Intraday dynamics of euro area sovereign credit risk contagion[*]

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Abstract

We examine the role of the CDS and bond market as transmission channels of credit risk contagion between sovereign entities during and before the recent euro area sovereign debt crisis. We analyse an intradaily dataset for GIIPS countries as well as Germany, France and Central European countries. Our findings suggest that prior to the crisis, the CDS and bond market were similarly important in the transmission of financial shock contagion while the bond market ceased in importance during the crisis period. We find flight to safety effects during the crisis in the German bond market which is not present in the pre-crisis sample. Our estimated sovereign risk contagion is much higher in magnitude during the crisis period with an average timeline of 2 hours in GIIPS countries. By using an exogenous macroeconomic news shock we can show that during the crisis period increased credit risk is not related to economic fundamentals. Further, we find that Central European countries have not been affected by sovereign risk contagion, independent of their debt level and currency.

JEL classification: E44, G12, G14 and G15.

Keywords: Sovereign credit risk, credit default swaps, contagion, spillover, sovereign debt crisis, panel VAR.

1 Introduction

The 2008-09 financial crisis let investors to look more critically at the fiscal outlook in a number of countries, including several of those in the euro area. These resulted in a sharp rise of sovereign credit spreads for a number of euro area countries. At their peak yield spreads on sovereign bonds relative to German bonds reached several hundred basis points, while before the beginning of the global financial crisis these spreads had averaged only a few basis points. At the same time the interest in trading credit risk protection on euro sovereign borrowers via credit default swaps (CDS) grew substantially and spreads on such instruments also surged. Due to these developments policy makers and regulators became increasingly interested in the market for sovereign CDS. Of particular interest has been firstly the interplay between the pricing of sovereign risk in CDS and in bond markets, secondly the possibility that one market could be systematically leading the other, and thirdly the potential for sovereign credit risk contagion effects. In this paper we focus on the latter.

We analyse euro area sovereign credit risk contagion effects in GIIPS[1] countries plus France and Germany from January 2008 to end-December 2011, which we split into a pre-crisis and crisis period. Further we investigate if and how sovereign credit risk contagion is transmitted from the GIIPS countries to Central European countries (Austria, Czech Republic, Hungary, Poland, and Slovakia) during the euro area sovereign debt crisis. Austria is included as reference country for the Czech Republic. Using intraday CDS and bond data enables us to estimate credit risk contagion effects substantially more accurate than existing studies on sovereign credit markets. In addition, little is yet known about the transmission channels of credit risk contagion (CDS/bonds) and their relative importance in the euro area sovereign debt crisis. As we have data for both, the CDS and bond market, we are able to assess the contagion impacts conditioned on the credit channel.

Existing research so far differentiated between cross-country and intra-country analysis. Using a Panel VAR methodology we can control for both, country-specific risk and contagion effects across countries. Panel VARs are built with the same logic of standard VARs but, by adding a cross-sectional dimension, they are a much more powerful tool to address interesting policy questions related to e.g. the transmission of shocks across borders (Canova and Ciccarelli; 2013). By using the method of Canova and Ciccarelli (2013) we are able to shock the credit risk of an individual country and derive the individual response for each country in the panel. The use of intraday data also allows us to capture the intradaily patterns of credit risk contagion. By using intraday data we are able to identify shocks that may seem to affect several countries simultaneously on a daily or lower data frequency, but may have their origin in one particular country with clear contagion

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[1] Greece, Ireland, Italy, Portugal, Spain

dynamics onto other countries when using intraday data. Also, Gyntelberg et al. (2013) discuss the advantages of using intradaily data due to the higher accuracy of the results compared to data with lower frequency.

A large body of literature on potential reasons and transmission channels of contagion as well as on theoretical modelling of contagion is available. Also a whole strand of literature focuses on empirical tests for the existence of contagion in a certain stress period, that is, if there are stronger cross-market linkages in times of crisis. This paper belongs to the latter type as we focus on testing for the existence of contagion during the euro area sovereign debt crisis.

An important motivation to provide financial support to Greece, despite the no-bailout clause in the Maastricht Treaty, was the fear of contagion as policymakers were afraid that a Greek default would spillover to other highly indebted countries in the euro area (Constancio; 2012). As pointed out by Corsetti et al. (2011), there is much disagreement among economists about the exact definition of contagion and how it should be tested. For Constancio (2012) and Forbes (2012) contagion occurs when financial or macroeconomic imbalances (shocks) create a systemic risk beyond that explained by economic fundamentals. Contagion differs from macroeconomic interdependence among countries in that transmission of risk to other countries is different under normal economic conditions. Forbes (2012) defines contagion as spillovers resulting from extreme negative effects. If comovements of markets are similarly high during non-crisis periods and crisis periods, then there is only evidence of strong economic linkages between these economies (Missio and Watzka; 2011). Kaminsky et al. (2003) describe contagion to be an episode in which there are significant immediate effects in a number of countries following an event, such as when the consequences are fast and furious and evolve over a matter of hours or days. When the effect is gradual, Kaminsky et al. (2003) refer to it as spillovers rather than contagion. We rely on the contagion definition according to Kaminsky et al. (2003), Constancio (2012) and Forbes (2012).

As there exists vast literature on contagion we limit our discussion on papers that measure contagion among sovereign credit markets. Kamin and von Kleist (1999), Eichengreen and Mody (2000), Mauro et al. (2002), Pan and Singleton (2005), Longstaff et al. (2011), and Ang and Longstaff (2011) concentrate on the relationship between sovereign credit spreads and common global and financial market factors. These papers empirically identify factors that are significant variables for CDS credit spreads as for example the U.S. stock and bond market returns as well as embedded volatility risk premium.

The issues of financial shock contagion and cross-country spillovers among countries in the euro area during the recent sovereign debt crisis have figured prominently in recent empirical research. Caporin and Rigobon (2012) analyse risk contagion using CDS spreads of the major euro area countries using different econometric approaches as Bayesian mod-

elling. They find that diffusion of shocks in euro area CDS has been remarkably constant while the risk spillover among countries is not affected by the size of the shock. Other examples are Bai et al. (2015), Neri and Ropele (2013), De Santis (2012), and Arghyrou and Kontonikas (2012). They all employ time series modelling approaches for contagion and include sovereign bond spreads (yield to maturity) to reflect pure credit risk considerations and macroeconomic variables. Results are mostly discriminated in terms of core (e.g. Germany and France), and peripheral countries (GIIPS). In general, they find that bond spreads of lower rated countries increase along with their Greek counterpart. However their results in terms of magnitude, responses to shocks, and contagion effects on core countries is somewhat mixed. Similar to these studies, Koop and Korobilis (2014) employ a panel approach which is superior in empirically modelling financial contagion (Canova and Ciccarelli; 2013). Their findings are at odds with the discrimination between core and peripheral countries as they find also contagion from GIIPS to core countries, however smaller in magnitude. The different results reported in these studies could be due to sample differences or to how bond spreads are calculated. Most empirical research use the "constant maturity" approach to calculate bond yield differences (relative to Germany). Further, they use daily or weekly data for the empirical analysis, which may lead to inaccurate shock and contagion estimations, especially in periods when activity in sovereign risk markets is high during times of stress.

One of the key contributions of our paper to the existing literature on sovereign risk contagion during the recent euro area sovereign debt crisis is that, in contrast to all before mentioned studies, we do not use simple yield differences as our measure of cash spreads but carefully constructed asset swap spreads (ASW) based on estimated zero-coupon government bond prices. This ensures that we are comparing "apples with apples" in our empirical analysis for sovereign credit risk, by matching exactly the maturities and the cash flow structures of the CDS and the cash components. The use of ASW is also in line with the practice used in commercial banks when trading the CDS-bond basis. In addition, by calculating ASW we are able to estimate contagion impacts on Germany as e.g. flight to safety. Germany is not included in most contagion studies since German Bund yields are used as riskfree interest rate. Moreover, our analysis relies on intraday price data for both CDS and bonds, allowing us to estimate the contagion dynamics and the transmission channel of contagion (CDS or bond market) substantially more accurately than existing studies. Further, by extending our model with the economic surprise index we are able to estimate how much of sovereign risk contagion can be attributed to macroeconomic news or overreactions/lack of beliefs by market participants.

The rest of the paper is structured as follows. Section 2 discusses our data and the relationship between CDS and bonds. Section 3 discusses the set-up and estimation of

the Panel VAR (PVAR) model and its extension. Section 4 provides the empirical results and Section 5 concludes.

2   Data

The core data we use in our empirical analysis consists of USD-denominated 5-year maturity intraday quotes on CDS contracts and government bonds for France, Germany, Greece, Ireland, Italy, Portugal and Spain (GIIPS). We choose this group of countries as it includes the countries that have been most affected by the euro sovereign debt crisis, as well as Germany which will serve as near-riskfree reference country, and France which we consider as a low-risk control country. Further, we include Austria, the Czech Republic, Hungary, Poland, and Slovakia in our sample where Austria serves as a reference country for the Czech Republic.

According to Gyntelberg et al. (2013) when considering the number of quotes of CDS contracts at the peak of the sovereign debt crisis in 2010, the 5-year segment is the most liquid. The use of intraday data in our empirical analysis enables us to obtain much sharper estimates and clearer results with respect to market mechanisms (Gyntelberg et al.; 2013). Further, they show that sovereign credit risk dynamics follow an intraday pattern.

Our sovereign bond price data comes from MTS (Mercato Telematico dei Titoli di Stato). The MTS data consists of both actual transaction prices and binding bid-offer quotes. The number of transactions of sovereign bonds on the MTS platform is however not sufficient to allow us to undertake any meaningful intraday analysis. Therefore, we will use the trading book from the respective domestic MTS markets.[2] The MTS market is open from 8:15 to 17:30 local Milan time, preceded by a pre-market phase (7.30 to 8.00) and an offer-market phase (8:00 to 8:15). We use data from 8:30 to 17:30.

The CDS data consists of price quotes provided by CMA (Credit Market Analysis Ltd.) Datavision. CMA continuously gathers information on executable and indicative CDS prices directly from the largest and most active credit investors. After cleaning and checking the individual quotes, CMA applies a time and liquidity weighted aggregation so that each reported bid and offer price is based on the most recent and liquid quotes. The CDS market, which is an OTC market, is open 24 hours a day. However, most of the activity in the CMA database is concentrated between around 7:00 and 17:00 London time. As we want to match the CDS data with the bond market data, we restrict our attention to the period from 8:30 to 17:30 local Milan time.

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[2]   We ignore quotes from the centralized European platform (market code: EBM), as quotes for government bonds on the centralised platform are duplicates of quotes on the domestic platforms.

We construct our intraday data on a 30-minute sampling frequency on our available data set that spans from January 2008 to end-December 2011. The available number of indicative quotes for CDS does not allow higher data frequency than 30 minutes. The euro area sovereign CDS markets were very thin prior to 2008, which makes any type of intraday analysis before 2008 impossible (for a discussion please refer to Gyntelberg et al. (2013)).

When implementing our analysis we split the data into two subsamples. The first subsample covers the period January 2008 to October 19th, 2009, and as such represents the period prior to the euro area sovereign debt crisis. While this period includes the most severe phase of the financial crisis, including the default of Lehman Brothers, it is relatively unaffected by market distortions coming from concerns about the sustainability of public finances in view of rising government deficits and therefore represents the pre-sovereign debt crisis period. The second subsample covers the euro area sovereign debt crisis period and runs from the 20th of October 2009 to end-December 2011. We choose the beginning of the crisis period as on the 20th of October 2009, the new Greek government announced that official statistics on Greek debt had previously been fabricated. Instead of public deficit estimated at 6% of GDP for 2009, the government now expected a figure at least twice as high.

We employ CDS and bond data in our analysis in order to be able to differentiate between the transmission of contagion according to the credit risk channel from one country to another. Duffie (1999) argues that since the CDS and the bond yield spread both price the same default of a given reference entity, their price should be equal if markets are perfect and frictionless. Thus, in a perfect market due to arbitrage, the CDS spread equals the bond yield over the riskfree rate. However, for this parity to hold, a number of specific conditions must be met, including that markets are perfect and frictionless, that bonds can be shorted without restrictions or cost, there are no tax effects, etc. Only floating rate notes should be used for the bond yield computation, because these bonds (unlike plain vanilla bonds) do only carry credit rate risk but no interest rate risk. However, they are relatively uncommon, in particular for sovereign entities. A further complication linked to the usage fixed-rate or plain vanilla bonds as substitutes is, that it is unlikely that the maturity of these instruments exactly match that of standard CDS contracts.

To ensure proper comparability with CDS, Gyntelberg et al. (2013) employ synthetic par asset swap spreads (ASW) for the bond leg of the basis. The use of ASW is in line with the practice used in commercial banks when trading the CDS-bond basis. By calculating ASW for our empirical analysis we ensure an accurate cash flow matching opposed to studies that use simple "constant maturity" yield differences.

An asset swap is a financial instrument that exchanges the cash flows from a given security - e.g. a particular government bond - for a floating market rate[3]. This floating rate is typically a reference rate such as Euribor for a given maturity plus a fixed spread, the ASW. This spread is determined such that the net value of the transaction is zero at inception. The ASW allows the investor to maintain the original credit exposure to the fixed rate bond without being exposed to interest rate risk. Hence, an asset swap on a credit risky bond is similar to a floating rate note with identical credit exposure, and the ASW is similar to the floating-rate spread that theoretically should be equivalent to a corresponding CDS spread on the same reference entity. Specifically, the ASW is the fixed value A required for the following equation to hold[4] (O'Kane (2000))

$$\underbrace{100 - P}_{\substack{\text{Upfront payment for bond} \\ \text{asset in return for par}}} + \overbrace{C \underbrace{\sum_{i=1}^{N_{\text{fixed}}} d(t_i)}_{\text{Fixed payments}} = \underbrace{\sum_{i=1}^{N_{\text{float}}} \big(L_i + A\big) d(t_i)}_{\text{Floating payments}}}^{\text{Interest rate swap}}, \tag{1}$$

where P is the full (dirty) price of the bond, C is the bond coupon, L_i is the floating reference rate (e.g. Euribor) at time t_i, and $d(t_i)$ is the discount factor applicable to the corresponding cash flow at time t_i.

In order to compute the ASW A several observations and simplifications have to be made. First, in practice it is almost impossible to find bonds outstanding with maturities that exactly match those of the CDS contracts and second, the cash-flows of the bonds and the CDS will not coincide. To overcome these issues, in what follows we use synthetic asset swap spreads based on estimated intraday zero-coupon sovereign bond prices. Specifically, for each interval and each country, we estimate a zero-coupon curve based on all available bond price quotes during that time interval using the Nelson-Siegel (1997) method. With this procedure we are able to price synthetic bonds with maturities that exactly match those of the CDS contracts, and we can use these bond prices to back out the corresponding ASW. As this results in zero coupon bond prices, we can set C in Equation (1) to zero.

A CDS contract with a maturity of m years for country j at time interval k of day t, denoted as $S_j(t_k, m)$, has a corresponding ASW $A_j(t_k, m)$:

$$100 - P_j(t_k, m) = \sum_{i=1}^{N_m} \big(L_i(t_k) + A_j(t_k, m)\big) \cdot d(t_k, t_i), \tag{2}$$

with $P_j(t_k, m)$ as our synthetic zero coupon bond price.

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[3] See O'Kane (2000) or Gale (2006) for detailed discussions of the mechanics and pricing of asset swaps.
[4] This assumes that there is no accrued coupon payment due at the time of the trade; otherwise, an adjustment factor would need to be added to the floating payment component.

For the reference rate L_i in Equation (2), we use the 3-month Euribor forward curve to match as accurately as possible the quarterly cash flows of sovereign CDS contracts. We construct the forward curve using forward rate agreements (FRAs) and Euro interest rate swaps. We collect the FRA and swap data from Bloomberg, which provides daily (end-of-day) data. 3-month FRAs are available with quarterly settlement dates up to 21 months ahead, i.e. up to 21×24. From two years onwards, we bootstrap zero-coupon swap rates from swap interest rates available on Bloomberg and back out the corresponding implied forward rates. Because the swaps have annual maturities, we use a cubic spline to generate the full implied forward curve, thereby enabling us to obtain the quarterly forward rates needed in Equation (2).

Given our interest in intraday dynamics, we follow Gyntelberg et al. (2013) and generate estimated intraday Euribor forward rates by assuming that the intraday movements of the Euribor forward curve are proportional to the intraday movements of the German government forward curve.[5] To be precise, for each day, we calculate the difference between our Euribor forward curve and the forward curve implied by the end-of-day Nelson-Siegel curve for Germany.[6] We then keep this difference across the entire curve fixed throughout that same day and add it to the estimated intraday forward curves for Germany earlier on that day to generate the approximate intraday Euribor forward curves. This approach makes the, in our view, reasonable assumption that the intraday variability in Euribor forward rates will largely mirror movements in corresponding German forward rates.

Finally, we need to specify the discount rates $d(t_k, t_i)$ in Equation (2). The market has increasingly moved to essentially risk-free discounting using the overnight index swap (OIS) curve. We therefore take $d(t_k, t_i)$ to be the euro OIS discount curve, which is constructed in a way similar to the Euribor forward curve. For OIS contracts with maturities longer than one year, we bootstrap out zero-coupon OIS rates from interest rates on long-term OIS contracts. Thereafter, we construct the entire OIS curve using a cubic spline. We use the same technique as described above to generate approximate intraday OIS discount curves based on the intraday movements of the German government curve.

For an in-depth discussion on the construction of our intraday ASW please refer to Gyntelberg et al. (2013) and for a general discussion to O'Kane (2000).

According to different panel unit root tests (see Appendix C) our CDS and ASW price data (displayed in Figure 1) is I(1). Therefore, we estimate our subsequent models in first differences.

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[5] Euribor rates are daily fixing rates, so we are actually approximating the intraday movements of the interbank interest rates for which Euribor serves as a daily benchmark.

[6] Here we use the second to last 30-minute interval, because the last trading interval is occasionally overly volatile.

Figure 1: CDS and ASW spreads in basis points

The figures are based on data with a 30-minute sampling frequency. Our split in a pre- and a crisis period is indicated by the vertical line in each figure. Due to the Greek debt restructuring the data for Greece ends in September 2011.
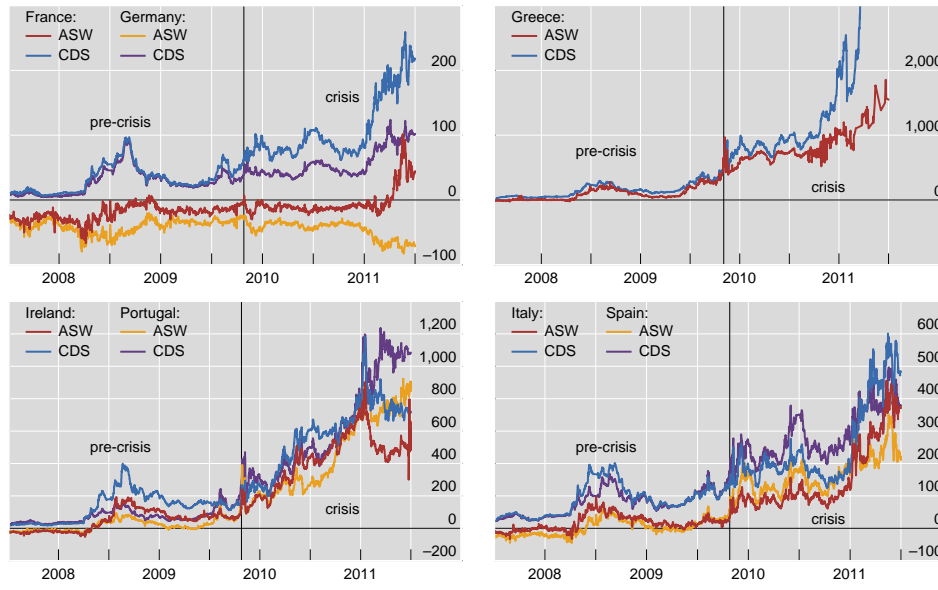
In our PVARX model extension (Section 3.2) we make use of the Citigroup economic surprise index for the euro zone as exogenous variable. This index is widely recognised in academia and by practitioners for measuring unexpected economic news. The Citigroup economic surprise index measures how economic news/data are progressing relative to the anticipated consensus forecasts of market economists. According to Citigroup, the index captures objective and quantitative measures of economic news, defined as weighted historical standard deviations of data surprises (actual releases versus Bloomberg survey median). A positive reading of the economic surprise index for the euro zone suggests that economic releases have on balance beaten the consensus and vice versa. The index captures economic news on macroeconomic and fiscal variables as e.g. employment change, housing market, retail sales, debt-to-GDP, budget deficit, and consumer confidence in the euro zone. Thus, the Citigroup economic surprise index does not include news on monetary policy decisions.

The economic surprise index has a daily frequency unlike the intraday data that we are analysing in this paper. However, as market participants are exposed to economic news throughout the whole day we disperse the actual Citigroup economic surprise index data given at the end of the trading day over that entire day. We conducted several simulations

with different distributions to generate a pseudo intraday economic surprise index. Our results remain extremely robust to this experiment.

3 Modelling sovereign credit spread contagion

To empirically measure the impact of euro area sovereign credit risk contagion effects according to the credit risk channel (CDS and bond market) we employ a Panel Vector Autoregressive (PVAR) model. PVARs have the same structure as VAR models, in the sense that all variables are assumed to be endogenous and interdependent, but a cross-sectional dimension is added to the representation. We define our PVAR model following Binder and Pesaran (2005) with fixed effects when N is finite and T is large, as $i = 1, ..., N$ is the cross-sectional dimension and $t = 1, ..., T$ is the time-series dimension in our model. According to Koop and Korobilis (2014) as well as Canova and Ciccarelli (2013) in this setup, the PVAR is the ideal tool for examining the international transmission of macroeconomic or financial shocks from one country onto another.

Further, Koop and Korobilis (2014) state that given the autoregressive structure of a PVAR, concerns about endogeneity are eliminated and the usual macroeconomic exercises involving multiple-period projections in the future (e.g. forecast variance decomposition and impulse responses) can be implemented. The PVAR has several advantages over individual country VARs in a time series framework. By analysing a panel of countries we can more accurately model contagion from one country to another since the panel approach captures country-level heterogeneity. We control for cross-sectional heterogeneity by including fixed effects in the regression. By using CDS and ASW as endogenous variables for each country in our cross-section[7], we can differentiate between the credit risk channel of contagion, which improves the understanding of the market microstructural dynamics. With an extension of the PVAR using a purely exogenous variable, we can assess the effect of unexpected economic news[8] on credit risk contagion of the countries in our sample.

3.1 Panel VAR

In vector autoregressive models (VAR) all variables are treated as endogenous and interdependent, both in a dynamic and static sense. The VAR model is formally defined as:

$$Y_t = A_0 + A(\mathrm{L})Y_{t-1} + u_t, \tag{3}$$

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[7] bi-variate estimation per country

[8] By using the economic surprise index as predetermined purely exogenous variable in the PVARX model.

where Y_t is a G x 1 vector of endogenous variables and $A(\text{L})$ is a polynomial in the lag operator, A_0 is a G x 1 vector, and u_t is G x 1 vector of i.i.d. shocks.

Panel VARs (PVAR) have the same structure as VAR models in Equation (3), as all variables are assumed to be endogenous and independent. However, a cross-sectional dimension i, in our case across countries, is added to the representation. Thus, Y_t is the stacked version of y_{it}, the vector of G variables for each entity $i = 1, ..., N$, i.e. $Y_t = (y'_{1t}, y'_{2t}, ..., y'_{Nt})'$ and $t = 1, ..., T$. The major difference between a VAR and the PVAR is that the covariance σ_{ij} of the residuals are zero by construction for entity i different from entity j. The PVAR is defined as follows:

$$y_{it} = A_{0i} + A_i(\text{L})Y_{t-1} + u_{it}. \tag{4}$$

A_{0i} are G x 1 vectors and A_i are G x GN matrices. We allow for country specific heterogeneity by including an entity specific intercept. Further, lags of all endogenous variables of all entities i enter the model. Canova and Ciccarelli (2013) call this feature "dynamic interdependencies". The residual u_{it} is a G x 1 vector and $u_t = (u_{1t}, u_{2t}, ..., u_{Nt})$. u_{it} is generally correlated across the cross-sectional dimension i. Canova and Ciccarelli (2013) call this feature "static interdependencies". Thus the variance-covariance matrix for a PVAR has the following property $E(u_{it}u'_{jt}) = \sigma_{ij} \neq 0$ for $i \neq j$, ie. static interdependencies occur when the correlations between the errors in two countries' VARs are non-zero. On the other hand, dynamic interdependencies occur when one country's lagged variables affect another country's variables. Hence, the PVAR is more flexible compared to a VAR ($\sigma_{ij} = 0$ for $i \neq j$). According to Canova and Ciccarelli (2013) these features distinguish a panel VAR typically used for macroeconomics and finance from a panel VAR used in microeconomics.

In our bivariate case with $G = 2$ we can rewrite the PVAR as:

$$\begin{pmatrix} \Delta CDS \\ \Delta ASW \end{pmatrix}_{it} = \begin{pmatrix} A_{01} \\ A_{02} \end{pmatrix}_i + \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix}_i (\text{L}) \begin{pmatrix} \Delta CDS \\ \Delta ASW \end{pmatrix}_{t-1} + \begin{pmatrix} u_1 \\ u_2 \end{pmatrix}_{it}, \tag{5}$$

where $i = 1, ..., N$ is the number of countries in the cross-sectional dimension.

For the estimation, we follow the approach proposed by Canova and Ciccarelli (2009) of an unrestricted PVAR which allows for the selection of restrictions involving dynamic interdependencies, static interdependencies, and cross-section homogeneities. According to an empirical model comparison by Koop and Korobilis (2014) they confirm that the proposed methodology by Canova and Ciccarelli (2009) shows best properties compared to other PVAR approaches. Canova and Ciccarelli (2009) suggest to adopt a flexible structure through a factorisation of the coefficients in Equation (4). Through the flexible coefficient factorisation, the PVAR can be rewritten as reparametrised multicountry VAR

and estimated using SUR (Canova and Ciccarelli; 2009). The advantage of this flexible factorisation is, that the overparametrisation of the original PVAR is dramatically reduced while in the resulting SUR model, estimation and specification searches are constrained only by the dimensionality of the estimated coefficient matrix (for a more in-depth discussion please refer to Canova and Ciccarelli (2009) and Koop and Korobilis (2014)).

3.2   Panel VARX

As an extension to the previous analysis, we consider the response of credit risk in CDS and bond markets in our GIIPS and low-risk country sample on unexpected macroeconomic news. We follow Canova and Ciccarelli (2013) by extending the PVAR model in Equation (4) with a predetermined purely exogenous variable X_t that results in a PVARX model which takes the following form:

$$y_{it} = A_{0i} + A_i(\text{L})Y_{-1} + F_i(\text{L})X_t + u_{it}, \tag{6}$$

with X_t as a M x 1 vector, common to all entities i. The PVARX can also be rewritten as:

$$\begin{pmatrix} \Delta CDS \\ \Delta ASW \end{pmatrix}_{it} = \begin{pmatrix} A_{01} \\ A_{02} \end{pmatrix}_i + \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix}_i (\text{L}) \begin{pmatrix} \Delta CDS \\ \Delta ASW \end{pmatrix}_{t-1} + \begin{pmatrix} \tilde{F}_1 \\ \tilde{F}_2 \end{pmatrix}_i (\text{L})X_t + \begin{pmatrix} u_1 \\ u_2 \end{pmatrix}_{it}. \tag{7}$$

We employ the economic surprise index as predeterminded exogenous variable X_t for unexpected macroeconomic news in the euro zone.

The extension to the PVARX model allows us to analyse whether credit risk responses can be attributed to macroeconomic fundamental news or if exaggerations in terms of lack of belief of economic agents also contributed to credit risk responses.

4   Results

We carry out an impulse response analysis to investigate contagion of financial shocks across euro area countries that have been most affected in the sovereign debt crisis. Further, we present results on shock contagion to Central European countries. We focus on individual country shocks emanating from GIIPS countries and analyse the impact of an unexpected 1% increase (one unit shock) in credit risk in both, the CDS and ASW markets. Finally, we present results of exogenous economic news shocks and the effect on sovereign risk in GIIPS countries.

In standard VAR models (see Equation (3)) shock identification is performed by imposing a Choleski decomposition in all countries. To decrease the number of identification

restrictions, it is assumed that $\sum_u$ is block diagonal, with blocks corresponding to each country. Canova and Ciccarelli (2009) state that block diagonality implies differences in the responses within and across countries as within an entity, variables are allowed to move instantaneously. But across entities, variables can only react with one lag.

The identification of shocks for PVAR models as defined in Equation (4) is more complicated due to the fact that the PVAR model allows for static interdependencies as u_{it} is correlated across entities i. Thus, cross entity symmetry in shock identification cannot be assumed. We compute the impulse responses following Canova and Ciccarelli (2009) as the difference between two conditional forecasts: one where a particular variable is shocked and one where the disturbance is set to zero. For a more in-depth discussion on the shock identification in PVAR models allowing for static interdependencies please refer to Canova and Ciccarelli (2009).

4.1 Results for GIIPS and low-risk countries

As a general result, we find that during the pre-crisis the bond and CDS markets are of similar importance, i.e. the response function of country i to a one unit shock in the ASW and CDS markets of country j is of comparable size in both markets (see Figure 2). These results are as expected as both markets should price the countries credit risk equally (Duffie; 1999). During the crisis period the CDS market becomes on balance more relevant (see Figure 3). Interestingly, the inter-market shock transmission, i.e. from CDS to ASW and vice versa, is not important during the pre-crisis. This weak connection between both markets during the pre-sovereign debt crisis period can be explained with different market participants and their distinct investment horizons. Insurance firms active in the bond market have a longer investment horizon than for example hedge funds in the CDS markets. Shocks to ΔCDS or ΔASW are very short lived and may not be seen by the market participant in the other market. During the crisis period the shock transmission between markets is becoming relatively more important, suggesting a stronger inter-market connectivity. Market participants are getting more vigilant to potential bad news, which may be spilled over from other markets.

Further, we find that the decay of a shock is on average faster in the pre-crisis period than in the crisis period (see Figures 2 and 3). The timelines of our estimated shock contagion and their absorption is dramatically shorter than in existing empirical studies as for example Koop and Korobilis (2014) who find that a shock contagion emanates on average within 1 to 2 months with shocks that do not decay over a timeline of 10 months. We find for both sample periods that contagion emanates within the first 30-minute time interval. Therefore, responses to shock contagion are typically not lagged as found for example in Koop and Korobilis (2014). Further, the average response of a shock absorption is around 1 to 1.5 hours in the pre-crisis period and slightly longer

12

with 1.5 to 2 hours on average during the crisis period. This result is clearly in line with generally accepted notion that financial markets are reacting very fast to new information (Gyntelberg et al.; 2013). The slower speed of shock absorption during the crisis seems to contradict our statement above, that market participants are more reactive to news during crisis periods. This can be explained by the fact that the estimated timeline of the shock absorption during the crisis period is strongly affected by turmoils in financial markets while the pre-crisis period represents the relative normal market environment for European sovereign states without fast and furios shock contagion but rather comovements across markets as defined by Constancio (2012) and Forbes (2012).

In the pre-crisis period, a credit risk shock emanating from the ASW to the CDS and vice versa had more or less the same impact in term of magnitude and shock absorption. Thus, both the derivatives and the spot market had similar importance in shock contagion prior to the euro area sovereign debt crisis. However, during the crisis period we find that shock transmission from ASW to CDS have a dramatically lower impact than vice versa. Leading to the assumption that the spot market lost its importance as a channel of financial shock contagion during the euro area sovereign debt crisis. Thus, contagion of shocks in credit risk has been predominantly transmitted through the derivatives market.

During the pre-crisis period a one unit shock to either ASW or CDS of country i results in a spread widening of all countries. However, during the crisis, we find evidence for flight to safety to German bonds as Germany is considered a safe haven for investors. This effect is visible in the inter-market connection, i.e. a positive shock in the GIIPS country's CDS or ASW leads to spread tightening in German ASW, while we cannot report a similar effect for German CDS. A similar behaviour is not visible for France, despite being considered a low risk control country.

During the pre-crisis period we find that the magnitude of the impulse responses is similar across all countries while during the crisis period, GIIPS countries exhibit much larger impulse responses than the rest of our sample countries.

The forecasting precision is much more accurate during the crisis period as confidence bands are much tighter than in the pre-crisis period.

Compared to the other empirical studies using this methodology, Koop and Korobilis (2014) find confidence bands for their impulse responses that all lie between positive and negative reactions to a 1% shock in Greek bond yields relative to Germany. The advantage of our approach, using ASW and intraday data, dramatically increases the precision of results during the crisis period.

In addition to the impulse response functions for a shock to Greek ASW and CDS in Figures 2 and 3 we present further impulse response functions for a shock to Spanish and Portuguese ASW and CDS in Appendix A[9].

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[9] Impulse response functions for a shock to Irish and Italian ASW and CDS show similar results and can be provided on request.
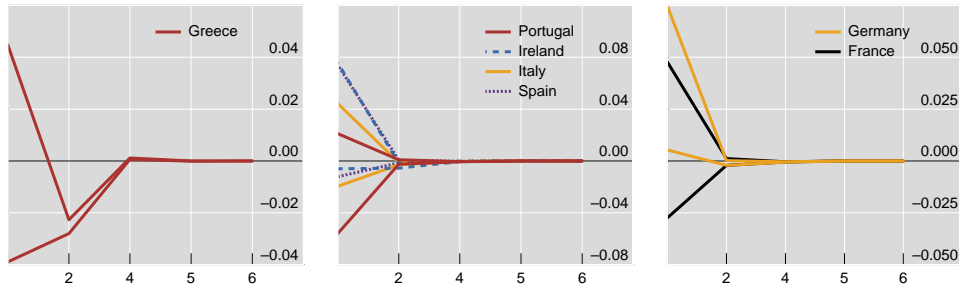
Figure 2: Impulse responses pre-crisis period - Greece

This figure illustrates the impulse response for ΔCDS and ΔASW to a one unit shock (increase) for the period from January 2008 to October 19th 2009. The figures are based on 5-year tenor data with a 30-minute sampling frequency. The y-axis represents the impulse response to a one unit shock in Greek ΔCDS or ΔASW. The number of 30-minute time intervals is described by the x-axis. For each impulse response we plot the upper and lower 95% confidence bands.

Propagation of a one unit shock to ΔASW and its impact on ΔASW

Propagation of a one unit shock to ΔASW and its impact on ΔCDS

Propagation of a one unit shock in ΔCDS and its impact on ΔASW

Propagation of a one unit shock in ΔCDS and its impact on ΔCDS

This figure illustrates the impulse response for ΔCDS and ΔASW to a one unit shock (increase) for the period from October 20th 2009 to end-December 2011. The figures are based on 5-year tenor data with a 30-minute sampling frequency. The y-axis represents the impulse response to a one unit shock in Greek ΔCDS or ΔASW. The number of 30-minute time intervals is described by the x-axis. For each impulse response we plot the upper and lower 95% confidence bands.

Propagation of a one unit shock to ΔASW and its impact on ΔASW

Propagation of a one unit shock to ΔASW and its impact on ΔCDS

Propagation of a one unit shock to ΔCDS and its impact on ΔASW

Propagation of a one unit shock to ΔCDS and its impact on ΔCDS

16

4.2 Results for Central European countries during the crisis period

This section presents results of an unexpected 1% increase in CDS credit risk emanating in GIIPS countries and the shock response in Central European countries. Due to the illiquidity of the bond markets in the Central European countries in our sample we were only able to conduct an intraday analysis based on CDS data during the crisis period. This however does not limit the validity of our analysis because results for GIIPS and low-risk countries in Section 4.1 strongly indicate that bond markets were not the main venue of sovereign credit shock contagion during the crisis. Thus, the PVAR model in Equation (4) applied in this section is estimated with G = 1.

Figure 4: CDS spreads in basis points

The figures are based on data with a 30-minute sampling frequency. Our split in a pre- and a crisis period is indicated by the vertical line in each figure.
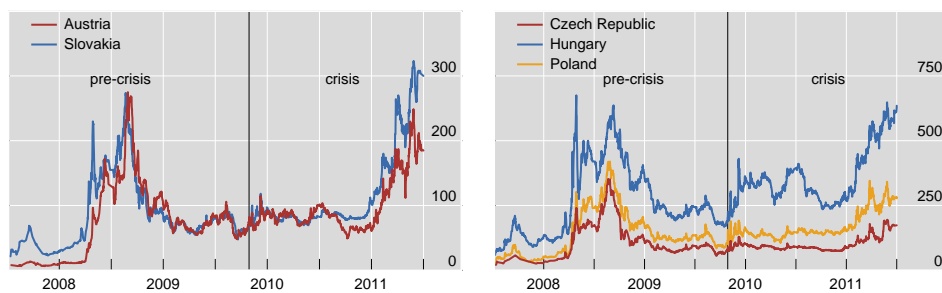
For the Central European countries in our sample we find that they have been much less affected by shocks compared to the GIIPS countries during the euro area sovereign debt crisis. We do not find differences in impulse responses for Central European euro area member countries (Austria and Slovakia) and non-euro member countries (see Figure 5, lower panel). Interestingly, we also do not find a difference in the response functions according to debt to GDP levels of Central European countries. The level of response for the Central European countries (see Figure 5, lower panel) is almost identical. We would have expected a stronger response to shocks in Central European countries with higher debt levels such as e.g. Hungary (see Table 1).

Table 1: Debt to GDP levels in percent, market adjusted (Source: National data, authors' calculations)

year	Austria	Czech Republic	Hungary	Poland	Slovakia
2008	67.4	27.2	65.5	44.0	29.2
2009	77.7	32.2	77.2	49.1	36.6
2010	88.3	39.1	82.6	53.1	41.6
2011	87.1	40.8	80.7	54.9	44.9
2012	91.8	47.6	79.4	54.8	54.4
2013	91.4	49.8	82.2	56.4	57.3
2014	93.3	49.2	86.7	49.2	56.6

This leads to the conclusion that countries that lie geographically at the periphery of the crisis region (GIIPS) are dramatically less sensitive to shocks emanating in the euro zone crisis regions. The speed of shock absorption is similar to the one found for the GIIPS countries in our bivariate PVAR model discussed in Section 4.1.

Figure 5: Impulse responses in Central European countries crisis period - Greece

This figure illustrates the impulse response of Central European countries for ΔCDS to a one unit shock (increase) in Greece for the period from October 20th 2009 to end-December 2011. The figures are based on 5-year tenor data with a 30-minute sampling frequency. The y-axis represents the impulse response to a one unit shock in Greek ΔCDS. The number of 30-minute time intervals is described by the x-axis. For each impulse response we plot the upper and lower 95% confidence bands.

Propagation of a one unit shock to ΔCDS and its impact on ΔCDS

Propagation of a one unit shock to ΔCDS and its impact on ΔCDS
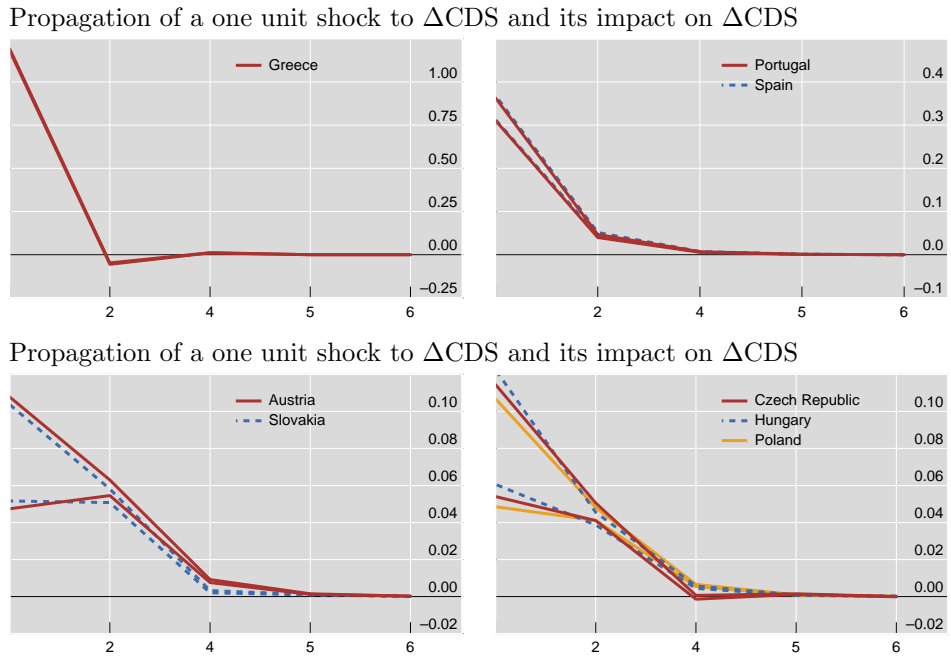
Further impulse responses to shocks to Portuguese and Spanish CDS and their impact on Central European countries can be found in Appendix B.

4.3 The impact of unexpected economic news on sovereign credit risk: Results from a PVARX experiment

In this section we conduct an experiment that aims analysing whether responses to shocks and shock contagion can be attributed to economic fundamentals or if overreactions in increased credit risk during the crisis period might also be due to self-fulfilling prophecies. Gibson et al. (2012) explain the effect of self-fulfilling prophecies with interest rate spreads that were lower than justified by fundamentals prior to the crisis, owing to the role played by Greece's euro area membership on biasing investor expectations. During the crisis period, Gibson et al. (2012) define this self-fulfilling prophecy effect that interest rate spreads have been higher than those predicted by fundamentals due to a lack of belief by

19

the market that sustainable financial consolidations measures and structural reforms will be implemented.

Our experiment is designed similar to Canova and Ciccarelli (2009) as follows: We distribute the data of the economic surprise index over each trading day (18 time intervals). The distribution is chosen such that the maximum is reached midday and the sum of the 18 different intraday values is equal to the value reported by the Citigroup economic surprise index. We have experimented with different distributions and despite the arbitrary distribution assumption we find robust results. The last 6 values are removed from all time series in order to be close to the last maximum (in case of a positive reading of the surprise index) or close to the last minimum (in case of a negative reading of the surprise index). We fit the PVARX model from Equation (6) and produce an out-of-sample forecast for 8 intervals beyond the last data point, which is in case of the pre-crisis the 19th October 2009 and in the case of the crisis the last trading day the 30th December 2011. We call this forecast the "real forecast". Further, we repeat this same procedure, but now set the data of the surprise index of the last day to zero, i.e. we artificially remove the last positive or negative "shock" given by the data. We produce again an out-of-sample forecast which we call the "counterfactual forecast". The difference between the real and the counterfactual forecast captures the impact of the positive or negative values of the Citigroup economic surprise index on the last day. In other words, the experiment mimics what would have happened if the last positive or negative economic news had not occurred and thus helps answering the question whether macroeconomic fundamental news can explain changes in sovereign credit risk.

During the pre-crisis period we find for all countries in the sample, that the positive shock from the economic surprise index at the last day (19th October 2009) leads to an expected decrease in credit risk and vice versa (see Figure 6). Prior to the crisis, the magnitude of the effect following an unexpected macroeconomic news shock is similar in bond and CDS markets. Our pre-crisis results indicate that markets reacted rationally in pricing macroeconomic news into sovereign credit risk.

During the euro area sovereign debt crisis period, a negative reading of the economic surprise index at the last available day (30th December 2011) leads surprisingly to a decrease in credit spreads in most countries (see Figure 7). In rational markets, a negative economic news shock should lead to an increase in sovereign credit risk and thus to an increase in spreads. Our results are, unlike for the pre-crisis period, counterintuitive. For the crisis period they show that credit markets did not rationally react to economic news, but were most likely driven by monetary policy, political decisions, and speculations. Figure 8 displays the individual components (the real and the counterfactual forecasts) of our unexpected economic news shock experiment. Subtracting the counterfactual forecast in row 2 from the real forecast in row 1 of Figure 8 produces the forecast in row 1 of Figure

7. The same applies to the remaining rows in Figures 7 and 8. Surprisingly, in most cases a negative economic shock leads to a tightening of credit spreads (row 1 and 3 of Figure 8).

The shapes of the curves in Figures 6, 7 and 8 are due to our particular choice of decomposing the daily Citigroup economic surprise index into intraday intervals. Other choices lead to different shapes of our curves, however do not change the results. This gives support to the self-fulfilling crisis theory, that changes in sovereign credit risk during the euro area sovereign debt crisis were only partially driven by economic fundamentals as markets did not react to economic news rationally in contrast to the pre-crisis period.

Figure 6: Shock to the Economic Surprise Index during the pre-crisis period

This figure illustrates a scenario of a real positive shock to the economic surprise index minus a counterfactual scenario where we have assumed that the shock did not happen. The period under consideration is from January 2008 until October 19th 2009. The figures are based on 5-year tenor data with a 30-minute sampling frequency. The y-axis represents the response of ΔASW (upper part) and ΔCDS (lower part). The number of 30-minute time intervals is described by the x-axis. We plot the upper and lower 95% confidence bands for each country.


21
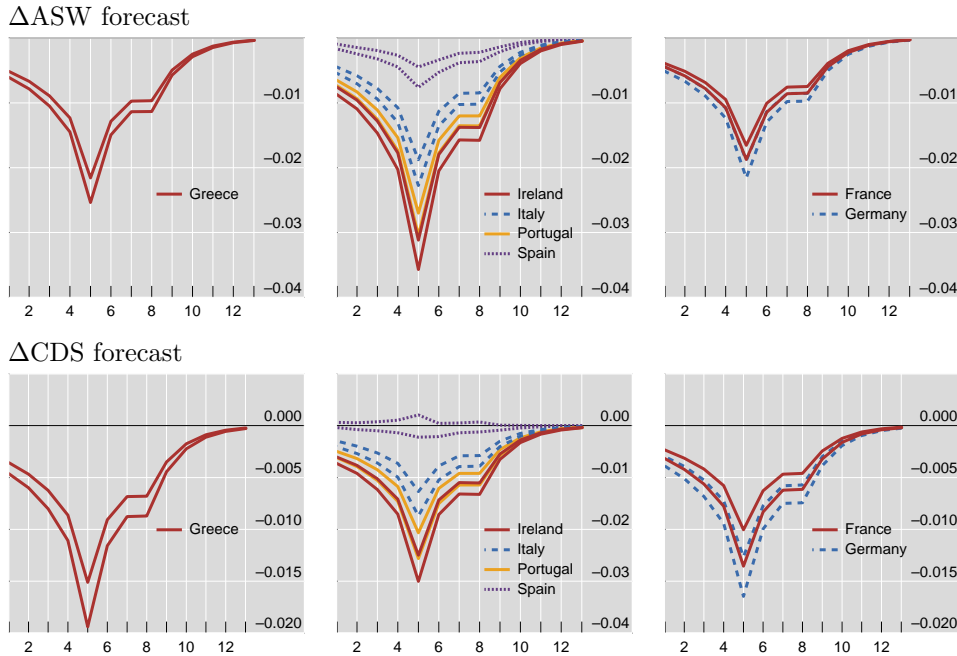
Figure 7: Shock to the Economic Surprise Index during the crisis period

This figure illustrates a scenario of a real negative shock to the economic surprise index minus a counterfactual scenario where we have assumed that the shock did not happen. The period under consideration is from October 20th 2009 until end-December 2011. The figures are based on 5-year tenor data with a 30-minute sampling frequency. The y-axis represents the response of ΔASW (upper part) and ΔCDS (lower part). The number of 30-minute time intervals is described by the x-axis. We plot the upper and lower 95% confidence bands for each country.
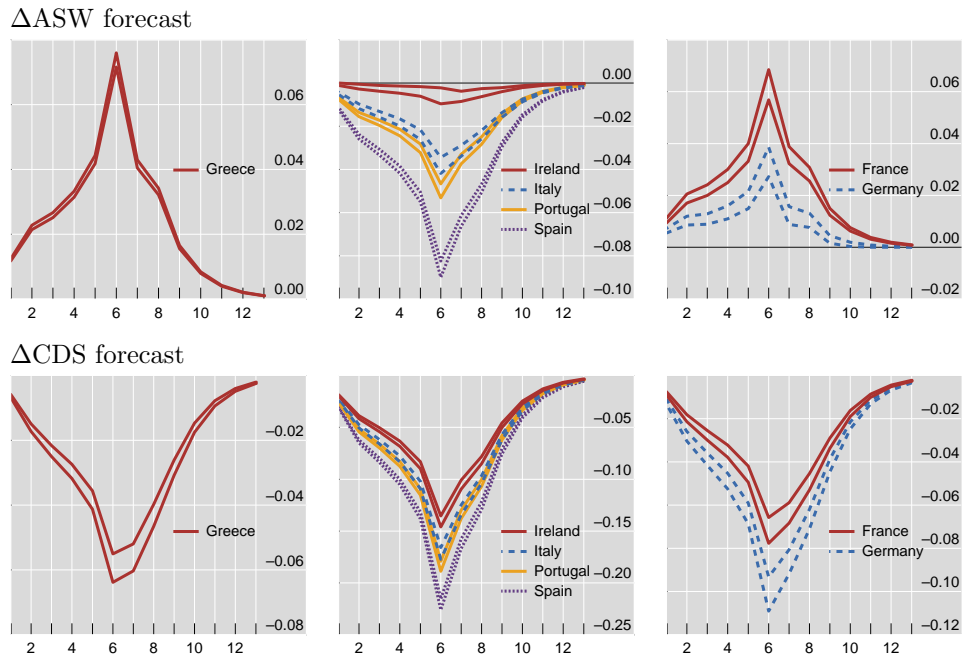
Figure 8: Real and counterfactual forecast decomposition

This figure presents the individual components, the real and the counterfactual forecasts, of our experiment for the crisis period October 20th 2009 until end-December 2011. The figures are based on 5-year tenor data with a 30-minute sampling frequency. The y-axis represents the response of ΔASW (upper part) and ΔCDS (lower part). The number of 30-minute time intervals is described by the x-axis. We plot the upper and lower 95% confidence bands for each country.
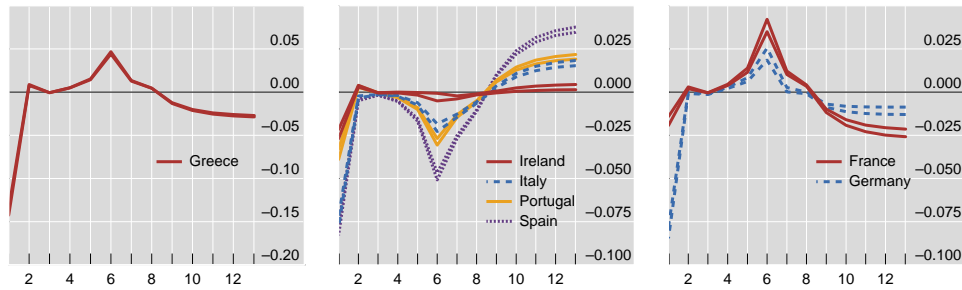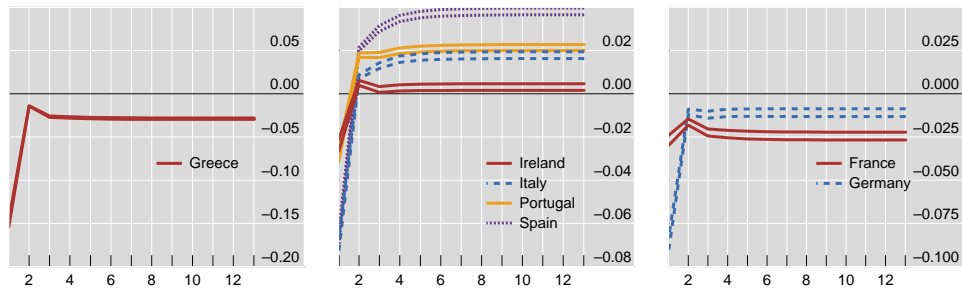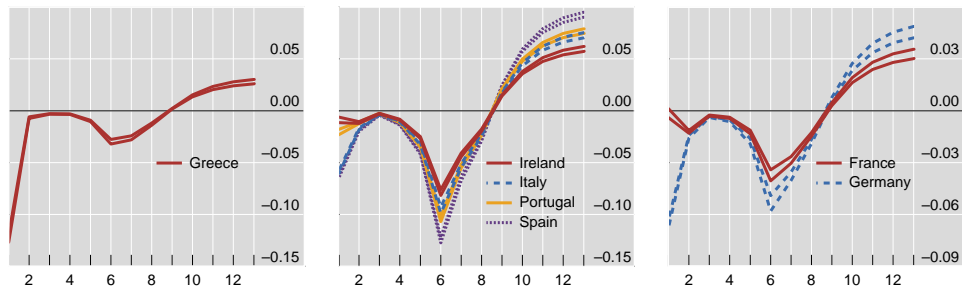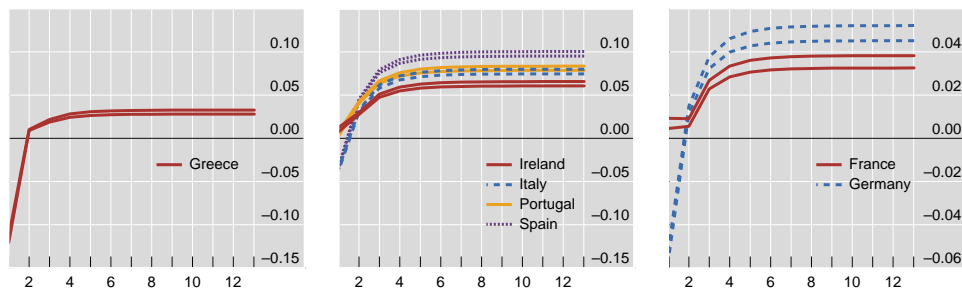
5 Conclusion

The CDS market has been the main venue for the transmission of sovereign credit risk contagion during the euro area sovereign debt crisis. In contrast, we find that prior to the crisis both markets (CDS and bond) have been similarly important in the transmission of financial contagion while the bond market ceased in importance during the crisis period. We find evidence for sovereign credit risk contagion during the euro area sovereign debt crisis period as our results show more drastic reactions to shocks in terms of magnitude and absorption compared to the pre-crisis period. Thus, our results on responses to sovereign credit risk shocks during the crisis period confirm the contagion across euro area countries as they result from extreme negative, systemic effects and are much higher in magnitude compared to the pre-crisis period which cannot be explained by macroeconomic fundamentals.[10] We do not find contagion but rather comovement effects during the pre-crisis period as markets react rationally to economic fundamentals while responses to sovereign credit risk shocks remain moderate in magnitude. Using intraday data substantially increases the precision of results as we find average timelines of financial shock contagion of 2 hours during the crisis period and 1 hour prior to the crisis. This is a clear indication of the efficiency of financial markets.

We find a flight to safety during the crisis period in the German bond market which is not present prior to the crisis and interestingly also not visible in the French bond market. The flight to safety effect can be explained by market participants' lack of belief in the future path of public finances (self-fulfilling crisis), which cannot be explained by macroeconomic news.

Our results using an unexpected exogenous macroeconomic news shock suggest that during the pre-crisis period markets reacted rationally in pricing macroeconomic news into sovereign credit risk as positive news lead to a decrease in credit spreads and vice versa. Using the same experiment for the euro area sovereign debt crisis period our results show that movements in sovereign credit spreads did not respond to macroeconomic news but were rather driven by either monetary policy or exaggerations in financial markets due to lack of belief (self-fulfilling crisis).

We find that Central European countries have practically not been affected by sovereign risk contagion during the crisis. Our model further does not indicate a difference in responses to shocks according to debt levels or whether the country belongs to the monetary union or not. This implies that in general countries that lie geographically at the periphery of the crisis region (GIIPS) were much less affected by sovereign risk contagion.

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[10] Please refer to the contagion definitions according to Constancio (2012), Forbes (2012), and Kaminsky et al. (2003) in the Introduction.

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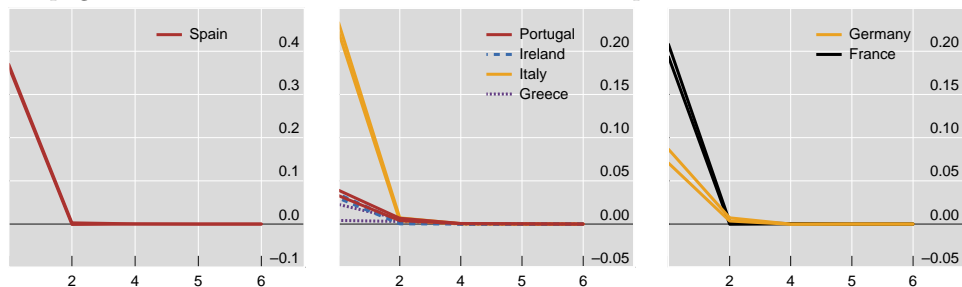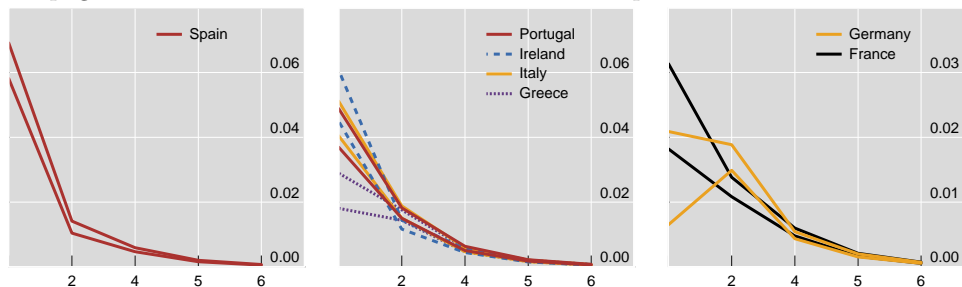
A Impulse response functions for Spain and Portugal

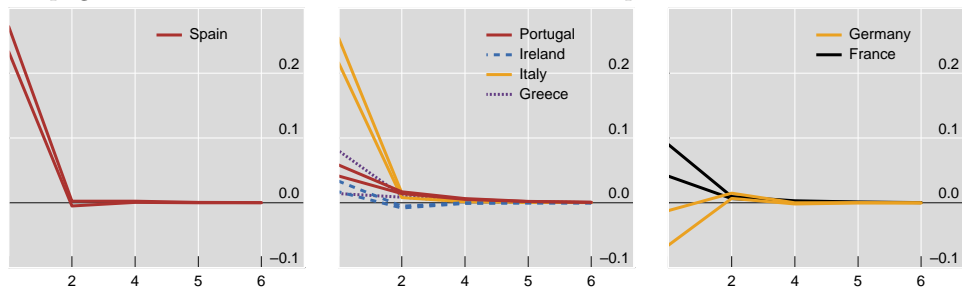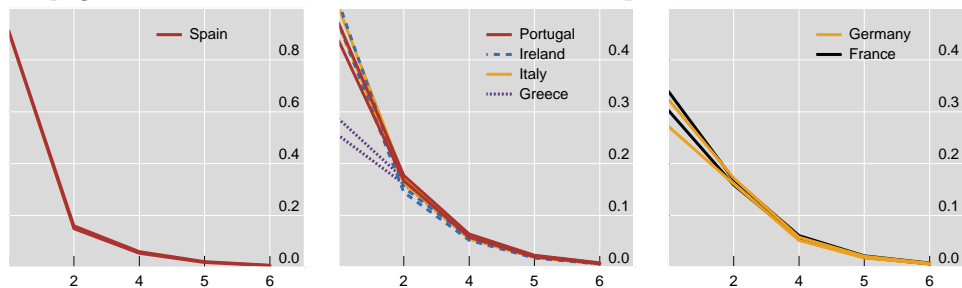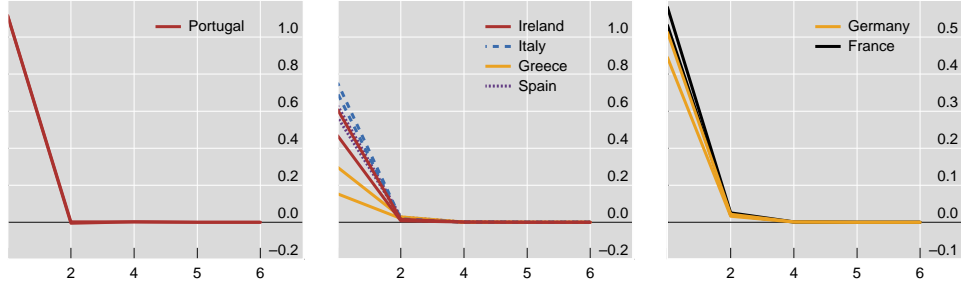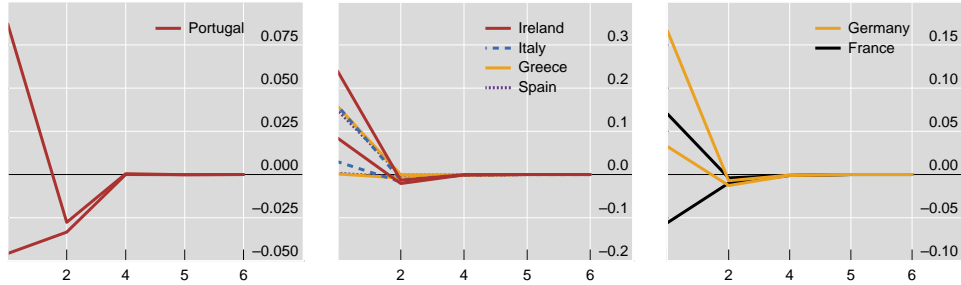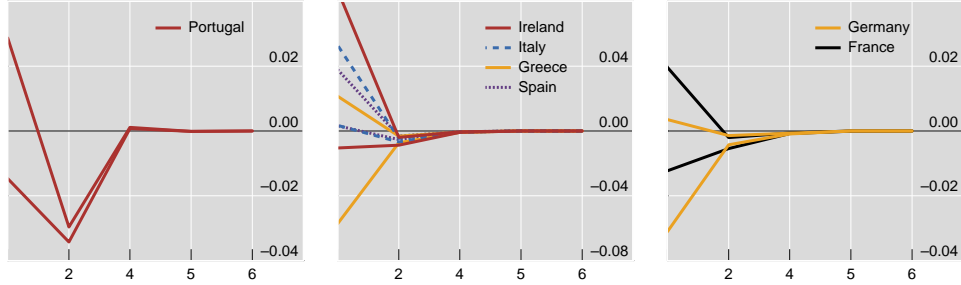Figure A.1: Impulse responses pre-crisis period - Spain

For details see Figure 2.

Propagation of a one unit shock to ΔASW and its impact on ΔASW
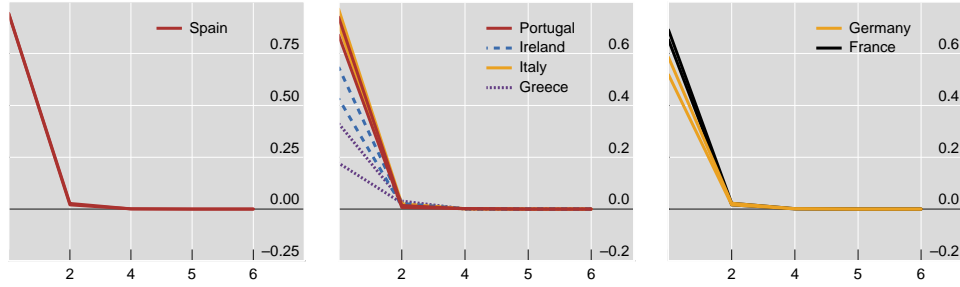
Propagation of a one unit shock to ΔASW and its impact on ΔCDS
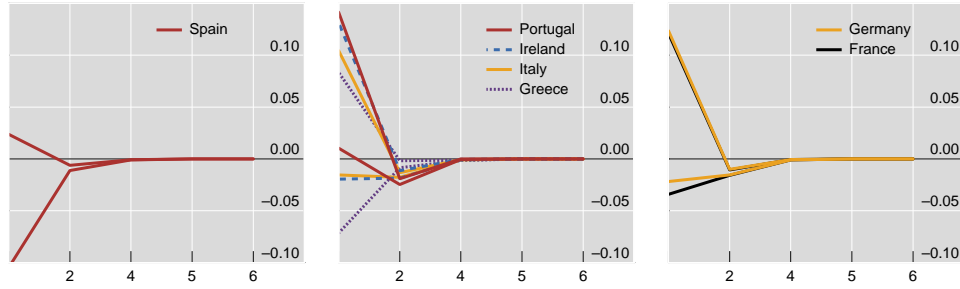
Propagation of a one unit shock to ΔCDS and its impact on ΔASW
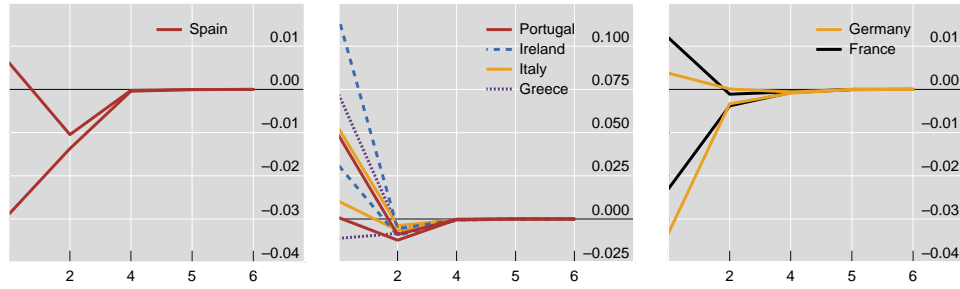
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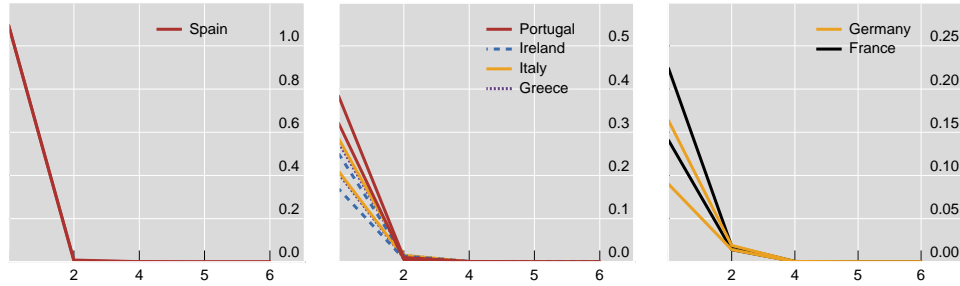
Figure A.2: Impulse responses crisis period - Spain

For details see Figure 3.

Propagation of a one unit shock to ΔASW and its impact on ΔASW

Propagation of a one unit shock to ΔASW and its impact on ΔCDS

Propagation of a one unit shock to ΔCDS and its impact on ΔASW

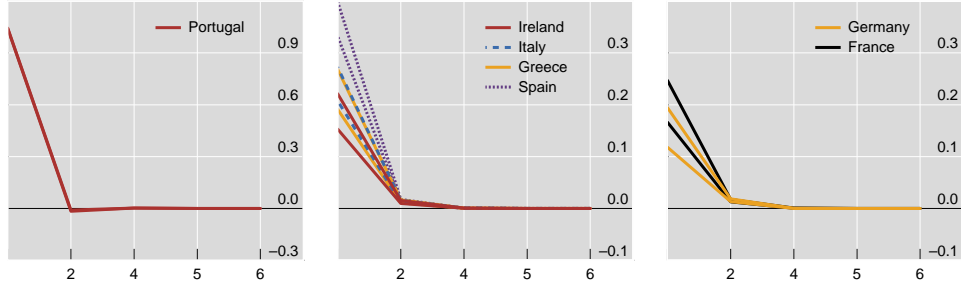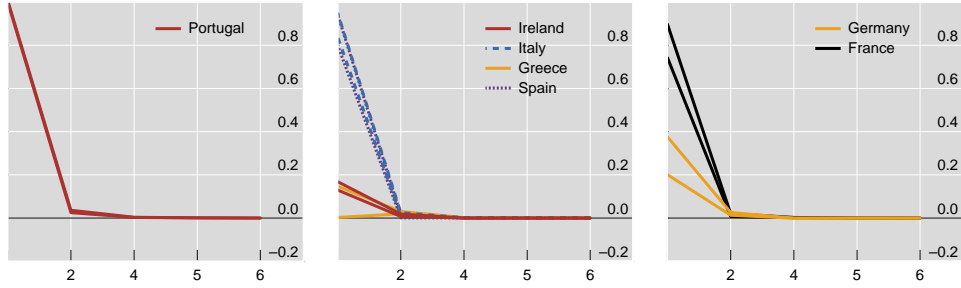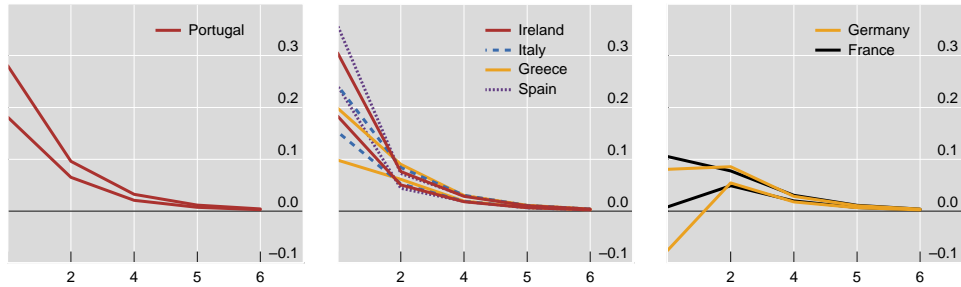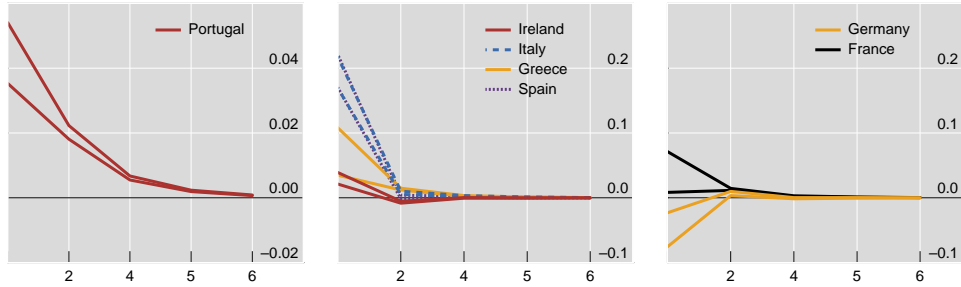Propagation of a one unit shock to ΔCDS and its impact on ΔCDS

Figure A.3: Impulse responses pre-crisis period - Portugal

For details see Figure 2.

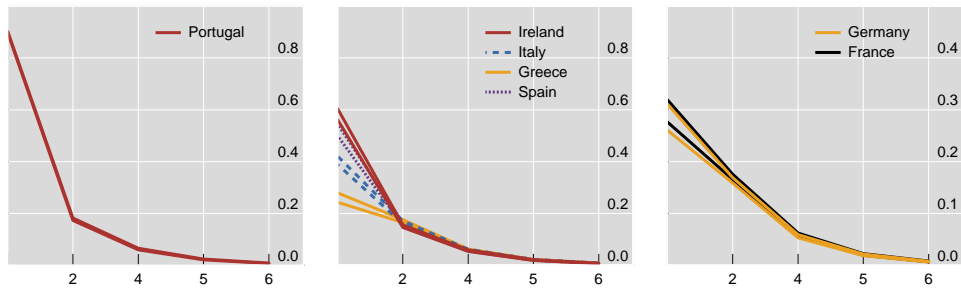Propagation of a one unit shock to ΔASW and its impact on ΔASW

Propagation of a one unit shock to ΔASW and its impact on ΔCDS

Propagation of a one unit shock to ΔCDS and its impact on ΔASW

Propagation of a one unit shock to ΔCDS and its impact on ΔCDS

For details see Figure 3.

Propagation of a one unit shock to ΔASW and its impact on ΔASW

Propagation of a one unit shock to ΔASW and its impact on ΔCDS

Propagation of a one unit shock to ΔCDS and its impact on ΔASW

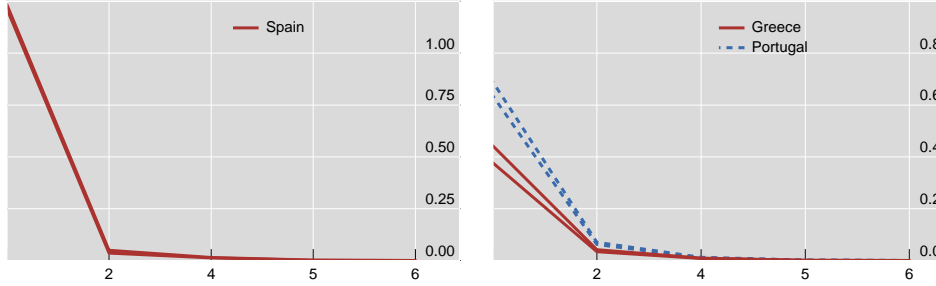Propagation of a one unit shock to ΔCDS and its impact on ΔCDS

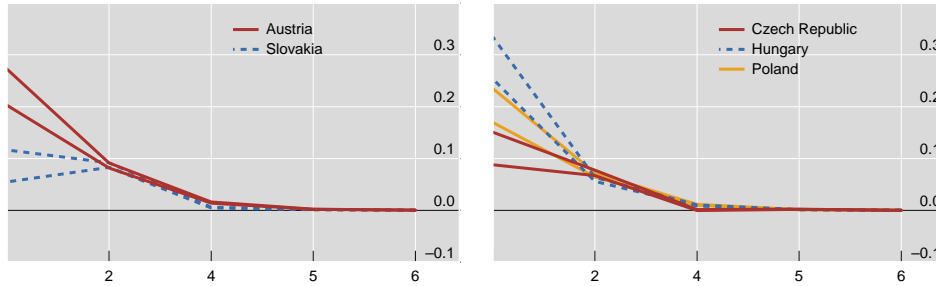# B Impulse response functions of Central European countries

Figure B.1: Impulse responses crisis period - Central European countries
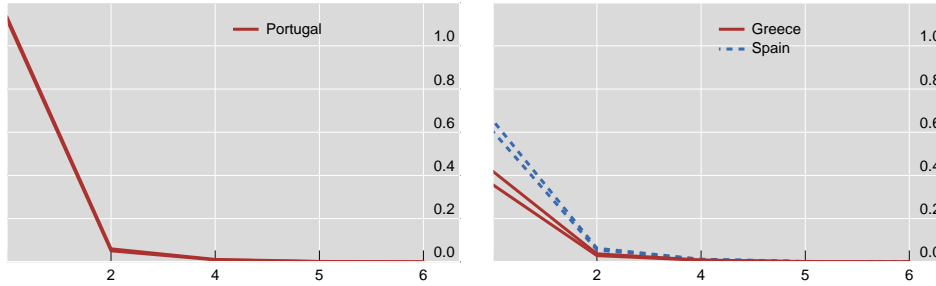
For details see Figure 5.

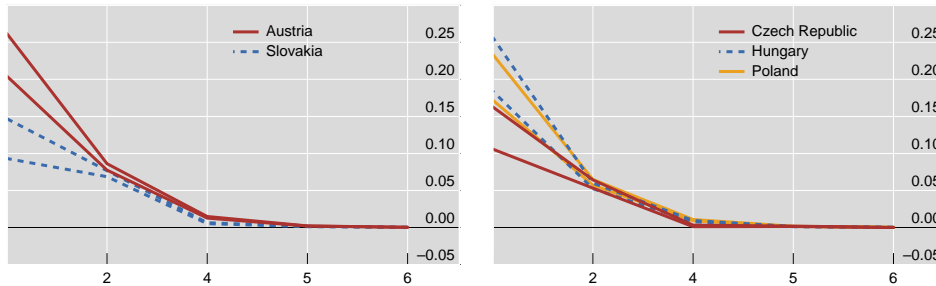Propagation of a one unit shock to Spanish ΔCDS and its response on ΔCDS

Propagation of a one unit shock to Spanish ΔCDS and its response on ΔCDS

Propagation of a one unit shock to Portuguese ΔCDS and its response on ΔCDS

Propagation of a one unit shock to Portuguese ΔCDS and its response on ΔCDS

C Panel unit root

Before analysing contagion effects within a panel framework, we perform unit root and stationarity tests on our CDS and ASW price data. Canova and Ciccarelli (2013) suggests that panel-based unit root or stationarity tests have higher power over univariate tests. For our ASW and CDS data we can not reject the $\mathscr{H}_0$ of a common unit root according to the Levin, Lin and Chu test. Further, we can also not reject the $\mathscr{H}_0$ of individual unit root processes according to the Im, Pesaran and Shin panel unit root test for our data (see Table C.1). Since all of our country series are considered simultaneously and our data for CDS and ASW is non-stationary (I(1)), we use first differences for our model estimations.

Our panel unit root test takes the following form:

$$\Delta y_{it} = \alpha_i + \rho_i y_{i,t-1} + u_{it} \qquad \text{with} \qquad \mathscr{H}_0 : \rho_1 = ... = \rho_N = 0. \tag{8}$$

While $i = 1, ..., N$ is the cross-sectional dimension and $t = 1, ..., T$ is the time-series dimension. Hence all series are independent random walks under the $\mathscr{H}_0$ and non-stationary.

We perform the Levin, Lin, Chu test that assumes a common unit root process where the homogenous alternative takes the following form:

$$\mathscr{H}_{1a} : \rho_1 = ... = \rho_N = \rho < 0,$$

where all series are stationary under the $\mathscr{H}_1$.

Further, we perform individual panel unit root tests based on Im, Pesaran and Shin where the heterogenous alternative takes the following form:

$$\mathscr{H}_{1b} : \rho_1 < 0, ..., \rho_{N_0} < 0, \qquad \text{where} \qquad N_0 \leq N.$$

Hence $N_0 \leq N$ series are stationary, with potentially different AR parameters.

Table C.1: Panel Unit Root Tests - p-values

This table reports the p-values of the panel unit root test for ASW and CDS with individual intercepts for the period from January 2008 to end-December 2011 and 30-minute sampling frequency. The cross-section consist of the 7 countries in our sample.

	Levin, Lin, Chu	Im, Pesaran, Shin
ASW	1.00	0.23
CDS	0.59	0.15