causality Analysis

The cointegration analysis uncovers a long-run relation in Stage 2, in which $\hat{\beta}_{AIB} = -0.567$. Interpreting the cointegration coefficients for the period before interventions, a 1% increase in bank CDS spreads translates into a 1.76%[26] gain in the Irish spread. The gap (the constant from the cointegration equation) between the two CDS series is insignificant.

Furthermore, in the period before government interventions there is evidence that the stochastic trend originates from the banking sector and impacts the sovereign CDS series. The estimated α coefficient for AIB is not significantly different from zero and the hypothesis of weak exogeneity for the banking sector series cannot be rejected. Thus, we conclude that the series of AIB influences IR in the long-run. In the short-run, Granger-causality is not significant in any of the two directions.

During and after interventions the dynamics change and emphasize a different role of the Irish CDS spread, which we argue occurs because of government interventions. The error correction equation can be written as

$$cds_{IR,t} = \underset{(0.105)}{0.724} \times cds_{AIB,t} + \underset{(0.587)}{1.116} - ec_t.^{27}$$

Comparing elasticities, we now find an increase of $\hat{\beta}_{AIB}$ to 0.724, implying that a 1% increase in the Irish spread augments the bank spread by 0.724%. The gap between the two series is enlarged and it is significantly different from zero.

The estimated α-coefficients suggest that during and after interventions the Irish spread provides the stochastic trend, as a test for weak exogeneity of this series cannot be rejected. Only the bank CDS spread adjusts to deviations from the long-run equilibrium with a rate of $\hat{\alpha}_{AIB} = 0.06$. The prominent role of the Irish CDS series is also emphasized in the short-run dynamics, where we find that the CDS spread of IR Granger-causes the CDS spread of AIB but not vice versa during this period.

Impulse Response Analysis

The generalized impulse response, depicted in Figure 5, underline the shift in the dependence between the two CDS series. Firstly, the graph in the upper right corner indicates that a shock from

[25] Preliminary test results and the graph of the respective time series are presented in Appendix C.3.

[26] This number is obtained by normalizing the coefficients by the estimated β-coefficient of AIB.

[27] The cointegration graph is provided in Appendix C.3, Figure **??**.

the banking sector permanently influences the government CDS spread before interventions, and only temporarily ($t \leq 2$) in the second period. The opposite pattern is found for a government sector shock. In the pre-intervention period the graph in the lower left corner highlights that the latter shock only temporarily influences the CDS spread of BOI (at $t = 1$), while there is a permanent impact in the period during and after the rescue schemes. Moreover, the remaining two graphs (upper left and lower right corner) suggest that there has been a change in sensitivity to a shock from the same sector. A banking shock yields a permanent effect on itself before interventions with a strongly decreasing impact. For the Irish spread the GIR results show an opposite development. Whilst both deviations are permanent, the one during the second period is by far stronger.

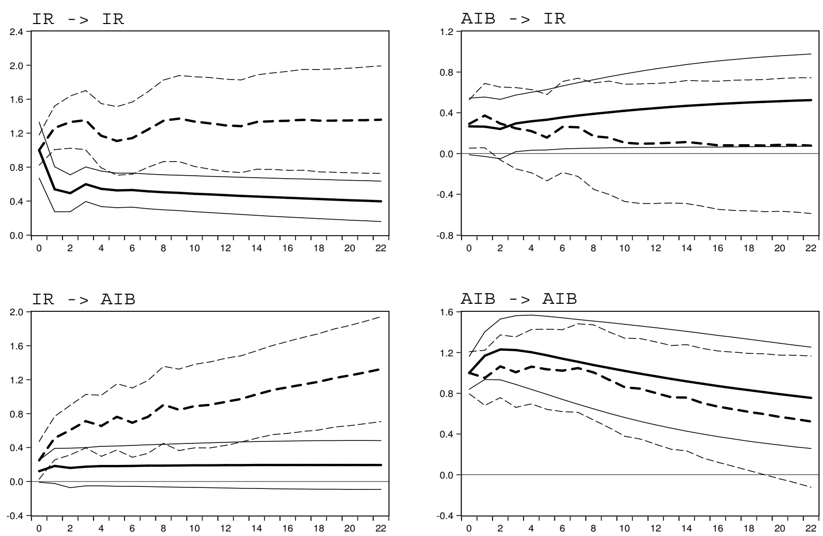


Figure 5: Generalized Impulse Responses for Ireland: (Solid) Before, (Dotted) During & After Gvt. Interv.
Note: Upper-Left: IR (impulse variable) - IR (response variable). Lower-Left: IR (impulse var.) - AIB (response var.). Upper-Right: AIB (impulse var.) - IR (response var.). Lower-Right: AIB (impulse var.) - AIB (response var.). Solid lines: responses before government interventions (bold) and the 95% bootstrapped confidence interval (thin). Dotted lines: responses after government interventions (bold) and the 95% bootstrapped confidence interval (thin). X-axis: number of days (after the shock). Y-axis: impact relative to one standard deviation shock of the impulse variable. Generalized impulse responses for BOI behave similarly to those of AIB.

Discussion

Not surprisingly the study of the Irish risk transfer mechanism depicts most clearly the change in the dynamics, as Ireland (IR) represents, by far, the one with the highest total commitment to the financial sector relative to its GDP. Remarkably it amounts to 319% of 2008's GDP; or put in monetary value EUR 592bn. Up to the end of May 2010, EUR 99.8bn were required in total by Irish banks. This amount includes EUR 19.3bn that were used as capital injections (Table 1). Both banks in our study were recapitalized by the Irish government on the 21st of December 2008 and approved by the European Commission on 26/03/2009 (BOI) and 12/05/2009 (AIB).[28]. Under this scheme AIB and BOI were each provided EUR 3.5bn. Similar public aid structures for both

[28] IP/09/744 and IP/09/483

banks lead to homogeneous findings, which supports our H3.

State interventions are shown to be most successful in the case of Ireland. The magnitude of the rescue scheme has been the highest (relative to GDP) among the countries analyzed, which led to the clearest results for the risk-transfer mechanism. The impact of a banking sector shock on itself decreases substantially after measures are provided. Furthermore, there is a significant impact on the government spreads only in the short-run. The flip side of the coin is the strong influence of a government sector shock on the banks after the rescue schemes, which amplified the serious issues of the Irish financial sector as the sovereign debt problems emerged.

Combining the results from the two analyses, we find strong evidence for H1, H2a, H2b. Before bailout programs the data shows that the channel through which risk is spread into the market originates from the banking sector rather than from the government. In the period after government interventions, the risk transfer mechanism puts more weight on the developments of the government CDS spread. As the government took over the tail risk from the banks, the development of the Irish CDS series plays an increasingly important role. Only in the very short-run changes in banks' CDS spreads impact on the government series during and after the state interventions. The effects of a banking sector shock on itself have weakened, underpinning the success of the Irish bailout schemes.

4.2.3 Italy

The main cointegration relations between Italy and the selected domestic banks (Intesa San Paolo (ISP) and Unicredito (UCR)) are presented in Table 4. Table 3 presents the findings for Granger-causality tests and Table 5 the generalized impulse responses.[29]

Cointegration and Granger-Causality Analysis

In the period preceding the government support for the Italian banking industry (i.e. Stage 1+2), we find that the banks' and sovereign CDS series are tied together in a long-run equilibrium. Interpreting the β coefficients, neglecting the remaining dynamics of the system, we argue that in the long-run a 1% increase in a ISP(UCR)'s CDS spread leads to a 0.71%(0.67%) increase in the CDS series of Italy. The gaps (i.e. the constants of the cointegration relations) between the two CDS series is in both setups estimated to be significantly different from zero. The speed of adjustment, reflected by the estimated α-coefficients, is faster for the CDS spreads of banks, i.e. $|\hat{\alpha}_{IT}| = 0.012 < 0.020 = |\hat{\alpha}_{ISP}|$ and $|\hat{\alpha}_{IT}| = 0.010 < 0.014 = |\hat{\alpha}_{UCR}|$. Regarding the short-run dynamics results reveal that Italy is Granger-caused by the developments in ISP's and UCR's CDS spread in Stage 1+2, consistent with our assumption that the information from the financial sector was systemically important.

During and after the Italian government bailout program for the financial sector the dynamics between the sovereign and banks' CDS spreads change. Firstly, UCR is found to be in a stable long-run equilibrium with the Italian government CDS series only during Stage 5. In this setup

[29]Preliminary test results and the graph of the respective time series are presented in Appendix C.4.

the estimated β-coefficients imply that a 1% increase in government's spreads induces an upward adjustment of UCR's CDS of 1.28%. The error correction mechanism of IT-ISP for the entire post-intervention period is as follows:

$$cds_{IT,t} = \underset{(0.087)}{0.864} \times cds_{ISP,t} + \underset{(0.385)}{0.922} - ec_t.^{30}$$

A marginal change of the Italian CDS series by 1% leads to an adjustment of cds_{ISP} by 0.86%. Elasticities of both banks cannot be compared as they refer to different stages of our sample. The constant is significantly different from zero in both setups.

In the period after government interventions, the loading coefficients indicate that Italy provides the stochastic trend, as the CDS series of the latter is tested to be weakly exogenous. This result implies that, although the Italian CDS spread does not adjust to deviations from the long-run equilibrium, the banks' CDS spreads react to these changes. In contrast with the results of the previous period, after state interventions the Italian CDS spread Granger-causes both bank's CDS spreads but not vice versa.

Impulse Response Analysis

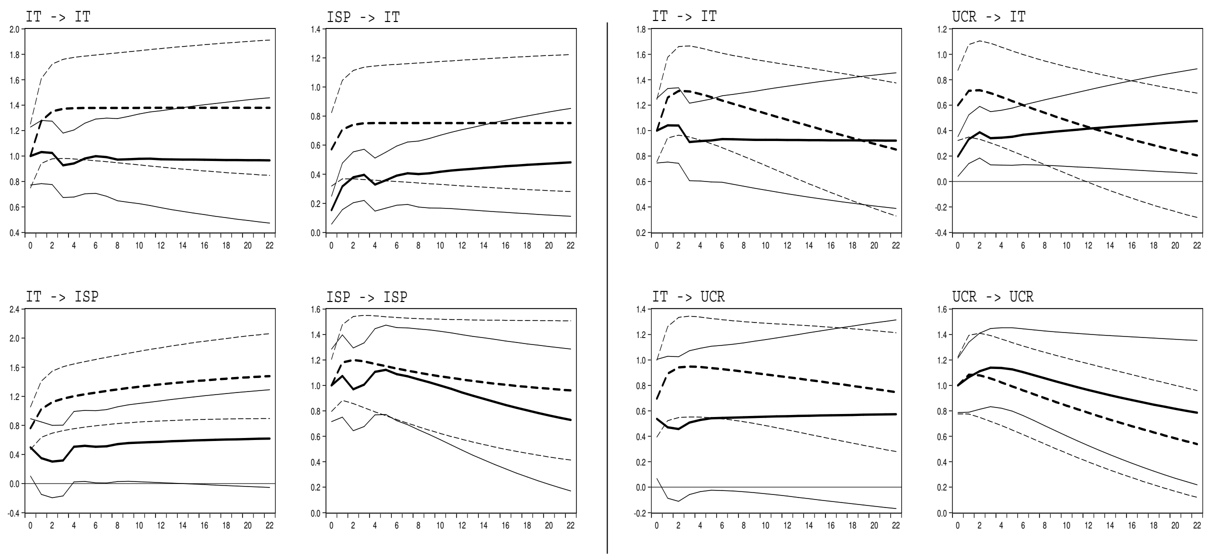


Figure 6: Generalized Impulse Responses for Italy: (Solid) Before, (Dotted) During & After Gvt. Interv.
Note: ***[Left Panel]*** Upper-Left: IT (impulse variable) - IT (response variable). Lower-Left: IT (impulse var.) - ISP (response var.). Upper-Right: ISP (impulse var.) - IT (response var.). Lower-Right: ISP (impulse var.) - ISP (response var.). ***[Right Panel]*** Upper-Left: IT (impulse var.) - IT (response var.). Lower-Left: IT (impulse var.) - UCR (response var.). Upper-Right: UCR (impulse var.) - IT (response var.). Lower-Right: UCR (impulse var.) - UCR (response var.). Solid lines: responses before government interventions (bold) and the 95% bootstrapped confidence interval (thin). Dotted lines: responses after government interventions (bold) and the 95% bootstrapped confidence interval (thin). X-axis: number of days (after the shock). Y-axis: impact relative to one standard deviation shock of the impulse variable.

The graph in the upper right corner of each panel depicts the effect of a banking shock to the sovereign CDS series. The solid line emphasizes that risk permanently spreads to the government

[30] The cointegration graph is provided in Appendix C.4, Figure **??**

CDS series before interventions, while after interventions the shock of UCR (right panel) shifts the Italian CDS series stronger but only temporarily ($t \leq 12$). A shock originating from ISP (left panel) leads to a permanent shift in the government CDS spread. These findings support our H2a and H3. On the other hand, in the period before interventions (solid lines) the effects of a shock from the government sector (the lower-left graph in each panel) are significant in the short-run for both banks. During/after interventions (dotted lines) the impact is stronger and permanent, in line with our H2b. The pattern of a bank shock on the series themselves is very similar in the two periods (the lower-right corner in each panel). A government shock on itself is stronger in the period afterwards for both setups.

Discussion

Italy has one of the highest debt burdens[31] among European Union countries. This fact determined the Italian government to pledge in total EUR 62bn, that represents slightly above 4% of the 2008 GDP. This ratio is the lowest among the analyzed countries in this paper. Capital injections accounted for EUR 4.1bn from a committed amount of EUR 12 bn. Italy also promised to support its domestic banks with an asset purchase scheme worth EUR 50bn. On 20 March 2009, ISP started the procedure to obtain EUR 4bn in state aid for recapitalization[32]. On the other hand, UCR which is the biggest Italian bank did not request any capital injection from the state of Italy. The formal inquiry of ISP for participating in the government aid scheme is reflected in our GIR analysis: the CDS series of ISP became more sensitive to unexpected changes in the Italian spread than the CDS series of UCR. This result and the cointegration relation between IT and ISP (in Stage 4+5+6) provide evidence for our third hypothesis (H3).

In the case of ISP, we also find that the rescue measures taken by the Italian government were not successful in absorbing partial risks of default from the latter bank.[33] A shock of the bank on itself has even a stronger effect after bailout schemes. The other finding underpins, that investors believed that the default risk of ISP would spread to the government sector. In the case of UCR, we detect a similar pattern like in other countries, since the effect of a banking sector shock on itself slightly decreases.

Before Lehman Brothers' default, the systemic banking crisis spreads to the sovereign market, which can be supported by the results from Granger-causality analysis, or the permanent effect of a banking sector shock in the context of the GIR analysis. However, movements of IT's CDS spread have an effect on the bank spreads as well, which contradicts partially our H1. After state interventions, this relation becomes more pronounced as now IT Granger-causes both banks, provides the stochastic trend in the cointegration relations, and government shocks cause strong deviations in the banks' CDS series. Nonetheless, banks still influence the government CDS series, albeit UCR only temporarily. Bailout schemes seem not to limit the effects of a banking sector shock on itself

[31] Italy's public debt was estimated around 105% of GDP in 2008.

[32] `http://www.group.intesasanpaolo.com/scriptIsir0/si09/contentData/view/content-ref?id=CNT-04-000000003F8D4`
According to this document, on 29 September 2009 ISP decided not to participate anymore in the Italian aid program for the banking sector, so-called "the Tremonti Bonds" program, but to issue debt to private investors.

[33] This can be also seen as a result of ISP's decision not to subscribe for the "Tremonti bonds" program in the end.

as the intensity of the impact is almost the same as in the period before government interventions. On the other hand, sovereign spreads are more sensitive to shocks after bank support schemes.

5 Conclusions

The recent financial crisis led governments to tailor aid programs for financial institutions. The magnitude and dimensions were unique in European history. A series of bank failures would threaten the functioning of the whole economy as important financial institutions incorporate a systemic component. Hence, governments, besides central banks, took crucial steps in the attempt to rescue the financial system. By arguing that government bailout programs marked an important event for investors, we derive our hypotheses about how the relations are expected to change. First, we hypothesize that the increase in default risk prior to interventions originates mainly from the financial sector. After bailout programs are set up by European governments, we argue that the sensitivity of the sovereign default risk to the financial sector increases due to the private-to-public risk transfer. Moreover, the default risk of the banking sector is asserted to be influenced strongly by the government sector. How the participation of a bank in the rescue schemes is perceived by market stakeholders should affect its CDS sensitivity to changes in sovereign credit risk. Finally, we argue that important determinants for the changes in linkages are country bailout-specific characteristics.

As stated in our first hypothesis, before government interventions, sovereign credit risk is strongly impacted by the movements in bank CDS spreads, while changes in the sovereign CDS spreads have a weak impact on both bank and sovereign CDS markets. Regarding the H1, our findings provide evidence for FR, DE, IR, NL, and SP but not for IT and PT. Portugal's and Italy's default risk seem to carry an important role in the development of their local banks' default risk even before the Lehman Brothers event.

For the second set of hypotheses (H2a, H2b), i.e. after government interventions, we can conclude homogeneously that changes in the sovereign CDS spreads contribute permanently to the financial sector CDS spreads. On the other hand, changes in banks' risk of default are found to affect the sovereign CDS spreads only transitorily. Relative to the period before the impact is stronger in the short-run (i.e. at day 0 and at day 1) in all countries, while for most countries insignificant in the long-run (i.e. after 22 days); exceptions are IT, SP, and PT.

Furthermore, the variability in interdependencies between domestic banks and the government cannot be clearly related to differences in the perceived default risk transferred. Countries with similar state aid[34] for both analyzed banks show an equal bank CDS sensitivity to the changes in sovereign credit risk. Banks in Germany (DB and COM) and Italy (ISP and UCR) were differently involved in the rescue schemes, but we only find heterogeneous linkages between Italian banks' and sovereign CDS spreads. Our results possibly suggest that the extra aid provided to COM has been successful in absorbing partially the risk of default while the government willing-

[34] FR, IR, SP, and PT

ness to help ISP strongly links the default risk of the latter to the development of the Italian CDS spread and amplifies its sensitivity to shocks in both, the banking and the sovereign sector. Furthermore, in the case of Ireland our results indicate that bailout schemes led to the desired results, in the sense that the spillover effects that originate from the financial sector are limited after the implementation of bank aid programs.

Lastly, the cross-country analysis reveals heterogeneity in the impact of bank support programs. On the one hand, the effects of a sovereign shock to banks from the same country are closely linked, on the other hand the effects of a sovereign shock to banks across countries can be clustered in INNER (FR, DE, NL) and OUTER (IR, IT, PT, SP).

With respect to future research, applying the same methodology but analyzing the credit risk interdependence of European states, one could shed light on the dynamics of the public-to-public risk transfer mechanism in the Eurozone. Drawing a comparison between the private-to-public and public-to-public risk transfer mechanisms, policy makers would gain important insights, especially in light of the "too-big-to-fail" argument.

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A Main Results

Table 3: Results of Granger-Causality Tests for all Countries.

Country	Period	Independent	Dependent	p-value	Independent	Dependent	p-value
France	Before	BNP	FR	0.948	SG	FR	0.662
		FR	BNP	**0.014**	FR	SG	**0.059**
	After	BNP	FR	**0.089**	SG	FR	**0.096**
		FR	BNP	**0.000**	FR	SG	**0.002**
Germany	Before	COM	DE	**0.005**	DB	DE	0.152
		DE	COM	0.711	DE	DB	0.772
	After	COM	DE	**0.008**	DB	DE	**0.003**
		DE	COM	**0.009**	DE	DB	**0.004**
Ireland	Before	AIB	IR	0.499	BOI	IR	**0.002**
		IR	AIB	0.333	IR	BOI	0.451
	After	AIB	IR	0.174	BOI	IR	0.216
		IR	AIB	**0.000**	IR	BOI	**0.000**
Italy	Before	ISP	IT	**0.000**	UCR	IT	**0.002**
		IT	ISP	0.156	IT	UCR	0.536
	After	ISP	IT	0.392	UCR	IT	0.348
		IT	ISP	**0.008**	IT	UCR	**0.002**
Netherlands	Before	ABN	NL	**0.062**	ING	NL	**0.012**
		NL	ABN	0.705	NL	ING	0.160
	After	ABN	NL	**0.003**	ING	NL	**0.040**
		NL	ABN	**0.059**	NL	ING	**0.033**
Portugal	Before	BCP	PT	**0.001**	BES	PT	**0.000**
		PT	BCP	0.909	PT	BES	0.846
	After	BCP	PT	0.871	BES	PT	0.871
		PT	BCP	**0.000**	PT	BES	**0.000**
Spain	Before	BBVA	SP	**0.001**	BS	SP	**0.000**
		SP	BBVA	**0.024**	SP	BS	**0.009**
	After	BBVA	SP	**0.023**	BS	SP	**0.020**
		SP	BBVA	**0.000**	SP	BS	**0.000**

Note: this table presents the Granger-causality tests for the entire period before government interventions and for the entire period during and after bailout programs. "Before" stands for *Stage 1+2* and "After" denotes *Stage 4+5+6*. We report the p-values of the tests. The significant results are emphasized in bold. The independent variable Granger-causes the dependent variable.

Table 4: Results of Cointegration Analysis for all Countries.

Country	Period	Sov - Bk_1	α_{Sov}	α_{Bk}	β_{Sov}	β_{Bk}	Constant
France	Stage 1 + 2	FR - BNP	-0.085	0.024	1.000	-1.059	2.031
			[-3.273]	**[2.050]**	-	**[-6.997]**	**[3.693]**
		FR - SG	-0.124	0.022	1.000	-0.892	1.584
			[-3.991]	**[1.864]**	-	**[-8.934]**	**[4.136]**
	Stage 4 + 5 + 6	FR - BNP	0.018	0.018	1.000	-2.795	8.237
			[3.582]	**[3.154]**	-	**[-5.636]**	**[3.889]**
		FR - SG	0.017	0.015	1.000	-3.821	13.769
			[3.712]	**[3.136]**	-	**[-5.614]**	**[4.425]**
Germany	Stage 1 + 2	DE - COM	-0.108	-0.009	1.000	-0.719	1.235
			[-3.943]	[-0.583]	-	**[-5.775]**	**[2.458]**
		DE - DB	-0.122	0.009	1.000	-0.930	2.087
			[-4.046]	[0.561]	-	**[-7.866]**	**[4.428]**
	Stage 5	DE - COM	-0.045	0.004	1.000	-1.007	1.330
			[-2.211]	[0.233]	-	**[-1.913]**	[0.541]
	Stages 4 + 5 + 6	DE - DB	0.015	0.011	1.000	-3.432	12.382
			[3.442]	**[3.068]**	-	**[-5.082]**	**[3.944]**
Ireland	Stage 2	IR - AIB	-0.278	0.008	1.000	-0.567	-0.520
			[-3.826]	[0.171]	-	**[-5.432]**	[-1.032]
		IR - BOI	-0.475	-0.043	1.000	-0.581	-0.349
			[-5.170]	[-0.655]	-	**[-10.122]**	[-1.212]
	Stage 4 + 5 + 6	IR - AIB	0.014	0.060	1.000	-0.724	-1.116
			[1.012]	**[4.582]**	-	**[-6.905]**	**[-1.903]**
		IR - BOI	-0.002	0.096	1.000	-0.694	-1.292
			[-0.086]	**[5.414]**	-	**[-10.794]**	**[-3.584]**
Italy	Stage 1 + 2	IT- ISP	-0.012	0.020	1.000	-1.404	2.003
			[-2.282]	**[2.078]**	-	**[-6.927]**	**[2.706]**
		IT - UCR	-0.010	0.014	1.000	-1.502	2.647
			[-2.110]	**[1.767]**	-	**[-5.845]**	**[2.658]**
	Stage 5	IT - UCR	0.021	0.097	1.000	-1.280	1.462
			[0.761]	**[3.318]**	-	**[-9.331]**	**[2.247]**
	Stage 4 + 5 + 6	IT - ISP	0.003	0.066	1.000	-0.864	-0.922
			[0.162]	**[3.167]**	-	**[-9.881]**	**[-2.393]**
Netherlands	Stage 1 + 2	NL - ABN	-0.097	0.002	1.000	-0.829	1.416
			[-3.865]	[0.146]	-	**[-8.708]**	**[3.734]**
		NL - ING	-0.152	-0.009	1.000	-0.741	1.013
			[-4.763]	[-0.410]		**[-13.565]**	**[4.787]**
	Stage 6	NL - ABN	-0.017	0.038	1.000	-1.596	4.158
			[-0.944]	**[2.929]**	-	**[-5.938]**	**[3.243]**
	Stage 4 + 5	NL - ING	0.007	0.042	1.000	-1.572	3.125
			[0.427]	**[3.353]**	-	**[-7.475]**	**[3.220]**
Portugal	Stage 2	PT - BCP	-0.031	0.128	1.000	-0.986	0.715
			[-1.030]	**[2.313]**	-	**[-8.592]**	[1.443]
		PT - BES	-0.151	0.072	1.000	-0.789	0.101
			[-2.916]	[0.682]	-	**[-15.128]**	[0.420]
	Stage 4 + 5 + 6	PT - BCP	0.021	0.037	1.000	-0.793	-0.701
			[1.808]	**[3.687]**		**[-4.811]**	[-0.892]
		PT - BES	-	-	-	-	-
Spain	Stage 1 + 2	SP - BBVA	-0.019	0.023	1.000	-1.631	3.658
			[-1.693]	**[2.975]**	-	**[-7.714]**	**[4.404]**
		SP - BS	-0.022	0.023	1.000	-1.619	3.632
			[-1.931]	**[2.871]**	-	**[-7.873]**	**[4.488]**
	Stage 4 + 5 + 6	SP - BBVA	0.032	0.061	1.000	-0.985	-0.009
			[1.927]	**[3.756]**	-	**[-5.796]**	[-0.012]
		SP - BS	0.043	0.072	1.000	-1.106	0.527
			[2.555]	**[4.258]**	-	**[-7.215]**	[0.743]

Note: this table presents the cointegration relationships which passed the stability test. Subperiods are only included if the longer period did not pass the stability test (see Subsection Econometric Methodology). Coefficients are labeled in reference to (1). β-coefficients describe the long-run relationship between banks and sovereign log-CDS spreads. The loading coefficients α measure *the speed of adjustment* with which a particular CDS, adjusts to the long-run relationship. In case that α_{Sov} is significant and has an opposite sign to β_{Sov} it means that the Sovereign adjusts back to the long-run equilibrium defined by $\beta' y_t = 0$, whenever $\beta' y_t \neq 0$. Whenever one of the α-coefficients is not significant, it means that the respective variable can be argued to provide the stochastic trend that determines the long-run relation and it is not adjusting at all to the long-run equilibrium. Whenever one α coefficient is significant but with the same sign as the respective β parameter, the variable moves the entire equilibrium. t-statistics are reported in square brackets.

Table 5: Generalized Impulse Responses

	Impulse	Response	**Before Gvt. Interventions**[1] **Days** 0	1	5	22	Remark	**During/After Gvt. Interventions**[2] **Days** 0	1	5	22	Remark
FR	FR	FR	**1.000**	**0.657**	**0.579**	**0.328**		**1.000**	**1.203**	**1.186**	**0.923**	
		BNP	0.046^{n}	**0.120**	**0.150**	**0.228**		**0.565**	**0.755**	**0.731**	**0.483**	
	BNP	BNP	**1.000**	**1.006**	**0.942**	**0.835**		**1.000**	**1.052**	**0.891**	0.290^{n}	
		FR	0.230^{n}	0.204^{n}	**0.418**	**0.764**		**0.452**	**0.584**	**0.416**	-0.227^{n}	
	FR	FR	**1.000**	**0.638**	**0.495**	**0.217**		**1.000**	**1.201**	**1.114**	**0.790**	
		SG	0.030^{n}	0.080^{n}	0.125^{n}	0.192^{n}		**0.499**	**0.691**	**0.642**	**0.348**	
	SG	SG	**1.000**	**1.121**	**1.083**	**1.004**		**1.000**	**1.041**	**0.843**	0.206^{n}	
		FR	0.202^{n}	0.246^{n}	**0.502**	**0.840**		**0.520**	**0.626**	**0.383**	-0.389^{n}	
DE	DE	DE	**1.000**	**0.780**	**0.474**	**0.157**		**1.000**	**1.132**	**1.072**	**0.587**	*VAR*
		COM	**0.088**	**0.125**	0.101^{n}	0.040^{n}		**0.425**	**0.592**	**0.627**	**0.550**	*VAR*
	COM	COM	**1.000**	**1.091**	**1.088**	**1.171**		**1.000**	**1.060**	**1.004**	**0.580**	*VAR*
		DE	0.285^{n}	**0.356**	0.285^{n}	**0.675**		**0.435**	**0.608**	**0.441**	-0.254^{n}	*VAR*
	DE	DE	**1.000**	**0.778**	**0.461**	0.201^{n}		**1.000**	**1.140**	**1.129**	**0.889**	
		DB	**0.071**	**0.103**	0.125^{n}	0.146^{n}		**0.433**	**0.615**	**0.611**	**0.412**	
	DB	DB	**1.000**	**1.092**	**1.117**	**1.094**		**1.000**	**1.156**	**1.034**	0.428^{n}	
		DE	0.267^{n}	**0.453**	**0.450**	**0.898**		**0.569**	**0.766**	**0.603**	-0.127^{n}	
IR	IR	IR	**1.000**	**0.539**	**0.526**	**0.397**	*VAR*	**1.000**	**1.266**	**1.123**	**1.270**	
		AIB	0.122^{n}	0.184^{n}	0.181^{n}	0.195^{n}	*VAR*	**0.251**	**0.512**	**0.769**	**1.276**	
	AIB	AIB	**1.000**	**1.168**	**1.172**	**0.755**	*VAR*	**1.000**	**0.953**	**1.063**	**0.676**	
		IR	0.266^{n}	0.263^{n}	**0.331**	**0.524**	*VAR*	**0.291**	**0.385**	0.221^{n}	0.282^{n}	
	IR	IR	**1.000**	**0.529**	**0.500**	**0.397**	*VAR*	**1.000**	**1.268**	**1.116**	**1.250**	
		BOI	0.115^{n}	**0.194**	0.211^{n}	0.222^{n}	*VAR*	**0.212**	**0.508**	**0.677**	**1.410**	
	BOI	BOI	**1.000**	**1.088**	**1.142**	**0.803**	*VAR*	**1.000**	**0.831**	**0.807**	0.459^{n}	
		IR	0.216^{n}	**0.400**	**0.365**	**0.431**	*VAR*	**0.220**	0.222^{n}	0.134^{n}	0.259^{n}	
IT	IT	IT	**1.000**	**1.031**	**0.981**	**0.966**		**1.000**	**1.275**	**1.378**	**1.379**	
		ISP	**0.498**	0.350^{n}	0.519^{n}	0.619^{n}		**0.760**	**1.021**	**1.226**	**1.477**	
	ISP	ISP	**1.000**	**1.074**	**1.122**	**0.729**		**1.000**	**1.179**	**1.156**	**0.960**	
		IT	**0.152**	**0.316**	**0.359**	**0.482**		**0.570**	**0.708**	**0.751**	**0.752**	
	IT	IT	**1.000**	**1.043**	**0.923**	**0.921**		**1.000**	**1.259**	**1.262**	**0.851**	*VAR*
		UCR	**0.537**	0.471^{n}	0.542^{n}	0.573^{n}		**0.696**	**0.892**	**0.936**	**0.746**	*VAR*
	UCR	UCR	**1.000**	**1.064**	**1.125**	**0.785**		**1.000**	**1.083**	**0.992**	**0.539**	*VAR*
		IT	**0.197**	**0.332**	**0.352**	**0.475**		**0.598**	**0.712**	**0.632**	0.205^{n}	*VAR*
NL	NL	NL	**1.000**	**0.658**	**0.469**	0.204^{n}		**1.000**	**1.143**	**1.095**	**0.744**	*VAR*
		ABN	0.047^{n}	0.093^{n}	0.094^{n}	0.073^{n}		**0.347**	**0.468**	**0.473**	**0.364**	*VAR*
	ABN	ABN	**1.000**	**1.003**	**1.132**	**1.173**		**1.000**	**1.111**	**1.084**	**0.836**	*VAR*
		NL	**0.104**	**0.095**	**0.328**	**0.730**		**0.408**	**0.594**	**0.506**	0.016^{n}	*VAR*
	NL	NL	**1.000**	**0.680**	**0.434**	0.160^{n}		**1.000**	**1.152**	**1.165**	**1.012**	*VAR*
		ING	0.109^{n}	**0.171**	0.184^{n}	0.136^{n}		**0.438**	**0.585**	**0.623**	**0.587**	*VAR*
	ING	ING	**1.000**	**0.962**	**1.075**	**1.135**		**1.000**	**1.123**	**1.011**	**0.539**	*VAR*
		NL	0.233^{n}	0.135^{n}	**0.400**	**0.759**		**0.606**	**0.785**	**0.723**	0.368^{n}	*VAR*
PT	PT	PT	**1.000**	**0.982**	**0.949**	**0.806**	*VAR*	**1.000**	**1.264**	**0.990**	**1.170**	
		BCP	**0.342**	**0.387**	**0.406**	**0.424**	*VAR*	**0.535**	**0.785**	**0.809**	**1.056**	
	BCP	BCP	**1.000**	**1.104**	**1.022**	**0.713**	*VAR*	**1.000**	**1.151**	**1.105**	**1.002**	
		PT	**0.227**	**0.358**	**0.396**	**0.450**	*VAR*	**0.724**	**0.897**	**0.675**	**0.653**	
	PT	PT	**1.000**	**0.980**	**0.941**	**0.791**	*VAR*	**1.000**	**1.259**	**1.306**	**1.079**	*VAR*
		BES	**0.295**	**0.325**	**0.353**	0.402^{n}	*VAR*	**0.542**	**0.804**	**0.941**	**1.000**	*VAR*
	BES	BES	**1.000**	**1.141**	**1.066**	**0.750**	*VAR*	**1.000**	**1.250**	**1.298**	**1.098**	*VAR*
		PT	**0.207**	**0.371**	**0.421**	**0.483**	*VAR*	**0.794**	**0.975**	**0.954**	0.599^{n}	*VAR*
SP	SP	SP	**1.000**	**0.554**	**0.527**	**0.482**		**1.000**	**1.202**	**0.953**	**1.012**	
		BBVA	0.061^{n}	0.128^{n}	-0.067^{n}	0.172^{n}		**0.648**	**0.874**	**0.682**	**0.806**	
	BBVA	BBVA	**1.000**	**1.083**	**1.018**	**0.595**		**1.000**	**1.172**	**0.804**	**0.586**	
		SP	0.133^{n}	0.175^{n}	**0.605**	**0.511**		**0.651**	**0.812**	**0.537**	**0.398**	
	SP	SP	**1.000**	**0.559**	**0.552**	**0.486**		**1.000**	**1.188**	**0.897**	**0.950**	
		BS	0.069^{n}	0.146^{n}	-0.053^{n}	0.168^{n}		**0.663**	**0.893**	**0.628**	**0.739**	
	BS	BS	**1.000**	**1.085**	**0.999**	**0.573**		**1.000**	**1.155**	**0.690**	**0.405**	
		SP	0.142^{n}	0.172^{n}	**0.648**	**0.511**		**0.652**	**0.808**	**0.418**	0.226^{n}	
Avg.	SOV	SOV	1.000	0.743	0.629	0.465		1.000	1.210	1.127	0.994	
		BK	0.174	0.206	0.205	0.256		0.501	0.714	0.741	0.804	
	BK	BK	1.000	1.077	1.079	0.865		1.000	1.094	0.985	0.615	
		SOV	0.205	0.277	0.419	0.609		0.535	0.677	0.528	0.197	

Note: Each impulse-variable has an effect on itself and the second variable of the bivariate system. A unit shock in the structural error leads to one standard deviation (in %) increase in the level of the impulse-variable. This effect is normalized to 1. The GIR of the second response-variable represent the percentage change of the levels given the normalized impulse. ^{n} denotes insignificant effects by considering bootstrapped 95% confidence intervals with 2000 replications. [1] denotes Stage 1+2 and [2] denotes Stage 4+5+6. We report contemporaneous responses (Days = 0) and effects after 1 day, 5 days (after one week), and 22 days (after one month). *VAR* means that we use a VAR in levels for obtaining the GIR. This is done when tests and/or cointegration relation checks do not indicate an equilibrium relation for entire Stage 1+2 or Stage 4+5+6. In "Avg." section we provide the mean impulse responses from a shock in sovereign CDS spreads (SOV) and from a shock in bank CDS spreads (BK).

B Further Issues on Methodology

VEC-Analysis - Selection of Sub-stages

The selection of sub-stages for the study of the long-run relations is carried out following the subsequent steps: if tests (see below) do not provide evidence for cointegration relations for a certain stage we consider sub-periods. Also if stability of a cointegration space is rejected we consider a finer grid for the time periods. For investigating this, we consider recursively estimated eigenvalues as proposed by Hansen and Johansen (1999). Cointegration results are only reported for the stages that pass the stability test using the 1% critical value as a decision boundary. If there is no evidence for a (stable) cointegration relation on the finer grid as well, we report none for the entire stage before or during/after government interventions.

Pre-Analysis of the Data, Model Specification, and Estimation

Firstly, we apply the standard unit root (stationarity) testing procedures, i.e. the Augmented-Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, to the respective time series in each sub-sample.[35] All of the latter include an intercept because we disregard the possibility of a zero mean or trend stationary process. The latter process is not considered as it is economically unreasonable to assume that CDS series rise perpetually. We do not analyze systems of CDS series in a vector error correction model (VECM) if there is evidence that one or both series are stationary as in this case they cannot share a joint stochastic trend. For detecting a common stochastic trend, this study considers on the one hand Engle-Granger ADF test and on the other hand Johansen's trace and maximum eigenvalue tests. The latter tests focus only on the setup with a restricted constant, as argued before, any deterministic trend in the variables or cointegration relation is economically unjustified. When a common stochastic trend is detected by one of the previous tests and stability of the cointegration space is not rejected, we model the series in a VECM framework. If not, we proceed as described above. In finalizing our exact specifications of the models we determine the optimal lag order p by, on the one hand, minimizing one of the common information criteria[36] and on the other taking care of remaining serial correlation in the residuals.[37] The VECM is estimated by Johansen's maximum likelihood procedure and the VAR model via ordinary least squares.

Interpretation of Long-Run Relations in a VECM

The loading coefficients, α, measure *the speed of adjustment* with which a particular CDS adjusts to the long-run relationship. The adjustment forces start acting, whenever the long-run relation (defined by $\beta' y_{t-1} = 0$, where $y_{t-1} = (cds_{Sov,t-1},\ cds_{Bk,t-1})'$) is out of equilibrium, i.e.

[35] Results are available upon request from the authors.

[36] Aikaike information criterion, Hannan Quinn criterion, Schwarz criterion, and final prediction error

[37] When applicable, we also look at the plots of the cointegration relations in order to check whether these can be argued to be stable. The plot is expected to a show a time series that fluctuates nicely around some mean

if $\beta' y_{t-1} \neq 0$. In case that α_{Sov} is significant and has an opposite sign to β_{Sov} (i.e. in our setup $\alpha_{Sov} < 0$) it means that the "Sovereign" is driven by the error correction mechanism. Or put differently, that it adjusts back to the long-run equilibrium defined by $\beta' y_{t-1} = 0$, whenever $\beta' y_{t-1} \neq 0$. Equivalently, when α_{Bk} is significant and has an opposite sign to β_{Bk}, it shows the speed of adjustment of the "Bank" to the equilibrium. With both α-coefficients being significant and having opposite signs to their respective β-coefficients, the variables are said to be in a real cointegration relationship; both series are taking part in the error correction mechanism. Whenever one of the α-coefficients is not significant, it means that the respective variable can be argued to provide the stochastic trend that determines the long-run relation. This can be formally tested using a Likelihood Ratio test through a zero restriction on this parameter. If the restriction cannot be rejected, the variable of the respective α coefficient is called *weakly exogenous*. Furthermore, it is not adjusting at all in case that the variables are not in long-run equilibrium, $\beta' y_{t-1} \neq 0$. Whenever one α coefficient is significant but with the same sign as the respective β parameter, the variable is said not to be part of the error correction mechanism as the forces in the model do not attract both series back to equilibrium. Series in this setup can only define a long-run relation if the variable that is in a formal error correction relation adjusts faster to the new equilibrium than the other one. One can think of this phenomenon in a way that the variable which is not part of the error correction mechanism moves the entire equilibrium (i.e. when the variable increases in value the long-run equilibrium will be established with both series achieving a higher value). In the literature the term overshooting is used to describe this occurrence.[38]

[38]For a discussion of a model with overshooting please refer to Hansen and Johansen (1998).

C Specific Country Analysis

C.1 France

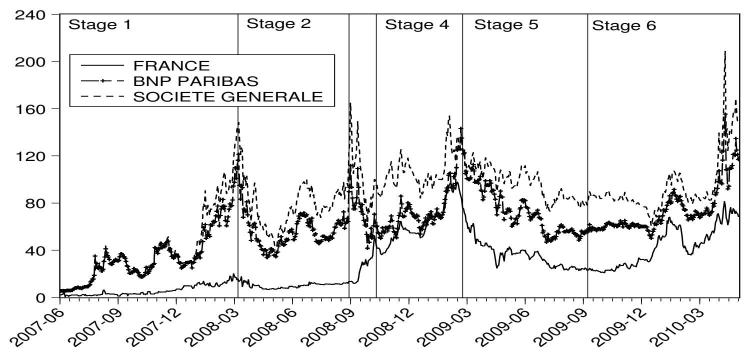

Figure 7: France: CDS Level Series

Table 6: France: Bivariate Cointegration Tests

Period	Variables	Lags	Trace Statistic		Max Eigenvalue		Engle-Granger Test
			$r = 0$	$r = 1$	$r = 0$	$r = 1$	
Stage 1	FR - BNP	0	**0.021**	0.212	**0.031**	0.212	-2.406
	FR - SG	0	**0.006**	0.119	**0.012**	0.119	**-4.446**
Stage 2	FR - BNP	*					
	FR - SG	1	**0.038**	0.332	**0.040**	0.332	**-5.701**
Stage 1 + 2	FR - BNP	1	**0.017**	0.109	**0.045**	0.109	**-3.102**
	FR - SG	1	**0.005**	0.147	**0.010**	0.147	**-4.455**
Stage 4	FR - BNP	6	*0.119*	0.130	0.296	0.130	-1.507
	FR - SG	5	0.764	0.779	0.706	0.779	-1.663
Stage 5	FR - BNP	2	0.321	0.290	0.477	0.290	-2.260
	FR - SG	8	**0.062**	0.124	0.158	0.124	**-3.101**
Stage 6	FR - BNP	1	0.611	0.583	0.631	0.583	-2.033
	FR - SG	1	0.507	0.504	0.554	0.504	-1.573
Stage 4 + 5	FR - BNP	1	0.282	0.735	0.192	0.735	-1.163
	FR - SG	1	0.295	0.944	0.142	0.944	-2.458
Stage 5 + 6	FR - BNP	1	0.211	0.447	0.216	0.447	-2.535
	FR - SG	1	**0.105**	0.297	0.138	0.297	-2.053
Stage 4 + 5 + 6	FR - BNP	1	**0.057**	0.313	**0.067**	0.313	-2.230
	FR - SG	1	**0.072**	0.514	**0.054**	0.514	-2.250

Note: Trace and Max Eigenvalue are the Johansen tests statistics (with a restricted constant). p-values are reported. The respective null hypothesis is denoted by $r = \{0, 1\}$, where e.g. $r = 1$ denotes one cointegration relation. * signifies that at least one of the series is stationary. For the Engle-Granger test the ADF test statistic is reported; critical values at 5% and 10% are -3.37 and -3.07 respectively.

C.2 Germany

Table 7: Germany: Bivariate Cointegration Tests

Period	Variables	Lags	Trace Statistic		Max Eigenvalue		Engle-Granger Test
			$r = 0$	$r = 1$	$r = 0$	$r = 1$	
Stage 1	DE - COM	0	**0.044**	0.171	**0.086**	0.171	**-3.696**
	DE - DB	3	0.113	0.177	0.226	0.177	**-4.024**
Stage 2	DE - COM	*					
	DE - DB	*					
Stage 1 + 2	DE - COM	3	**0.014**	**0.062**	**0.057**	**0.062**	**-4.441**
	DE - DB	3	**0.005**	**0.048**	**0.027**	**0.048**	**-5.273**
Stage 4	DE - COM	1	0.413	0.663	0.350	0.663	-1.012
	DE - DB	1	**0.064**	0.331	**0.071**	0.331	-1.596
Stage 5	DE - COM	1	0.164	0.496	0.146	0.496	-2.983
	DE - DB	7	**0.0471**	0.117	0.124	0.117	-1.778
Stage 6	DE - COM	1	0.688	0.529	0.763	0.529	-1.368
	DE - DB	1	0.724	0.682	0.711	0.682	-0.900
Stage 4 + 5	DE - COM	1	**0.0421**	0.2814	**0.052**	0.2814	-1.485
	DE - DB	*					
Stage 5 + 6	DE - COM	*					
	DE - DB	*					
Stage 4 + 5 +6	DE - COM	1	**0.0063**	0.1166	**0.0145**	0.1166	-1.774
	DE - DB	1	**0.0692**	0.2769	**0.0919**	0.2769	-2.088

Note: Trace and Max Eigenvalue are the Johansen tests statistics (with a restricted constant). p-values are reported. The respective null hypothesis is denoted by $r = \{0, 1\}$, where e.g. $r = 1$ denotes one cointegration relation. * signifies that at least one of the series is stationary. For the Engle-Granger test the ADF test statistic is reported; critical values at 5% and 10% are -3.37 and -3.07 respectively.

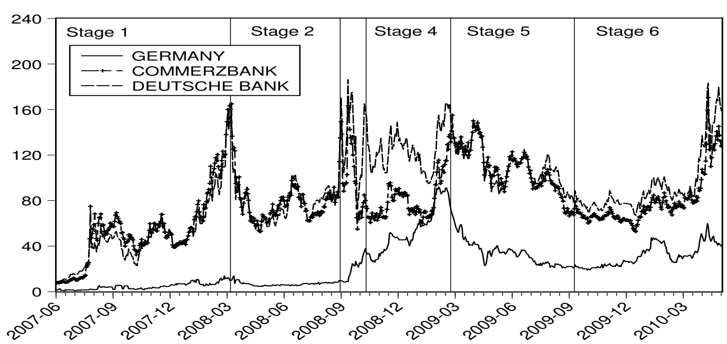

Figure 8: Germany: CDS Level Series

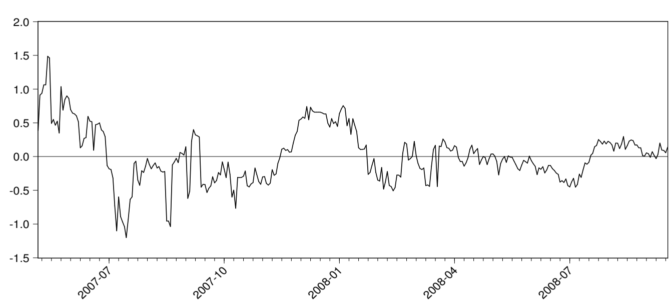

Figure 9: Cointegration Graph of Germany and Commerzbank (Before Government Interventions)

C.3 Ireland

Table 8: Ireland: Bivariate Cointegration Tests

Period	Variables	Lags	Trace Statistic		Max Eigenvalue		Engle-Granger Test
			$r=0$	$r=1$	$r=0$	$r=1$	
Stage 1	IR - AIB	2	0.429	0.620	0.389	0.620	-1.361
	IR - BOI	2	0.390	0.601	0.354	0.601	-1.325
Stage 2	IR - AIB	1	0.232	0.999	**0.080**	0.999	-2.577
	IR - BOI	1	**0.010**	0.997	**0.002**	0.997	**-3.376**
Stage 1 + 2	IR - AIB	2	0.323	0.354	0.421	0.354	-2.099
	IR - BOI	2	0.436	0.306	0.628	0.306	-2.155
Stage 4	IR - AIB	0	**0.016**	0.233	**0.021**	0.233	-1.806
	IR - BOI	1	0.260	0.330	0.349	0.330	-1.981
Stage 5	IR - AIB	1	0.227	0.183	0.445	0.183	-1.630
	IR - BOI	1	0.269	0.151	0.579	0.151	-2.149
Stage 6	IR - AIB	4	**0.049**	0.679	**0.024**	0.679	-1.918
	IR - BOI	4	0.177	0.786	**0.098**	0.786	-2.900
Stage 4 + 5	IR - AIB	1	**0.005**	0.129	**0.011**	0.129	-1.948
	IR - BOI	1	**0.027**	0.393	**0.023**	0.393	-1.892
Stage 5 + 6	IR - AIB	9	**0.003**	0.122	**0.005**	0.122	-3.080
	IR - BOI	9	**0.001**	0.117	**0.002**	0.117	-3.202
Stage 4 + 5 + 6	IR - AIB	9	**0.001**	0.057	**0.006**	0.057	-2.446
	IR - BOI	9	**0.000**	0.164	**0.000**	0.164	-3.055

Note: Trace and Max Eigenvalue are the Johansen tests statistics (with a restricted constant). p-values are reported. The respective null hypothesis is denoted by $r = \{0, 1\}$, where e.g. $r = 1$ denotes one cointegration relation. * signifies that at least one of the series is stationary. For the Engle-Granger test the ADF test statistic is reported; critical values at 5% and 10% are -3.37 and -3.07 respectively.

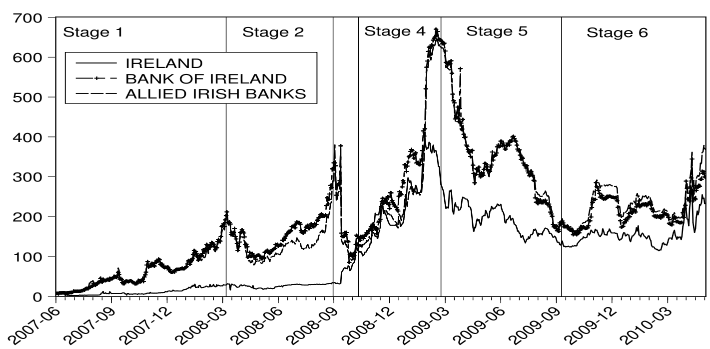

Figure 10: Ireland: CDS Level Series

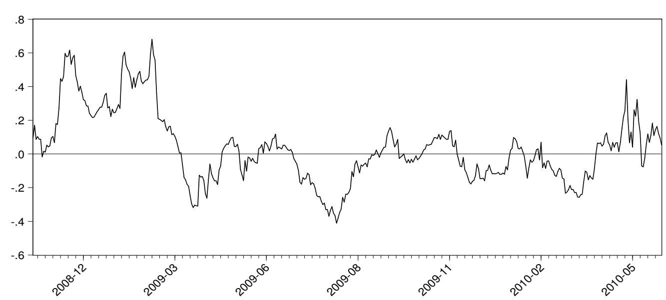

Figure 11: Cointegration Graph of Ireland and Allied Irish Banks (During and After Government Interventions)

C.4 Italy

Table 9: Italy: Bivariate Cointegration Tests

Period	Variables	Lags	Trace Statistic		Max Eigenvalue		Engle-Granger Test
			$r = 0$	$r = 1$	$r = 0$	$r = 1$	
Stage 1	IT - ISP	3	0.107	0.130	0.267	0.130	-1.948
	IT - UCR	3	0.140	0.180	0.278	0.180	-1.538
Stage 2	IT - ISP	1	**0.089**	0.919	**0.032**	0.919	-2.574
	IT - UCR	1	0.195	0.936	**0.083**	0.936	-1.797
Stage 1 + 2	IT - ISP	4	**0.052**	0.131	0.125	0.131	-2.313
	IT - UCR	3	**0.083**	0.108	0.236	0.108	-1.883
Stage 4	IT - ISP	1	0.761	0.561	0.829	0.561	-1.931
	IT - UCR	1	0.946	0.898	0.910	0.898	-1.696
Stage 5	IT - ISP	2	**0.091**	0.125	**0.231**	0.125	-2.334
	IT - UCR	2	**0.044**	0.143	**0.098**	0.143	-2.140
Stage 6	IT - ISP	4	0.248	0.389	0.293	0.389	**-3.125**
	IT - UCR	1	0.821	0.530	0.908	0.530	-1.762
Stage 4 + 5	IT - ISP	3	0.158	0.803	**0.082**	0.803	-2.181
	IT - UCR	1	0.590	0.584	0.605	0.584	-1.554
Stage 5 + 6	IT - ISP	4	**0.042**	0.768	**0.017**	0.768	-2.846
	IT - UCR	*					
Stage 4 + 5 + 6	IT - ISP	1	**0.059**	0.514	**0.042**	0.514	**-3.450**
	IT - UCR	1	0.284	0.256	0.453	0.256	-1.893

Note: Trace and Max Eigenvalue are the Johansen tests statistics (with a restricted constant). p-values are reported. The respective null hypothesis is denoted by $r = \{0, 1\}$, where e.g. $r = 1$ denotes one cointegration relation. * signifies that at least one of the series is stationary. For the Engle-Granger test the ADF test statistic is reported; critical values at 5% and 10% are -3.37 and -3.07 respectively.

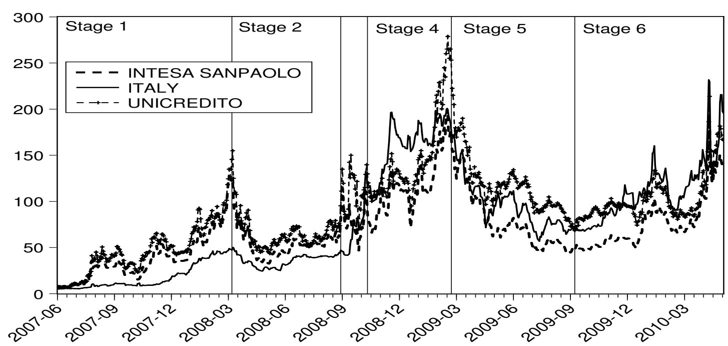

Figure 12: Italy: CDS Level Series

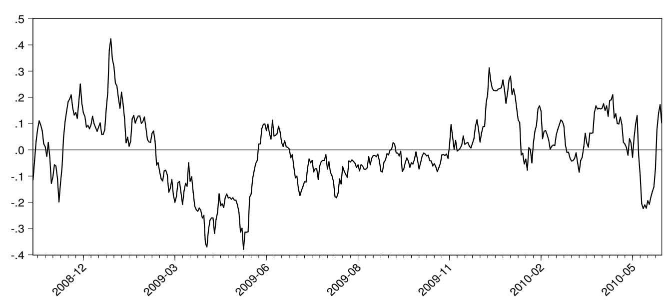

Figure 13: Cointegration Graph of Italy and Intesa San Paolo (During and After Government Interventions)

C.5 Netherlands

Table 10: Netherlands: Bivariate Cointegration Tests

Period	Variables	Lags	Trace Statistic		Max Eigenvalue		Engle-Granger Test
			$r = 0$	$r = 1$	$r = 0$	$r = 1$	
Stage 1	NL - ABN	0	**0.029**	**0.099**	**0.085**	**0.099**	**-3.646**
	NL- ING	0	**0.007**	0.155	**0.014**	0.155	**-4.389**
Stage 2	NL - ABN	*					
	NL- ING	*					
Stage 1 + 2	NL - ABN	2	**0.005**	**0.059**	**0.021**	**0.059**	**-3.422**
	NL- ING	2	**0.002**	**0.145**	**0.004**	**0.145**	**-3.918**
Stage 4	NL - ABN	5	0.151	0.474	0.139	0.474	-2.419
	NL- ING	0	0.932	0.761	0.940	0.761	-1.385
Stage 5	NL - ABN	1	0.106	0.085	0.349	0.085	-2.801
	NL- ING	1	**0.095**	0.119	0.252	0.119	-2.662
Stage 6	NL - ABN	6	**0.082**	0.617	**0.051**	0.617	**-3.350**
	NL- ING	7	0.862	0.862	0.794	0.862	**-3.053**
Stage 4 + 5	NL - ABN	1	0.132	0.536	*0.104*	0.536	-1.622
	NL- ING	8	0.220	0.890	*0.107*	0.890	-2.243
Stage 5 + 6	NL - ABN	*					
	NL- ING	*					
Stage 4 + 5 + 6	NL - ABN	1	0.624	0.848	0.487	0.848	-1.422
	NL- ING	1	0.522	0.750	0.427	0.750	-2.372

Note: Trace and Max Eigenvalue are the Johansen tests statistics (with a restricted constant). p-values are reported. The respective null hypothesis is denoted by $r = \{0, 1\}$, where e.g. $r = 1$ denotes one cointegration relation. * signifies that at least one of the series is stationary. For the Engle-Granger test the ADF test statistic is reported; critical values at 5% and 10% are -3.37 and -3.07 respectively.

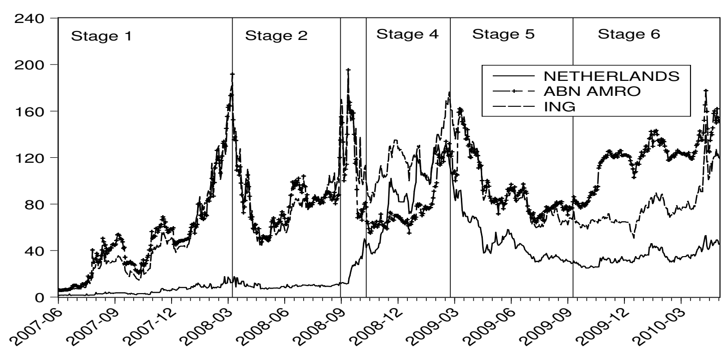

Figure 14: Netherlands: CDS Level Series

C.6 Portugal

Table 11: Portugal: Bivariate Cointegration Tests

Period	Variables	Lags	Trace Statistic		Max Eigenvalue		Engle-Granger Test
			$r=0$	$r=1$	$r=0$	$r=1$	
Stage 1	PT - BCP	1	0.272	0.420	0.307	0.420	-1.997
	PT - BES	3	0.280	0.464	0.293	0.464	-1.986
Stage 2	PT - BCP	1	*0.103*	0.599	**0.069**	0.599	**-3.570**
	PT - BES	2	**0.028**	0.688	**0.013**	0.688	**-3.374**
Stage 1 + 2	PT - BCP	0	**0.038**	0.078	0.135	0.078	-2.647
	PT - BES	0	**0.038**	0.093	*0.119*	0.093	-2.349
Stage 4	PT - BCP	6	0.291	0.717	0.206	0.717	-0.711
	PT - BES	6	0.257	0.874	0.135	0.874	-1.036
Stage 5	PT - BCP	1	0.302	0.182	0.584	0.182	-2.256
	PT - BES	*					
Stage 6	PT - BCP	1	**0.057**	0.596	**0.034**	0.596	-1.573
	PT - BES	1	0.188	0.546	0.157	0.546	-1.711
Stage 4 + 5	PT - BCP	1	0.344	0.411	0.408	0.411	-2.074
	PT - BES	1	0.318	0.643	0.258	0.643	-0.837
Stage 5 + 6	PT - BCP	1	**0.054**	0.652	**0.029**	0.652	-1.458
	PT - BES	1	0.349	0.659	0.283	0.659	-1.724
Stage 4 + 5 + 6	PT - BCP	1	**0.049**	0.472	**0.037**	0.472	-2.104
	PT - BES	1	0.378	0.571	0.355	0.571	-1.769

Note: Trace and Max Eigenvalue are the Johansen tests statistics (with a restricted constant). p-values are reported. The respective null hypothesis is denoted by $r = \{0, 1\}$, where e.g. $r = 1$ denotes one cointegration relation. * signifies that at least one of the series is stationary. For the Engle-Granger test the ADF test statistic is reported; critical values at 5% and 10% are -3.37 and -3.07 respectively.

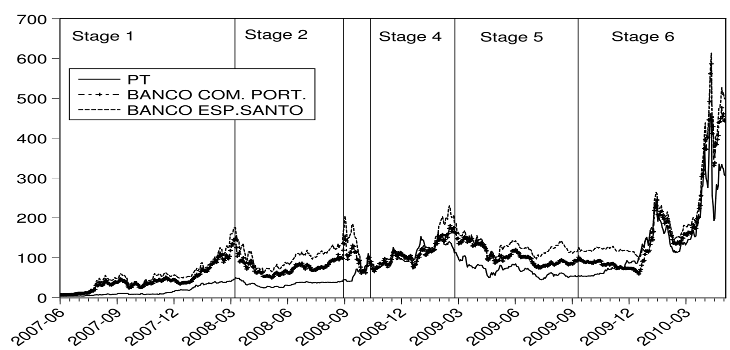

Figure 15: Portugal: CDS Level Series

C.7 Spain

Table 12: Spain: Bivariate Cointegration Tests

Period	Variables	Lags	Trace Statistic		Max Eigenvalue		Engle-Granger Test
			$r=0$	$r=1$	$r=0$	$r=1$	
Stage 1	SP - BBVA	1	0.130	0.148	0.296	0.148	-2.712
	SP - BS	1	**0.086**	0.146	0.196	0.146	-2.860
Stage 2	SP - BBVA	1	**0.017**	0.468	**0.011**	0.468	**-6.240**
	SP - BS	2	**0.020**	0.578	**0.011**	0.578	**-6.905**
Stage 1 + 2	SP - BBVA	1	0.013	0.102	**0.036**	0.102	**-3.851**
	SP - BS	1	**0.006**	0.090	**0.018**	0.090	**-3.420**
Stage 4	SP - BBVA	1	0.503	0.569	0.506	0.569	-1.395
	SP - BS	2	**0.026**	0.136	**0.058**	0.136	-2.000
Stage 5	SP - BBVA	1	0.507	0.407	0.628	0.407	-1.828
	SP - BS	1	0.545	0.441	0.651	0.441	-2.348
Stage 6	SP - BBVA	4	0.778	0.535	0.862	0.535	-2.008
	SP - BS	4	0.740	0.561	0.804	0.561	-2.108
Stage 4 + 5	SP - BBVA	1	0.300	0.416	0.345	0.416	-1.589
	SP - BS	2	**0.080**	0.243	0.121	0.243	-1.987
Stage 5 + 6	SP - BBVA	1	0.606	0.563	0.640	0.563	-2.088
	SP - BS	4	0.487	0.927	0.299	0.927	-2.012
Stage 4 + 5 + 6	SP - BBVA	11	**0.078**	0.459	**0.065**	0.459	-2.427
	SP - BS	1	**0.066**	0.184	0.124	0.184	-2.619

Note: Trace and Max Eigenvalue are the Johansen tests statistics (with a restricted constant). p-values are reported. The respective null hypothesis is denoted by $r = \{0, 1\}$, where e.g. $r = 1$ denotes one cointegration relation. * signifies that at least one of the series is stationary. For the Engle-Granger test the ADF test statistic is reported; critical values at 5% and 10% are -3.37 and -3.07 respectively.

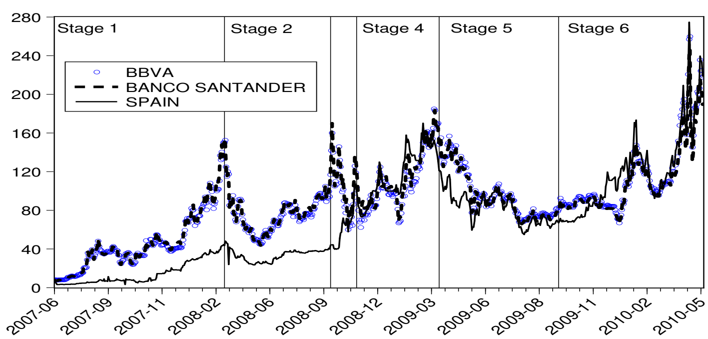

Figure 16: Spain: CDS Level Series