Spillovers of the Credit Default Swap Market

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Abstract

Credit Default Swap prices have soared on the edge of a potential sovereign default from some European countries. Interestingly not only countries on the verge of receiving bail-outs have seen their CDS prices rise, but also those from which most of the bailout financing comes from, such as Germany. If in fact default probabilities of countries like Germany have risen, should we still view them as safe-havens? In particular, to what extent should we see bond yields rise (as bond prices decline) vis-a-vis with CDS spreads? This paper tackles this question by estimating the dynamic responses of bond yields to changes in the CDS spreads. The second, more fundamental question, is to assess if the apparent contagion from troubled countries to otherwise-healthy economies is in fact so. I address this question using the Diebold - Yilmaz spillover index methodology for CDS data. I conclude that sovereign debt from Germany, Chile and Japan are both, unaffected by contagion from other economies and have served as store-of-value assets during the current turbulence.

JEL Codes: F34, G14

Key words: Sovereign Credit Default Swaps, Contagion, Spillover.

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1 Introduction

Credit Default Swap prices have soared on the edge of a potential sovereign default from some European countries. Interestingly not only countries on the verge of receiving bail-outs have seen their CDS prices rise, but also those from which most of the bailout financing comes from, such as Germany. If in fact Germany's default probability has risen, should we still view it as a safe-haven? To what extent should we see bond prices rising vis-a-vis with CDS spreads? Using a VAR(p) for CDS and bond yields and an augmented VAR(p) with the VIX index, this paper tackles this question by estimating impulse response functions on bond yields from innovations in the CDS spreads. A second, more fundamental question is how to interpret the rise in CDS spreads in trouble-free countries. Is there contagion in this market? To assess this question I use the Diebold Yilmaz (2010) methodology to compute a "contagion index" which relies on the forecasts generated by a large VAR(p) comprised by of seven economies. The results for the two main questions in this paper are consistent. There exist a group of economies for which bond yields have a negative or negligible response to CDS innovations, which I categorize as safe-havens. When examining for evidence of contagion due to the apparent higher co-movement in CDS spreads, I find no evidence of contagion in the last couple of years in the Diebold Yilmaz (2010) sense, for CDS levels. However there exists a period of time in the aftermath of the global financial crisis and recession of 2008, in which we could defend the argument of contagion. For CDS volatility, on the other hand, we cannot reject the existence of some marginal contagion from the second quarter of 2012 onwards.

2 CDS in Practice and Theory

This section aims at explaining how the CDS market operates, describe its behavior in the unfolding of the European debt crisis of 2012, and summarize the relevant literature.

2.1 CDS Market

The credit default swap spread is the cost per annum for a kind of protection against a "credit event"; usually a loan default. The buyer of the CDS makes a series of fee payments to the seller and, in exchange, receives the face value of the underlying asset when (if at all) the loan defaults [1]. If a credit event were to happen, the defaulted asset

[1]It is not straightforward to define a sovereign default though, as countries can not go into bankruptcy the way companies do. Usually we can define default according to the *International*

goes to the CDS seller, or the latter compensates the former with the price difference between the face value of the asset and the mark to market price of the defaulted asset. Hence, it is tempting to praise the following argument. If an investor buys an asset which bears extra risk and simultaneously buys protection to this risk in the form of a CDS, then this must be equivalent to buying a risk-free asset. Then we could think of the CDS fee as a "spread" on risk-free instruments. This arbitrage relation does not hold perfectly in the data, and indeed some papers focus on testing this relation statistically, for instance Blanco et. al. (2005) or Hull et.al. (2004). Most of the work has focused on corporate data and the bottom line is that the relation holds most of the time but there exist deviations which sometimes are systematic and long-lasting. Hull et.al. (2004) explains in great detail (in the context of corporate bonds) the reasons why we may not observe perfect arbitrage. Among them, those that are more relevant to sovereign CDS contracts (specially those not subject to naked bid/sell) are

- To take full advantage of the arbitrage opportunity it must be the case that participants can quickly short bonds or be prepared to sell these bonds, buy riskless bonds, and sell default protection (or the reverse operation).
- The perfect arbitrage argument assumes the "cheapest to deliver" option which results from the re-structuring of the debt.
- There is counterparty risk.
- The argument assumes perfectly elastic supply of CDS contracts, whereas it is more likely that this is not the case, specially if naked CDS are banned (more on this later).
- It is difficult to extend the argument to CDS on the safest, yet risk-bearing, possible asset (i.e. German bonds or Treasuries)

CDS are interesting derivatives as one does not need to hold the underlying asset to buy them. Even buyers who do not hold the loan instrument and who have no exposure to the credit event can buy the protection (these are called "naked" CDS). However, as of December 2011 the European Parliament approved a ban on

Swap and Derivatives Association (ISDA) as (*i*) suspension of payments, (*ii*) bankruptcy (although this is not the case here), (*iii*) unilateral restructuration of payments or payment dates, (*iv*) forced acceleration or technical default due to violations to bond convenants. And even these definitions of *default* need to be agreed by the so-called "Determinations Commitee" which is comprised by 10 dealers and 5 buyers of the protection, plus three consultants. A majority of 12 out of 15 is required to determine that a credit event has indeed occurred, so that this decision is not subject to further legal external auditing.

naked CDSs for sovereign nations (Bloomberg, 2011). Another peculiarity of these instruments is that we can interpret the CDS "spread" as a way of measuring default probability although it is not entirely so. When entering into this agreement both, the buyer and the seller, take on counterparty risk. Therefore there also exists a probability that the buyer looses protection if the seller defaults. Alternatively, given that a seller normally limits its risk by buying offsetting protection from another third party - that is, it hedges its exposure-, then if the buyer defaults and no longer pays the revenue streams, the seller needs to unwind its position with the reverse operation and may do so at a different price.

My analysis is based on seven economies, namely, Portugal, Spain, Italy, France, Germany, Japan and Chile. The choice of the first five is straightforward as they are in the center of the discussion of fiscal sustainability and share the same currency. Additionally I include Chile and Japan as two economies which are outside the problem but in some sense have been seen as alternatives to investment in the USA, Germany and Switzerland, at least by domestic investors

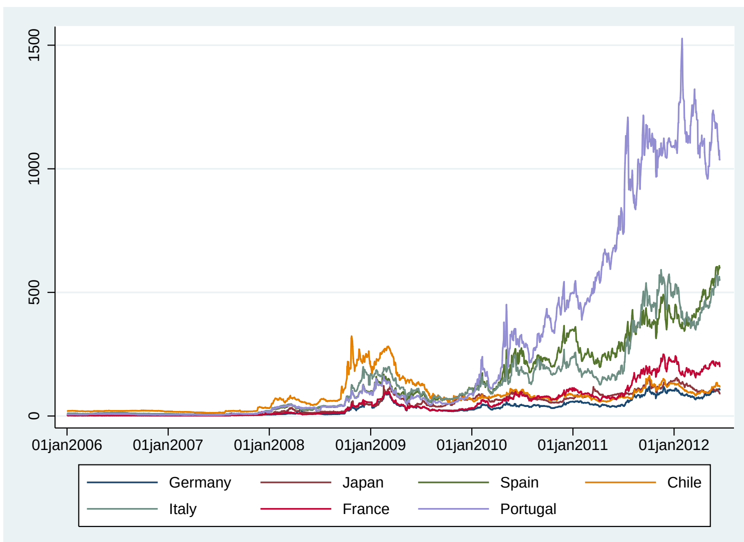


Figure 1: CDS by country (daily data) in basis points

We can see from figure (1) that most of the action in the sovereign CDS market starts in the aftermath of the global financial crisis and recession of 2008. Interestingly in the 2008-2009 period, emerging countries such as Chile saw their CDS spreads soar in contrast to countries like France or Portugal. From 2010 to date, the pattern is the opposite. Portugal's CDS are an order of magnitude larger than Chile's and the contrast with Spain and Italy is not any different. Another feature that may call upon our attention is that there seemingly appears to be an increasing correlation of the CDS of countries such as Germany, with its currency fellows, and we might be tempted to use the contagion argument from danger-of-default countries to the rest. However closer examination is required. On a first round let me present the pairwise correlations of German CDS with other countries' CDS spreads. In tables (1) and (2) I present these correlations for daily and weekly data (measured by the Friday close price). We can readily observe that German CDS is less correlated in 2010 than in its past, is more correlated in 2011, and in 2012 this correlation drops again[2]. It is common practice to refer to the synchronization – beyond fundamentals – of cross-country variables as *contagion*, and this phenomenon usually coincides with times of economic or financial distress, which contain high dosses of unprecedent uncertainty. Nevertheless, the analysis in tables (1) and (2) is flawed to detect contagion as it may be the case that a third (and different) variable is explaining higher synchronization of CDS series. A thorough statistical examination that incorporates this caveat is developed in section 3.2.

Why should we be interested in learning from the cross-dynamics in the CDS spreads for different countries? Simply put, if there is a link between CDS and bond prices there is money involved. Furthermore, if the dynamics in the CDS market can help us know the most likely future path on bond yields, then we should be apprehensive when looking at figure (16) and question Germany's bonds as a risk-free instrument. Section 3.1 is devoted to analyzing this relationship.

Table 1: Pairwise correlations for Germany's and other countries' CDS: Daily data

	2006-2007	2008-2009	2010	2011	2012
Portugal	0.42	0.91	0.65	0.79	*-0.09*
Spain	0.54	0.91	0.74	0.89	0.46
France	0.42	0.99	0.81	0.97	0.84
Italy	0.30	0.92	0.69	0.96	0.90
Japan	0.26	0.82	0.38	0.88	0.38
Chile	0.40	0.83	0.50	0.96	0.90

Source: Author's calculations on Bloomberg data.
Note: All non-italic pair-wise correlations are significant to the 1% level, using the Bonferroni-adjusted significance level.

2.2 Literature Review

The literature on credit risk is large and growing. Most of it has concentrated on pricing this risk and we can identify two main strands in this literature. First, we

[2]Full pairwise correlation matrices are presented in appendix A

Table 2: Pairwise correlations for Germany's and other countries' CDS: Weekly data

	2006-2007	2008-2009	2010	2011	2012
Portugal	0.44	0.90	0.63	0.79	*-0.12*
Spain	0.52	0.89	0.72	0.90	*0.51*
France	0.38	0.98	0.76	0.98	0.83
Italy	0.35	0.91	0.70	0.96	0.90
Japan	0.36	0.81	*0.33*	0.90	*0.30*
Chile	0.43	0.82	0.48	0.96	0.89

Source: Author's calculations on Bloomberg data.
Note: All non-italic pair-wise correlations are significant to the 1% level, using the Bonferroni-adjusted significance level.

have structural models of valuation of default probabilities, or "value at risk" in the Merton (1974) tradition. There are several references applying this framework to firm level data and even some to sovereign credit risk like Gapen et. al. (2008). The second strand of the literature, models the timing of the default as a hazard rate. Lando (1997) provides a summary of this approach. All in all, this paper stands apart from these two branches as it does not propose a way of calculating the credit risk. Instead I take the CDS as a measure, however imperfect it may be, as discussed by Blanco et. al (2005), of default premia and how likely it is to influence the fixed income credit spread (over a sovereign risk-free asset).

This paper relates to previous work that tests the relation between credit spreads and CDS premia. This relationship hinges on an arbitrage argument. Assume one can buy a risky asset with yield r and simultaneously buy a CDS protection with implied yield c [3]. Since by doing these operation the investor has an asset with no default risk then $y-c$ should be very similar to the yield x of a risk free asset for the same maturity. For instance, Blanco et. al (2005) use this arbitrage relation and test its validity for a sample of 33 U.S. and European investment-grade firms. They conclude that at the corporate level this relationship holds with some two types of deviations. First, for three of the firms there exist large and prolonged deviations which they attribute to imperfections in the contract specification and second, they find short-lived deviations which revert to zero for the rest of the firms. They attribute these differences to the hypothesis that CDS spreads would precede credit spreads and in the long run these two would co-integrate. A similar analysis is done by Norden and Weber (2009) who also use corporate data in a VEC system that analyzes CDS-spreads, credit spreads

[3] Recall that in a CDS contract the buyer of the protection pays a quarterly fee for the notional value of the underlying asset, then the ratio of these two results in c.

and stock returns to conclude that CDS Granger-cause bond spread changes "most of the time", and this effect is stronger in US firms than it is in the European firms. Finally, Hull et.al. (2004) also carry out the same exploration for a number of well known American firms and conclude that the arbitrage relation holds most of the time and that the risk-free rate used by market participants is about 10 basis points below the 5-year swap rate. More interesting, however, is how this paper stands out from the previous literature. In sum, all the previous analysis relies on testing the error in the arbitrage equation, which implicitly assumes a fairly quick (if not immediate) price adjustment in the credit spreads. However due to all the imperfections mentioned in section 2.1 this adjustment could be far from instantaneous and thus, we need to consider non-contemporaneous relations of these variables. Hence, looking at how long it takes for bond yields to respond to sudden changes in CDS spreads (if any at all) is in itself a relevant contribution.

This paper is also a contribution to the literature as it addresses the spillover hypothesis directly by using a tractable measure of contagion. The literature of contagion in financial markets has defined such a concept as a "significant but temporary increase in the linkages between different financial markets" Longstaff (2010). It identifies three major channels by which shocks in one market can propagate to others. The first channel is the *correlated information* channel and hinges on the hypothesis that events in one market (usually more liquid markets) signal (or are correlated with) events in other markets whose price has yet to change. The second channel can be named the *liquidity channel*. In this mechanism a shock in one market causes the decrease in the overall liquidity of the whole financial sector because investors who suffer losses find their ability to obtain funding impaired which results in declines in the liquidity of other financial market assets Brunnermeier and Pedersen (2009). Finally, the literature identifies the "risk-premium" channel, in which shocks in one market affect the willingness of market participants to bear any risk. Although it is important to mention the rationale to observe a contagion event, I do not try to distinguish which one is the operational channel for the sample under analysis. Instead I simply test if any one of these channels is operating through a tractable measure of contagion, developed by Diebold and Yilmaz (2010).

3 Statistical Analysis

3.1 CDS to Bond Yields pass-through

Do CDS spreads and credit spreads meet the no-arbitrage condition – even after a non negligible period of time–? Further, if derivative markets are imperfect as I discussed earlier, how long does this adjustment take? To address these questions, consider the following VAR(p) for any given country [4].

$$\begin{bmatrix} CDS_t \\ Y_t \\ x_t \end{bmatrix} = \Phi(L) \begin{bmatrix} CDS_t \\ Y_t \\ x_t \end{bmatrix} + \begin{bmatrix} \varepsilon_t^{CDS} \\ \varepsilon_t^{Y} \\ \varepsilon_t^{x} \end{bmatrix} \tag{1}$$

where Y_t stands for bond yields in their original currency denomination and is expressed in % points; x_t may or not be included, and stands for any other exogenous variable we may want to include in the system; $\Phi(L)$ is the corresponding lag polynomial associated with the VAR(p) process. Finally, let me assume the vector $\varepsilon_t \sim \mathcal{N}(\mathbf{0}, \Sigma)$. In my analysis we collapse the original daily information into weekly data and use the Friday-closing price. This is, of course, just an arbitrary decision to balance the tradeoff between working with the highest available frequency and the statistical benefits in interpreting the results of impulse response functions in a parsimonious VAR(p) system. Also, I am reluctant to using weekly averages as I may be introducing unknown MA(q) structure to the error terms whose covariance structure is of particular importance in this exercise.

Let me start our exercises using no exogenous variables; that is not including variable x_t. Consider the following three periods: (a) January 2010 to date, (b) January 2011 to date and (c) January 2010 to September 2011. The first time window considers que period in which CDS markets begin to exhibit some action and incorporates all available information to date. The second period simply drops year 2010 to leave behind the aftermath of the global financial crisis and recession of 2008 and put more weight on the European fiscal solvency crisis. Finally the third time window comprises year 2010 and the part of 2011 in which Long Term Refinancing Operations were not in place, so as to not account for some effect these operations may have had on bond yields (See European Central Bank (2012)) [5]. I try several lag structures, obtaining very similar results (both quantitatively and qualitatively) and settle for $p = 3$ in favor of parsimony. In figures (2) to (4) I show the orthogonalized impulse response functions derived from a VAR(3) system in which the exogeneity ordering for the Cholesky decomposition places CDSs as the most "exogenous" variable and bond yields as the less exogenous variable. For each figure the left-most panel corresponds to time window (a), and the right-most panel corresponds to time window (c). Also, to make things comparable across countries, for which the one-standard-deviation

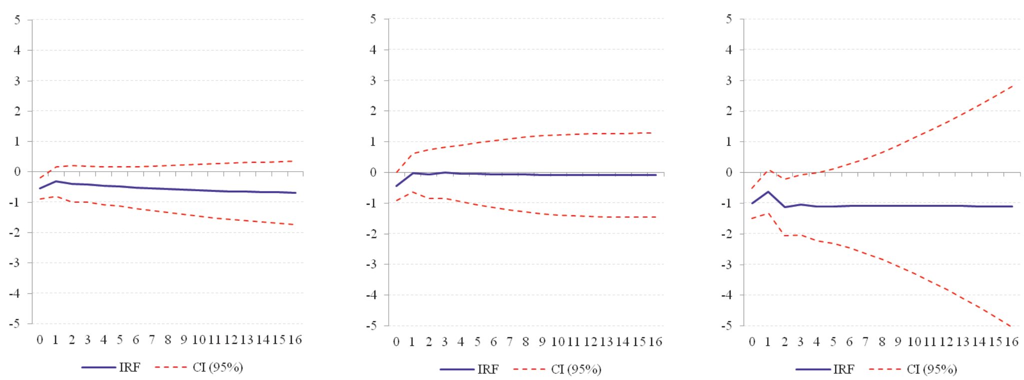
[4] CDS data is usually expressed in basis points. In order to make the magnitudes of yield data and CDS data comparable, I divide the latter by 100 and work with percentage points

[5] For the sake of brevity we include in Appendix A the results of the estimation for Germany and Spain. Other results are available upon request.

shock is different, I constraint the shock magnitude to be the same for all countries; a 1% shock (100 basis points) to the CDS variable, while keeping the orthogonalization structure by adjusting accordingly both, the shock response and the variance as appropriate to compare different VAR(p) IRFs (i.e. Bloom (2009)).

From the results it is straightforward to see the following: there exist two countries which respond negatively to the initial shock to CDS; Germany and Chile. For the sample that ranges from January 2010 to June 2012 Germany shows a negative, although not significant IRF for the first 16 weeks following the shock. This holds if we drop from the sample year 2010 (sample (b)). For the sample that ranges from January 2010 to September 2011, just before the LTRO operations, we can actually see that for the two week horizon Germany exhibits a negative one to one response of bond yields to a 1% shock in its CDS. In the case of Chile we see that the post-2010 and post 2011 samples feature significant, negative and reverting-towards-zero responses to a 1% positive shock in the CDS. For the sample that ranges from January 2010 to September 2011 we observe that the response is also negative but the confidence interval gets wider. All in all, the response of Chilean nominal bond yields tell us that when the Chilean CDS rises so do bond prices dragging down temporarily its yields.

Figure 2: IRF function, response of bond yields to shock in CDS in Germany



The rest of the countries have different dynamics. First, Japan bond yields in figure (4) exhibit no response to its own CDS shocks. France has a similar behavior to a lesser extent, as sample (c) tells us of a negative response that disappears within 4 weeks. Italy, Portugal and Spain have positive, long lasting responses to a 1% shock in CDS. For Spain figure(5) shows we can see that the response of Spanish nominal bond yields to the CDS shock is positive, significant and in the 0.5-0.6 % neighborhood. Although including the LTRO period (going from sample (c) to sample

Figure 3: IRF function, response of bond yields to shock in CDS in Chile

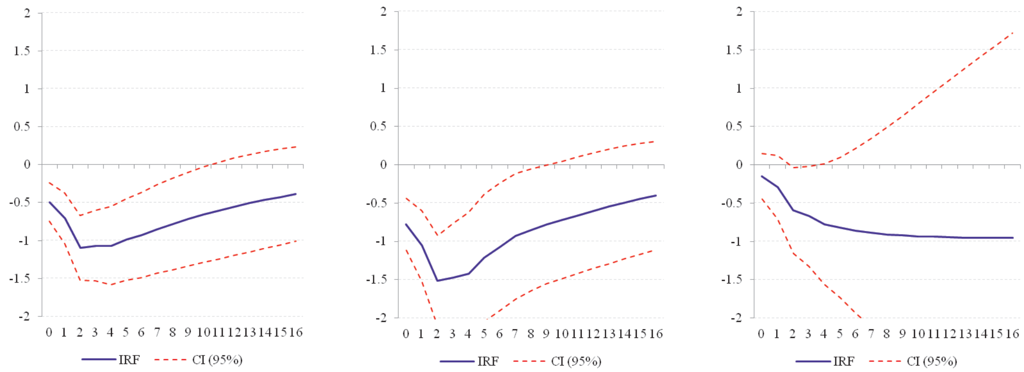
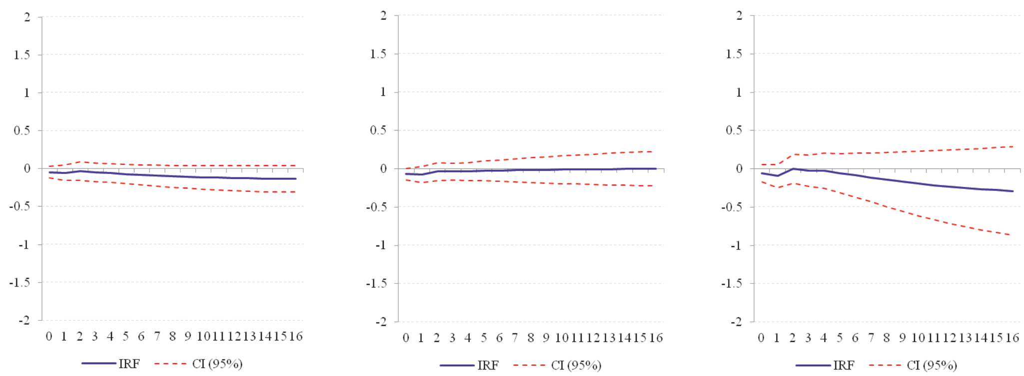


Figure 4: IRF function, response of bond yields to shock in CDS in Japan



(b)) shows that the response is not significant after 5 weeks (as opposed to 9), still, the point estimate is quite similar between these two samples. Also, figure (6) shows that Portugal shows a one to one pass-through from the initial shock to CDS to its bond yields. Finally, Italian bond yields show very similar responses to the CDS shock as Spain does; positive and long-lasting.

Thus on one hand we have countries like Germany and Chile which exhibit a negative and temporary response, or Japan which exhibits no response whatsoever to such a shock. On the other hand we have countries like Spain, Italy and Portugal which show positive and sometimes temporary, and sometimes long lasting responses to the same CDS shock. Pushing the argument to the extreme we could separate countries as safe-havens and the rest. A safe-haven would be a country whose sovereign debt perceived–probability of default is such that, in events of extreme uncertainty, is relatively low enough compared to other economies', resulting on increased demand of sovereign instruments. For instance, even if Germany's CDS rises, still, it is this

Figure 5: IRF function, response of bond yields to shock in CDS in Spain

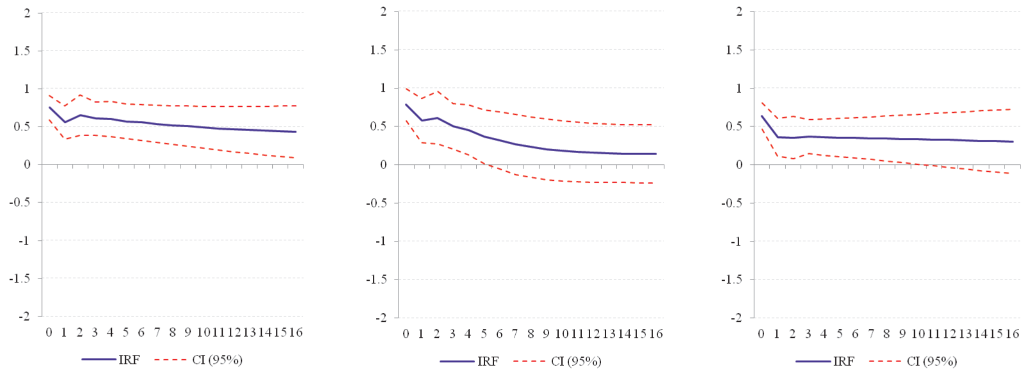


Figure 6: IRF function, response of bond yields to shock in CDS in Portugal

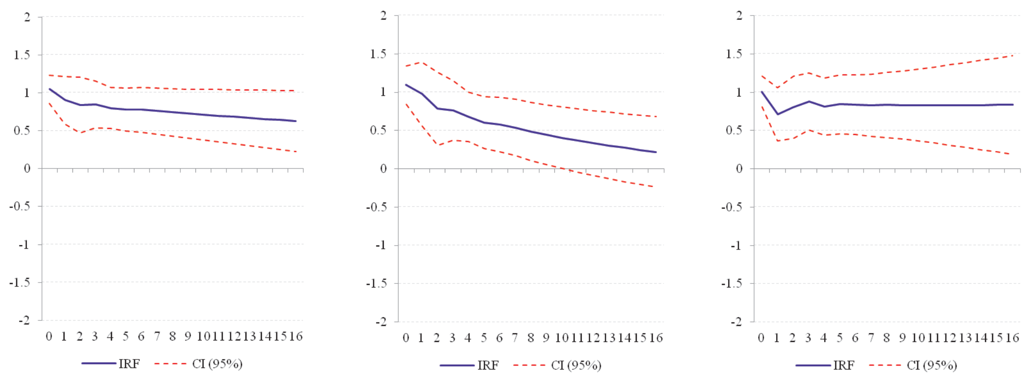
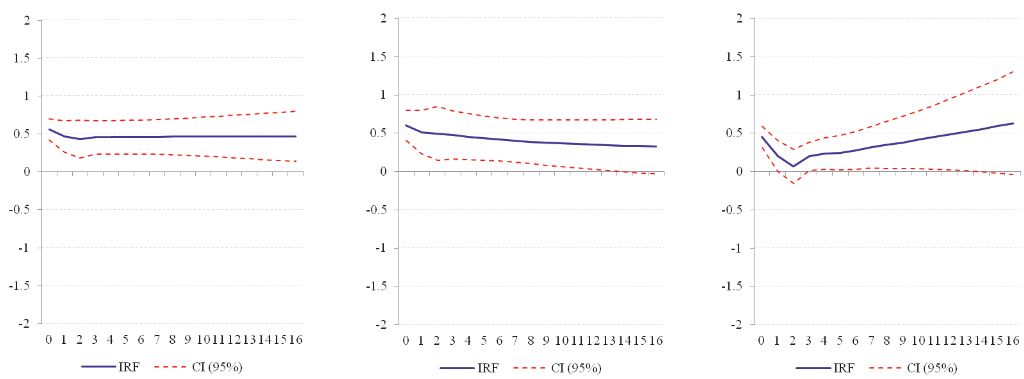
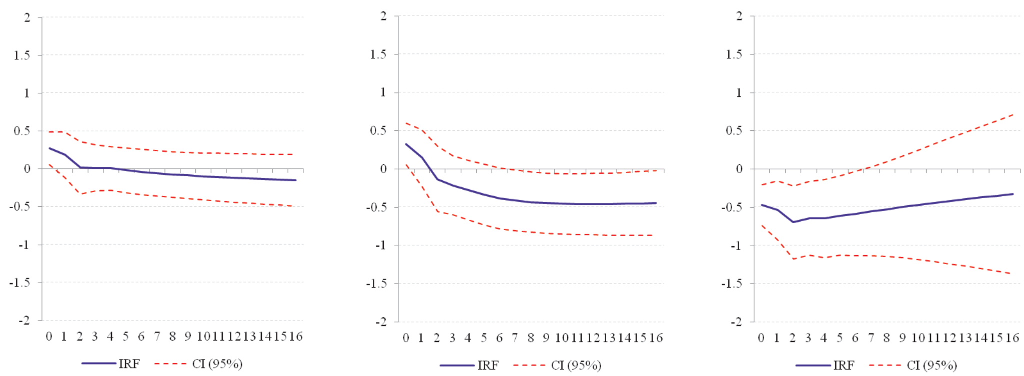


Figure 7: IRF function, response of bond yields to shock in CDS in Italy



country's instruments which are bought in replacement of other countries' sovereign

Figure 8: IRF function, response of bond yields to shock in CDS in France



debt [6]. The same argument applies between countries in the two different groups we identified earlier.

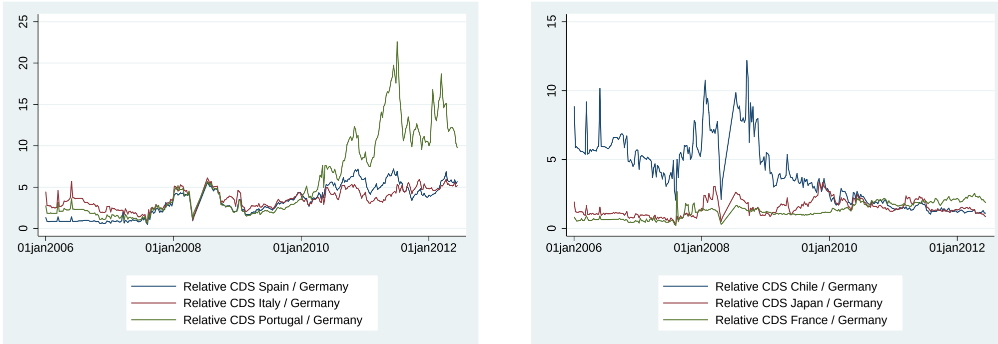
This should come as no surprise if one looked at figure (9) in which we can see that in relative terms the German CDS has actually fallen if compared to Portugal, Spain and Italy. On panel (b) of the same figure we can see that Chile, Japan and to a lesser extent France, do not show the same pattern as the former countries, thus in a way are also countries which enjoy a good sovereign default probability perception. In particular for Chile, it is the case that fixed income debt is remarkably more profitable than in developed economies, vis-a-vis lower default risk perception. This two facts nicely fit to account for figure (3)

3.2 Contagion Index

This section describes the spillover index proposed by Diebold and Yilmaz (2009) and Diebold and Yilmaz (2010). The general idea is quite simple. We need to estimate a VAR(p) which stacks CDS spreads for the seven economies under analysis and look at

[6]It is useful to examine how CDS spreads and bond yields for Germany relate. In order to do this we need to make an adjustment to the bond yield of the instrument as it comes expressed in Euros rather than in US dollars. Let us take five year maturity bond yields in Euros, transform them into floating rates in the same denomination, use a currency swap to transform it into a floating rate in US dollar and then take the floating rate into a fixed rate for the same original maturity. The instruments correspond to the following Bloomberg tickers: EUSW5V3, EUBS5 and USSQA5. The mechanics of this adjustment are nicely explained in Álvarez and Opazo (2009). In figure (17) in appendix A, panel (a) shows this adjusted rate vis a vis the 5-year maturity Treasury rate. Panel (b) shows the risk premia, measured as German bond yields minus the Treasury rate, along with the CDS spread. The negative correlation is apparent, which together with assuming that the supply for CDS contracts is sort of inelastic, *hints* to a demand-led escalation of CDS spreads together with rising demand for risk-free assets (flight to quality), reinforcing the results of the IRF analysis in which I make the case of German bonds as a form of safe-haven asset.

Figure 9: Relative CDS to Germany's CDS



the forecast error variance decomposition (FEVD) of this VAR for each economy and how much of it can be attributed to different countries. The intuition is straightforward, the larger the part of the error in predicting variable x that can be accounted for by *other* errors, then the larger the contagion.

Alternatively we could proceed with two exercises. First we could simply use rolling window correlations, which are equivalent to estimating univariate regressions between pairs of countries. This approach is more likely to be flawed than not. First, by not including anything else but the current CDS of the benchmark country, we abstract from the dynamics of the series and potentially generate spurious correlations. Imagine for instance two processes which are trend-stationary. Clearly, their correlation would be very high, but they could be not related at all. Second, if there is a third variable whose current value influences the CDS of both economies, then this univariate approach suffers from omitted variable bias. The VAR approach is known to circumvent these problems quite efficiently by including the dynamics of each series. Second, we could use a Markov Switching approach with two states for the state variable s_t: $s_t = 1$ in presence of contagion and $s_t = 0$ in absence of contagion, in the spirit of Edwards and Susmel (2001). The advantage of using the Diebold-Yilmaz approach over the latter hinges on not relying on in-sample fit, but on forecasts, and having a continuous index instead of a discrete one.

As mentioned, the notion of the spillover index follows from the forecast error variance decomposition of a VAR system. For simplicity of exposition, let me sketch Diebold and Yilmaz's example. Consider the simple first order two-variable VAR,

$$\mathbf{x}_t = \Phi \mathbf{x}_{t-1} + \varepsilon_t \tag{2}$$

where $\mathbf{x}_t = (x_{1,t}, x_{2,t})'$ and Φ is a 2×2 parameter matrix. Then covariance stationarity implies that we can express it in the Wiener-Kolmogorov representation,

$$\mathbf{x}_t = \Theta(L)\varepsilon_t$$

where $\Theta(L) = (I - \Phi L)^{-1}$. Equation (2) can also be written as,

$$\mathbf{x}_t = \mathbf{A}(L)\mathbf{x}_{t-1} + \mathbf{u}_t \tag{3}$$

with $\mathbf{A}(L) = \Theta(L)\mathbf{Q}_t^{-1}, \mathbf{u}_t = \mathbf{Q}_t\varepsilon_t, E(\mathbf{u}_t\mathbf{u}_t') = I$ and $\mathbf{Q}_t^{-1}$ is the unique lower triangular Cholesky factor of the covariance matrix of ε_t. Then the one-step ahead error is

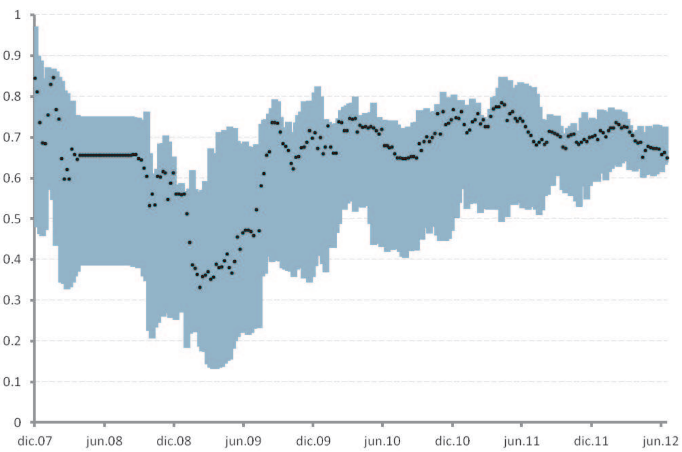
$$\mathbf{e}_{t+1,t} = \mathbf{x}_{t+1} - E(\mathbf{x}_{t+1}|\mathbf{x}_t \dots \mathbf{x}_1) = \mathbf{A}_0\mathbf{u}_{t+1} = \begin{bmatrix} \alpha_{0,11} & \alpha_{0,12} \\ \alpha_{0,21} & \alpha_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix}$$

which has covariance matrix $E(\mathbf{e}_{t+1,t}\mathbf{e}_{t+1,t}') = \mathbf{A}_0\mathbf{A}_0'$, since $E(\mathbf{u}_t\mathbf{u}_t') = I_k$, with $k = \#$ of countries. If we were considering a one-step-ahead error in forecasting $\mathbf{x}_{1,t}$, its variance would be $\alpha_{0,11}^2 + \alpha_{0,12}^2$. Then we can decompose variances in parts attributable to the various system shocks. We can readily see which part of the FEVD is due to shocks in x_1 and which part is due to shocks in x_2. In this example we have two possible spillovers, one from x_1 to x_2 and the other from x_2 to x_1. For instance, in the case of the former, the relative contribution to the FEVD is $\widehat{\alpha}_{0,12}^2 = [\alpha_{0,12}^2/(\alpha_{0,11}^2 + \alpha_{0,12}^2)]$ with (conveniently) $\widehat{\alpha}_{0,12}^2 \in [0,1]$.

A key issue for this exercise to work appropriately, is the identification of the VAR. It is known that identifying assumptions are made implicitly in the ordering we impose in the Cholesky decomposition. We could impose "structural" restrictions on the very estimation of the VAR system, restricting some parameters in matrix Φ or we could go for the Pesaran and Shin (1998) alternative who develop variance decompositions which are invariant to the ordering. Instead, for the sake of robustness of the results I follow Diebold and Yilmaz (2009) approach with a little twist. These authors propose to calculate the entire set of spillovers corresponding to all $N!$ variance decompositions associated with the set of all possible VAR orderings. This is not a very hard task if N is not too large (they work with $N = 4$). In my case $N = 7$, so $N!$ begins to escalate. However we know from the analysis in section 3.1 that we can classify countries in two categories. Let me split N in two categories, $N_1 = 3$ countries (Germany, Japan and Chile) and the rest in N_2 (Spain, Portugal, Italy and France). Since the null hypothesis is that the second group generates a spillover on the first, then the ordering in the Cholesky decomposition always stacks Group 1 countries above Group 2 countries, resulting in $N_1! \times N_2! < N!$. Also, I let the VIX index be included to control for "risk aversion", and place it as the least or most exogenous variable when extracting the Cholesky orthogonalization. In the results, I report the median, minimum and maximum that stem from all these orderings for 100 week rolling windows, thus the shaded area in figures (10) to (15) is the distance between the minimum and maximum from the $N!$ Cholesky orderings.

3.2.1 Spillovers for Levels

Figure 10: Diebold-Yilmaz Contagion Index for Germany



The literature has concentrated on spillovers on returns of the stock market. Modeling returns rather than levels is only natural, as most stock indices are expressed in numbers which possess no meaning by themselves. In this paper this is not the case. In fact CDS have an interpretation. Thus I work with levels instead of returns, using the Friday-closing price to go from daily to weekly data, just like in the analysis in section 3.1. Surprisingly, the results with rates of return are very similar and not presented here for the sake of brevity. Results are shown in figure (10) for Germany, (11) for Chile and (12) for Japan. As my sample starts on January 02, 2006 and ends on June 22, 2012, I can afford to estimate 100 week long VARs in rolling windows. Thus, the first available estimation is for Novermber 26, 2007.

In the figures I plot $\widehat{\alpha}_{0,ij}$ for $j \neq i$. That is, the contribution $\in [0,1]$ to total FEVD in 8 step ahead forecast. We can readily see that contagion is something that we may have to rule out for the European-debt crisis. Even when CDS spreads for Germany, Japan and Chile rose in the last months of the sample to record levels it is hardly the case to assume that spikes in CDS in troubled countries contaminate innovations in non-troubled countries. More importantly, if anything, spillovers are diminishing and the largest upwards movement happened in the aftermath of the great financial crisis and recession of 2008, in particular in the second half of 2009. In the first half of year

Figure 11: Diebold-Yilmaz Contagion Index for Chile

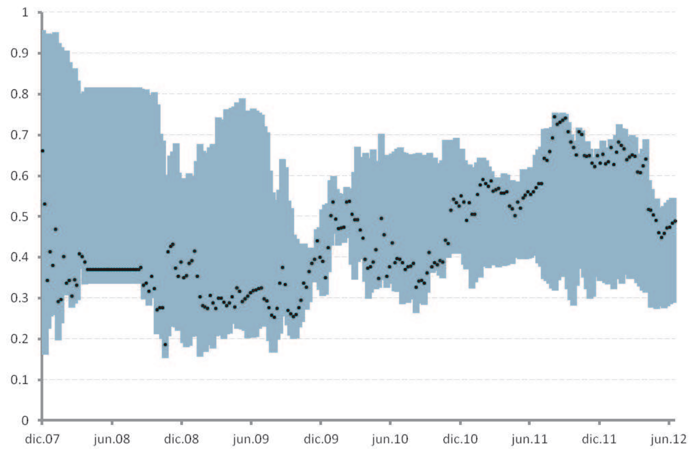
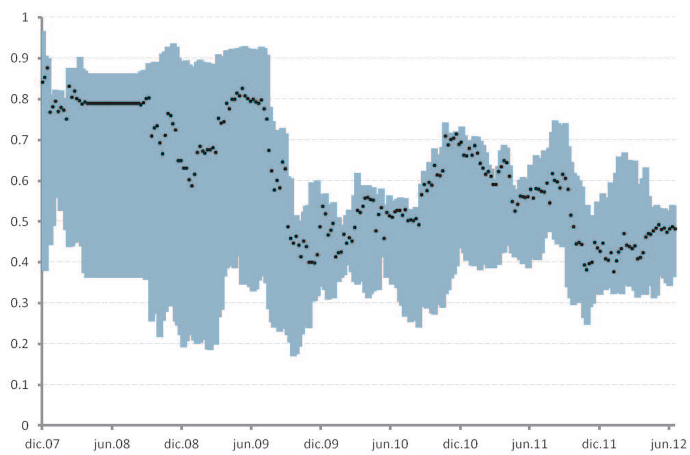


Figure 12: Diebold-Yilmaz Contagion Index for Japan



2012 for Germany, the median of the Diebold-Yilmaz Contagion index goes from 0.75 to 0.65, reducing in 10% the share of forecast error variance that can be attributed to different countries' innovations. Similarly for Chile and Japan, the index declines from 0.67 to 0.51 and from 0.62 to 0.49 respectively, suggesting decoupling instead of contagion.

3.2.2 Spillovers on Volatilities

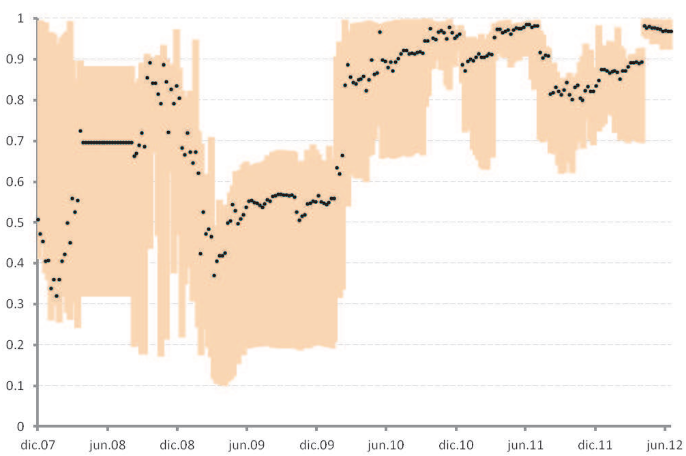
Calculating volatility is a tricky business if we want to work with rolling windows. Since we work with weekly data but we have available daily data for any given week we can rely on Garman and Klass (1980) measure of intra-week volatility.

$$
\begin{aligned}
\sigma^2_{it} &= 0.511(H_{it} - L_{it})^2 - 0.383(C_{it} - O_{it})^2 \\
&\quad -0.019\left[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) - 2(H_{it} - O_{it})(L_{it} - O_{it})\right]
\end{aligned} \tag{4}
$$

where

- $H_{i,t}$ is the highest value attained in the underlying index for country i in week t.
- $L_{i,t}$ is the lowest value attained in the underlying index for country i in week t.
- $C_{i,t}$ is the closing value attained in the underlying index for country i in week t.
- $O_{i,t}$ is the opening value attained in the underlying index for country i in week t.

Figure 13: Diebold-Yilmaz Contagion Index for Germany (volatility)



In order to get an idea of what this volatility looks like consider figure (19) in Appendix A. Again we plot the 100 week rolling window estimation results. The black points are the median of the contribution to total FEVD of country i from other countries ($j \neq i$). The estimations for Germany, Japan and Chile are very similar with a decline around December 2008, followed by a sudden increase in contagion in the end of 2009. This level of contribution to FEVD from other countries remains in high levels from there on, and in fact, climb to record levels in the last month for all three countries. This tells us that even though levels of CDS in troubled economies have not contaminated levels of not-troubled countries, their volatility has.

Figure 14: Diebold-Yilmaz Contagion Index for Chile (volatility)

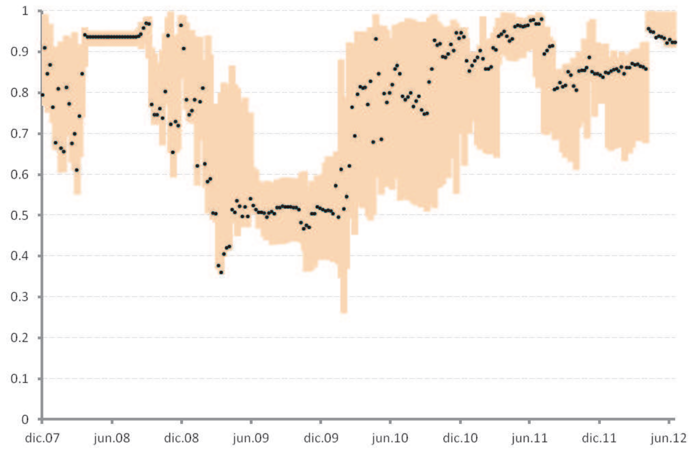
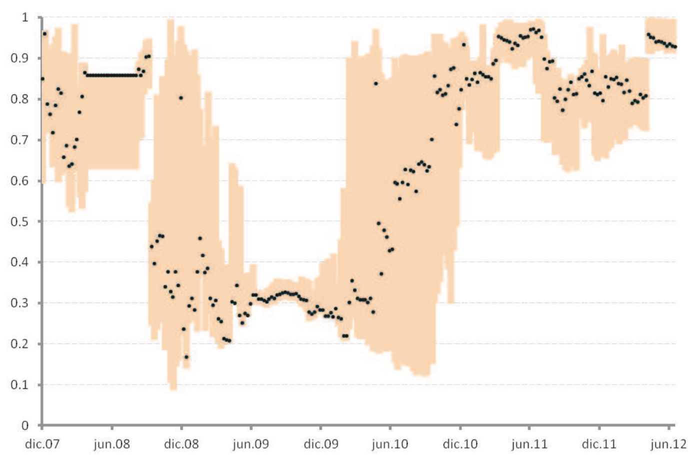


Figure 15: Diebold-Yilmaz Contagion Index for Japan (volatility)



4 Conclusions

In this paper I have examined two dimensions of the Credit Default Swap Market for Sovereign Debt, and thus extend the literature in two dimensions as well. First, this paper examines the relation between credit spread in sovereign debt vis a vis the CDS spreads. Unlike the previous literature which tests this arbitrage assuming instantaneous arbitrage, I examine a 16 week horizon by looking instead at the impulse response functions of bond yields to shocks in the CDS market. I do this for seven economies, four of which are European and are in the midst of the European debt crisis. We can conclude that there exist two groups of countries. The first one is composed by countries in which CDS spreads do affect bond yields positively; that is there exists pass-through from the swap market to credit spreads. The second group of countries is composed of countries which we call “safe-havens”, whose main feature is that their bond yields do not react, or do so negatively and temporarily to shocks in CDS spreads. The countries which we find to share these dynamics are Germany, Chile and Japan. On a second dimension, this paper extents the literature by addressing straightforwardly the contagion argument. I use the Diebold-Yilmaz (2009) spillover index to assess CDS level and volatility. Using rolling windows it is possible to estimate this index on a weekly basis for both moments. I conclude that there is no evidence of (extra) contagion during the second quarter of 2012 or the first for that matter, when it comes to levels or return rates of CDS spreads. However we could make an argument that CDS volatility from troubled countries has had a contagion on volatility of CDS on sovereign debt of non-troubled economies.

Acknowledgements

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A Tables and Figures

Table 3: Pairwise correlation for CDS levels 2006-2009

	GER	CHL	JPN	SPN	ITA	FRA	POR
GER	1.00						
CHL	0.91	1.00					
JPN	0.91	0.82	1.00				
SPN	0.93	0.90	0.93	1.00			
ITA	0.95	0.94	0.90	0.98	1.00		
FRA	0.99	0.95	0.91	0.95	0.97	1.00	
POR	0.94	0.93	0.91	0.99	0.98	0.97	1

Note: All pair-wise correlations are significant to the 1% level, using the Bonferroni-adjusted significance level

Table 4: Pairwise correlation for CDS levels 2010

	GER	CHL	JPN	SPN	ITA	FRA	POR
GER	1.00						
CHL	0.50	1.00					
JPN	0.38	0.70	1.00				
SPN	0.74	0.37		1.00			
ITA	0.69	0.35		0.92	1.00		
FRA	0.81	0.47		0.95	0.89	1.00	
POR	0.65	0.22		0.93	0.88	0.88	1.00

Note: All pair-wise correlations are significant to the 1% level, using the Bonferroni-adjusted significance level

Table 5: Pairwise correlation for CDS levels 2011

	GER	**CHL**	**JPN**	**SPN**	**ITA**	**FRA**	**POR**
GER	1						
CHL	0.957	1					
JPN	0.881	0.891	1				
SPN	0.891	0.839	0.724	1			
ITA	0.958	0.919	0.846	0.95	1		
FRA	0.974	0.933	0.854	0.934	0.983	1	
POR	0.786	0.757	0.785	0.849	0.873	0.82	1

Note: All pair-wise correlations are significant to the 1% level, using the Bonferroni-adjusted significance level

Table 6: Pairwise correlation for CDS levels 2012

	GER	**CHL**	**JPN**	**SPN**	**ITA**	**FRA**	**POR**
GER	1.00						
CHL	0.90	1.00					
JPN	0.38	0.52	1.00				
SPN	0.46		-0.57	1.00			
ITA	0.90	0.82		0.74	1.00		
FRA	0.84	0.68		0.64	0.89	1.00	
POR			0.38	-0.40		-0.35	1.00

Note: All pair-wise correlations are significant to the 1% level, using the Bonferroni-adjusted significance level

Table 7: VAR(3) for Germany. No exogenous variable included

	Sample (1)		Sample (2)		Sample (3)	
	CDS	Yield	CDS	Yield	CDS	Yield
Constant	0.071*	0.039	0.245*	0.086	0.023	0.037
	[0.07]	[0.49]	[0.00]	[0.62]	[0.53]	[0.57]
CDS $(t-1)$	0.872*	0.203	0.731*	0.408*	0.986*	0.416
	[0.01]	[0.28]	[0.00]	[0.09]	[0.01]	[0.14]
CDS $(t-2)$	0.076	-0.215	0.097	-0.269	0.265	-0.971*
	[0.54]	[0.39]	[0.52]	[0.38]	[0.13]	[0.03]
CDS $(t-3)$	-0.007	-0.031	-0.032	-0.069	-0.223	0.538
	[0.94]	[0.87]	[0.78]	[0.77]	[0.1]	[0.11]
Yield $(t-1)$	-0.045	0.957*	-0.098*	0.944*	0.024	1.033*
	[0.31]	[0.01]	[0.08]	[0.00]	[0.6]	[0.01]
Yield $(t-2)$	0.017	0.105	0.021	0.216	0.032	-0.085
	[0.78]	[0.4]	[0.78]	[0.17]	[0.62]	[0.61]
Yield $(t-3)$	0.01	-0.09	0.016	-0.148	-0.069	0.022
	[0.82]	[0.33]	[0.79]	[0.23]	[0.13]	[0.85]
RMSE	0.062	0.126	0.069	0.141	0.069	0.141
R^2	0.941	0.963	0.922	0.968	0.922	0.968
Num. Of Obs	128	128	76	76	91	91

Note: $p-$ values in brackets. * stands for 1% significance level

Table 8: VAR(3) for Spain. No exogenous variable included

	Sample (1)		Sample (2)		Sample (3)	
	CDS	Yield	CDS	Yield	CDS	Yield
Constant	0.146	0.132*	0.187	0.349*	0.095	0.135
	[0.27]	[0.05]	[0.59]	[0.05]	[0.48]	[0.13]
CDS $(t-1)$	0.652*	-0.068	0.741*	-0.013	0.545*	-0.257*
	[0.00]	[0.60]	[0.00]	[0.94]	[0.00]	[0.06]
CDS $(t-2)$	0.229	0.069	0.141	-0.057	0.408*	0.196
	[0.13]	[0.67]	[0.49]	[0.8]	[0.02]	[0.25]
CDS $(t-3)$	0.147	0.058	0.149	0.107	0.01	0.077
	[0.25]	[0.67]	[0.37]	[0.55]	[0.95]	[0.59]
Yield $(t-1)$	0.065	0.83*	0.018	0.754*	0.128	0.967*
	[0.58]	[0.00]	[0.91]	[0.00]	[0.39]	[0.00]
Yield $(t-2)$	-0.059	0.225	-0.063	0.313	-0.21	-0.039
	[0.7]	[0.17]	[0.75]	[0.14]	[0.3]	[0.84]
Yield $(t-3)$	-0.048	-0.158	-0.01	-0.254	0.092	0.019
	[0.69]	[0.22]	[0.95]	[0.13]	[0.55]	[0.90]
RMSE	0.262	0.25	0.319	0.345	0.262	0.249
R^2	0.897	0.91	0.906	0.662	0.8965	0.909
Num. Of Obs	128	128	76	76	91	91

Note: $p-$ values in brackets. * stands for 1% significance level

Figure 16: CDS by country (daily data) in basis points

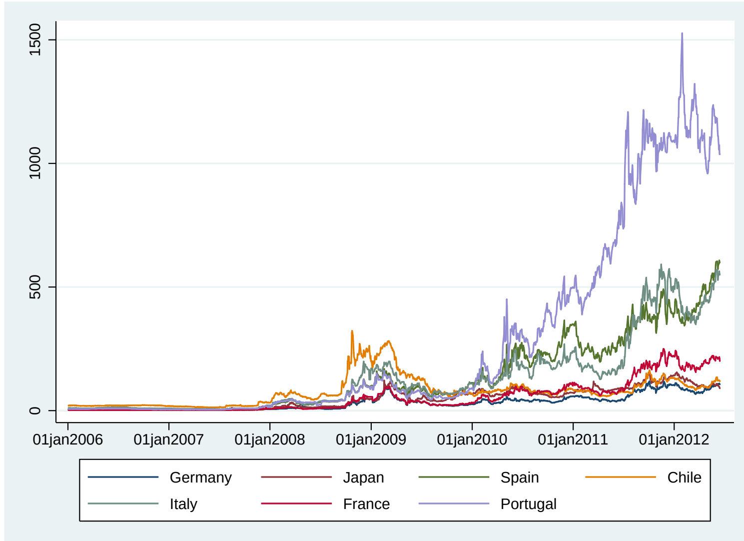


Figure 17:

(a) Germany and USA yields (both in USD)

(b) Risk Premia for Germany vs. CDS

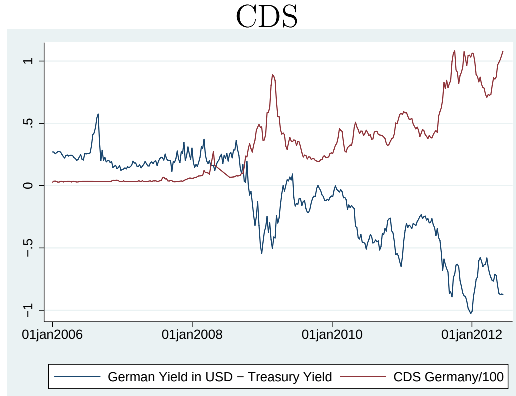
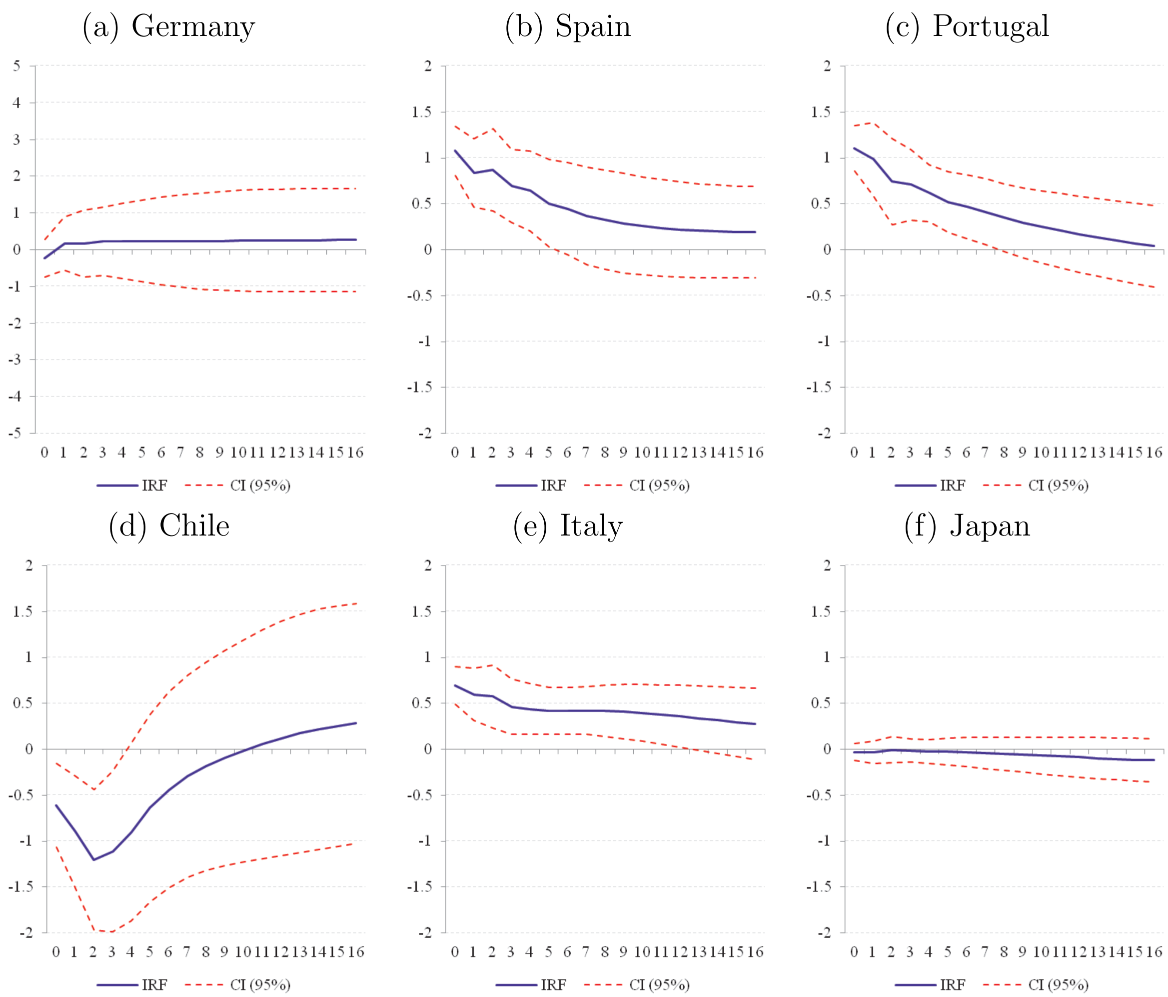


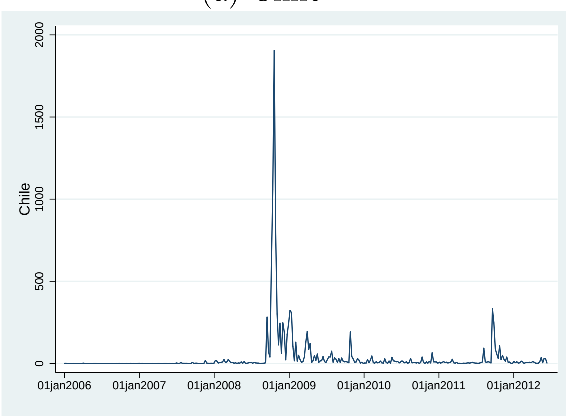
Figure 18: Impulse Response Functions including VIX



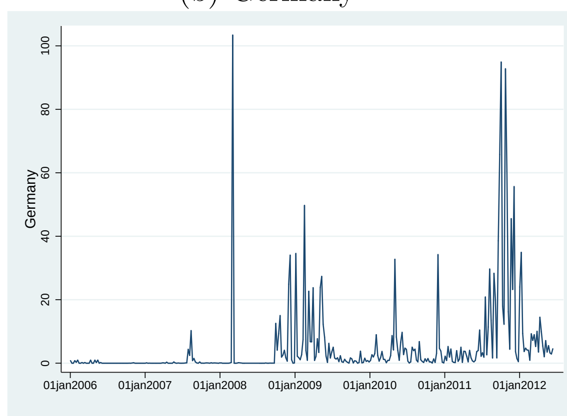
Source: Own computations

Figure 19: Garman and Klass (1980) measure of intra-week volatility

(a) Chile



(b) Germany



Note: Note that this is the raw index of volatility and consequently the vertical axes show different magnitudes.