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Massimiliano Caporin
Loriana Pelizzon
Francesco Ravazzolo
Roberto Rigobon

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ABSTRACT

This paper analyzes the sovereign risk contagion using credit default swaps (CDS) and bond premiums for the major eurozone countries. By emphasizing several econometric approaches (nonlinear regression, quantile regression and Bayesian quantile regression with heteroskedasticity) we show that propagation of shocks in Europe's CDS has been remarkably constant for the period 2008-2011 even though a significant part of the sample periphery countries have been extremely affected by their sovereign debt and fiscal situations. Thus, the integration among the different eurozone countries is stable, and the risk spillover among these countries is not affected by the size of the shock, implying that so far contagion has remained subdue. Results for the CDS sample are confirmed by examining bond spreads. However, the analysis of bond data shows that there is a change in the intensity of the propagation of shocks in the 2003-2006 pre-crisis period and the 2008-2011 post-Lehman one, but the coefficients actually go down, not up! All the increases in correlation we have witnessed over the last years come from larger shocks and the heteroskedasticity in the data, not from similar shocks propagated with higher intensity across Europe. This is the fi˝rst paper, to our knowledge, where a Bayesian quantile regression approach is used to measure contagion. This methodology is particularly well-suited to deal with nonlinear and unstable transmission mechanisms.

Massimiliano Caporin
Department of Economics and Management
Via del Santo 33
Padova, Italy
massimiliano.caporin@unipd.it

Loriana Pelizzon
University of Venice
Department of Economics
Cannareggio 873
Venice, 30100 ITALY
pelizzon@unive.it

Francesco Ravazzolo
Norges Bank
Francesco.ravazzolo@norges-bank.no

Roberto Rigobon
MIT Sloan School of Management
100 Main Street, E62-516
Cambridge, MA 02142
and NBER
rigobon@mit.edu

1 Introduction

The sovereign debt crisis in Europe that began in late 2009 has reignited the literature on contagion. How much contagion to countries in the European Monetary Union could be expected as a result of a possible credit event in Greece, Italy or Spain?

How much are France and Germany going to be affected? How about countries outside the European Union? Through which channel is the shock going to be transmitted? Clearly these are some of the important questions for economists, policymakers, and practitioners. However, addressing these questions requires surmounting some extraordinary empirical challenges.[1]

The first challenge is definitional. What exactly is contagion? Is it the "normal" or "usual" propagation of shocks, or is it the transmission of shocks that takes place under unusual circumstances?[2]

Some literature tends to define contagion as the co-movement that takes place under extreme conditions — or tail events[3]— while another sizeable proportion of the literature compares how shocks propagate differently during normal and rare events. The first definition concentrates on measuring the transmission after a bad shock occurs, while the second definition investigates how different the propagation mechanism is after a negative shock appears. It is impossible to solve this definitional problem in this paper; rather our objective is to present convincing evidence of the amount of contagion that takes place according to the second definition. In other words, we are interested in understanding how much potential contagion exists within the European sovereign debt market, where contagion is defined as how different the propagation is after a large negative realization has taken place compared to the propagation after an average realization.

The second challenge is an empirical one. Contagion is an unobservable shock and there-

[1]Rigobon (2001).

[2]See Forbes and Rigobon (2002), as well as Dungey and Zhumabekova (2001).

[3]As it has been defined by the copula approach to measure contagion (Rodriguez, 2007)

fore most empirical techniques have problems dealing with omitted variables and simultaneous equations. The problem is even more complicated because the data suffers from heteroskedasticity — which implies that if the conditional volatility moves in the sample it might result in econometric biases. In other words, if the correlation between two variables is different in normal and in crisis times, how can we be sure that this difference is due to the outcome of a shift in the propagation mechanism and not the result of the fact that correlations are not neutral to shifts in volatility? Crisis periods are usually associated with higher volatility and simple correlations are unable to deal with this problem.[4] Moreover, if a linear regression has been estimated across different regimes, how can the researcher be sure that the coefficients are different because the underlying parameters are shifting, as opposed to the fact that the omitted variables and simultaneous equation biases are not neutral to changes in the volatility?

Finally, the third challenge is that the channel of contagion is rarely understood before the crisis occurs. For example, very few would have ever predicted that the transmission channel of the 1998 Russian crisis was going to be Long Term Capital Management. Furthermore, even though several economists anticipated the 2008 U.S. crisis, none could foretell that the transmission would be from the subprime mortgage market to insurance companies, to AIG, and then to the rest of the world. The economics profession is extremely good at describing the channels through which shocks are transmitted internationally immediately after the contagion has taken place. This puts a significant constraint on structural estimations of contagion the problem being that the channel has to be specified ex-ante. Reduced-form estimations, on the other hand, have the advantage that they are channel-free and therefore might capture the presence of contagion that was not fully accounted for prior to the shock's occurrence.

In this paper we first evaluate the extent of contagion in the eurozone credit default swaps (CDS) by using a reduced-form approach based on quantile regressions. The main advantage of using the quantile regressions is that this is a very natural and powerful way to deal with possible

[4] See Forbes and Rigobon (2002).

nonlinearities or parameter instability in the data. By conditioning on the size of the shocks and evaluating the propagation mechanisms via the reduce-form model-based coefficients linking the dependent variable and the explanatory ones, this methodology allows us to understand and to estimate the extent of asymmetries — such as the transmission of positive and negative shocks. Since, we define contagion as a shift in the intensity of propagation when large shocks occur compared to normal times, we compare the coefficient of the propagation of shocks between two countries when the country of interest shows values that belong to the highest quantiles during turbulent times and the middle ones during normal times. When the coefficients are stable over quantiles we reject the contagion hypothesis.

Indeed this is the result we find: for every pair of countries in our data, at the extreme quantile the coefficient for the propagation of shocks between two countries is not statistically different from the coefficient for the propagation of shocks that exists in the median quantile. Potential econometric problems such as omitted variables and endogeneity biases are not significant enough to reject the hypothesis. Again, our analysis shows no evidence of contagion and we do not observe a shift in the propagation of shocks when a given country goes through a turbulent period. For the period from November 2008 to September 2011 we examine sovereign CDS for seven European countries on the Euro area: France, Germany, Greece, Ireland, Italy, Portugal, Spain, plus a European country that is not in the European Monetary Union: the United Kingdom.

The biggest drawback of using the CDS data is that it starts in November 2008 – well into the U.S. financial crisis. Then, the comparison we perform is between two different periods when the Lehman meltdown began in September 2008 a time during which European sovereign CDS did not show any increased default risk and the European fiscal crisis which began on late 2009 when CDS, on the contrary, fluctuated substantially, as shown in Figure 1. The advantage of the CDS data is that it captures the sovereign risk and therefore yields a very clean exercise.

To deal with the weaknesses in the data we also measure the extent of contagion in bond spreads, for which we have data beginning in 2003. When we perform the exact same exercise that we did for the CDS but use the bond spread, we find two main results. One, there is a change in the intensity of the shock propagation in the pre-crisis period (2003–2006) and the post-crisis one (2008–2011). However, the coefficients actually go down, not up! This is encouraging as it that the methodology is powerful enough to reject certain samples. Second, the propagation between 2008–2011 is stable and, quite surprisingly, the coefficients are very similar between bonds and CDS. Third, we observe a reduction in the propagation of the shocks between the 2003–2006 pre-crisis period and the 2008–2011 post-crisis one rather than an increase.

All our results offer a consistent message: the propagation of shocks in Europe's CDS and bond spreads has been remarkably constant across quantiles between 2008 and 2011 even though for a significant part of that sample periphery countries have been affected by their sovereign debt and fiscal situations. All the increases in correlation we have witnessed the last two years are coming from larger shocks, not from similar shocks propagated with higher intensity (contagion) across Europe. Finally, we find that the bond market provides the only evidence of parameter instability, and this result actually points to a weakening of the contagion channel between the 2003–2006 period and the period after 2008.

We start by measuring over time the correlations for country-pairs and show that these shift substantially. In this particular case the Forbes and Rigobon (2002) correction cannot be used because that procedure requires knowing which country or variable caused the increase in volatility. This is impossible for several of our pairs.[5] The next step is to directly test for nonlinearity by using a polynomial specification within a time-series regression framework. We estimate this by allowing for second- and third-order terms and test for the significance of nonlinearity. In our regressions we find a large number of significant coefficients (73%), but when we evaluate their economic impact we find that the nonlinearity is small. The problem

[5] In addition, as indicated by Rigobon (2003) the adjustment in Forbes and Rigobon (2002) requires that the variables not suffer from omitted variables or endogeneity bias.

with these regressions is that they impose too much structure and might be underestimating the transmission of extreme events.

Next, we propose quantile regressions as a powerful methodology to measure contagion. We apply a standard quantile regression and show that the transmission of shocks is the same across different quantiles. Although this specification allows for changes in the conditional densities across time, through the impact of covariates, it might suffer from inefficiencies due to time-varying volatility. This leads us to the estimation using quantile regressions, as these allow for heteroscedasticity.

Following Chen, Gerlack, and Wei (2009) and Xiao and Koenker (2009) we assume that the conditional variance of the residuals follows a GARCH(1,1) specification. The model is estimated using Bayesian inference and accounts for parameter uncertainty through simultaneous inference of all model parameters. Moreover, the methodology used is efficient and flexible in handling the nonstandard likelihood and is based on the use of prior information. We choose a weak informative prior to allow the data to dominate inference. Again the results show that sovereign risk is largely a linear phenomenon, i.e. we are not able to find significant evidence of sovereign risk contagion among the European countries for the sample considered. Posterior distributions of the parameters show lower uncertainty than the standard quantile regressions, in particular for extreme quantile.

It is impossible to adequately review the extensive literature on contagion in this paper. We direct the interested reader to the multiple iterative reviews that already exist in the literature. Among others, we cite Pericoli and Sbracia (2003), Dungey et al. (2005), and Pesaran and Pick (2007). We concentrate here on those papers that have measured the degree of co-movement among sovereign CDS. In particular, some recent research on this topic concentrates on the relationship between sovereign credit spreads and common global and financial market factors. For example, see Kamin and von Kleist (1999), Eichengreen and Mody (2000), Mauro, Sussman, and Yafeh (2002), Pan and Singleton (2008),Longstaff *et al.* (2011) and Ang and Longstaff

(2011). This body of works shows that the most significant variables for CDS spreads are the U.S. stock and high-yield market returns as well as the volatility risk premium embedded in the VIX index. Moreover, using a broad panel of bank and sovereign CDS data, Acharya, Drechsler and Schnabl (2011) concentrate on the financial sector bailouts and show that bank and sovereign credit risk are intimately linked. Kallestrup, Lando and Murgoci (2012) also show that cross-border financial linkages affect CDS spreads beyond what can be explained by exposure to common factors. Our paper complements and extends this literature by investigating the degree of co-movement among sovereign CDS (and bond spreads) after controlling for common factors that explain credit spreads, as highlighted by the previous literature.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 presents the different approaches used to investigate the linearity of the relationship across CDS and bond spreads and its stability and the results. Section 4 concludes by discussing the implications of our paper.

2 The Data

A CDS contract obliges the seller to compensate the buyer in the event of a loan default, see the definitions provided in Duffie (1999), Longstaff, Mithal, and Neis (2005), Pan and Singleton (2008), Longstaff, Pan, Pedersen, and Singleton (2011), among others. It is generally a swap agreement because in the event of a default, the buyer of the CDS receives money (usually the face value of the bond) and the seller of the CDS receives the defaulted bond. We obtain five-year sovereign CDS spreads from Datastream. We consider daily data of the euro-denominated CDS for seven eurozone countries: France, Germany, Greece, Ireland, Italy, Portugal and Spain, plus the United Kingdom, acountry which is not in the monetary union. Therefore, our sample considers periphery countries (Greece, Ireland, Portugal and Spain) and the four largest economies in the European Community: France, Germany, Italy and the United

Kingdom. The three year sample covers the period from November 2008 to September 2011. The start of this sample period is dictated by the availability of CDS data for all of the seven countries in the study. Figure 1 reports the evolution of the CDS levels in the sample period considered.

Table 1 provides summary information for the daily sovereign CDS spread.[6] The average values of the CDS range widely across countries. The lowest average is 35.43 basis points for Germany; the highest average is 785 basis points for Greece. The standard deviations as well as the difference between the maximum and the minimum values indicate that spread for sovereign CDS present significant time-series variation. In Figure 2 we reports the dynamic of the changes in the CDS spreads through time. It is important to observe that the magnitude of the changes differs over time indicating that heteroskedasticity is present.

Since we focus on the co-movement in CDS spreads among the different countries in addition to common changes attributable to a set of global common factors, we also consider the variables that the previous literature has identified as the most significant for CDS spreads. We therefore consider the changes in Euribor, the spread between Euribor and EONIA, and the risk appetite calculated as the difference between the VSTOXX (volatility index for the EuroStoxx50) and the volatility of the EuroStoxx50 obtained by a GARCH(1,1) model. Table 1 also provides the summary statistics for these variables as well as the summary statistics of the daily changes in sovereign CDS spreads.

To provide some additional descriptive statistics, Table 2 reports the correlation matrix of daily changes in the five-year CDS spreads. Table 2 shows that while there is clearly significant cross-sectional correlation in spreads, the correlations are far from perfect. Most of the correlations are less than 0.7, and several are less than 0.50. The average correlation across the eight sovereign countries is 0.502.

[6] All the CDS spreads are denominated in basis points.

3 Methodology and Results

3.1 Nonparametric Inference

As a first evaluation of the linearity and stability of the relationship across CDS, we consider the rolling evaluation of the linear correlation. We calculate the correlation among changes in CDS spreads by considering 60 observations, roughly equivalent to one quarter.[7] Figure 3 plots rolling window correlation from January 2009 through September 2011, and overall shows high correlation values between changes in the CDS national indices; these generally range between 0.3 and 0.7. Furthermore, we observe that the correlations across the countries largely change over the sample period. An examination of the last part of the sample shows that the overall correlation among the different countries has been reduced. However, this is not the case for all the countries. As an example we report the correlation of France's CDS compared with all the other countries. As Figure 4 shows, in the last part of the sample the correlation with all the other countries decrease, with the exception of an increase with Italy and Ireland.[8]

To evaluate the possible presence of nonlinearities in the relationship across CDS, we consider the exceedence correlation measures proposed by Longin and Solnik (2001). Given a quantile level q, the exceedence correlations are computed as follows:

$$\rho^{-} = Corr\left[\Delta CDS_{i,t}, \Delta CDS_{j,t} | F_i\left(\Delta CDS_{i,t}\right) < q, F_j\left(\Delta CDS_{j,t}\right) < q\right], \tag{1}$$

$$\rho^{+} = Corr\left[\Delta CDS_{i,t}, \Delta CDS_{j,t} | F_i\left(\Delta CDS_{i,t}\right) > 1-q, F_j\left(\Delta CDS_{j,t}\right) > 1-q\right]. \tag{2}$$

where $\Delta CDS_{i,t}$ indicates changes of CDS ($\Delta CDS_{i,t} = CDS_{i,t} - CDS_{i,t-1}$) and i, j denote any two different countries, while F_i and F_j are the cumulative density functions of the correspond-

[7] We have repeated the same analysis using the delta-log of CDS instead of using the delta of the CDS and the results are qualitatively the same.

[8] The rolling window correlations among the other countries are provided upon request.

ing CDS variations. Therefore, the exceedence correlation ρ^- measures the association across two given CDS changes when both are located in their lower q quantile, while ρ^+ refers to the joint occurrence of positive changes above $1-q$. By construction, the quantile q assume values in the range $(0, 0.5]$. For the purposes of this study, the quantity ρ^+ is more interesting. Figure 5 presents the results for France.[9] We graphically represent the exceedence correlations by reporting in the middle of the panels the full sample standard correlation while on the left and right sides we report ρ^- and ρ^+, respectively. In most cases the exceedence correlation ρ^+ is decreasing as q decreases (note that ρ^+ considers the correlation above the quantile $1-q$), suggesting that large positive CDS changes correspond to lower correlations across countries. This is not the case for the opposite direction: for large negative CDS changes, the correlation across countries tends to increase (in most cases).

Despite being interesting, exceedence correlation measure has a drawback: it is affected by the changes in the marginal density of the variables. Moreover, it suffers from the problem highlighted by Forbes and Rigobon (2002): the ΔCDS volatility might differ during market turbulent periods compared to the volatility that occurs during tranquil market periods, and these changes may bias the correlation measure. This problem clearly emerges when looking at Figure 2, where the volatility tended to increase during 2010. For this reason these exceedence correlation measures cannot be used to investigate the sovereign risk spillover among countries.

Yet, the adjustment proposed in Forbes and Rigobon (2002) cannot be used in this case. The primarily reason is that such an adjustment requires knowing the source of the increase in volatility. For instance, the 1994 Tequila Crisis originated in Mexico and therefore the proposal adjustment can be implemented. During the European sovereign debt crises there are several countries in crisis. This renders the correlation measures uninformative of the degree of co-movement in the data.

[9] The exceedence correlations among the other countries are provided upon request.

3.2 Parametric Inference

To deal with the problem that arises from the heteroskedasticity in the data and the bias it produces in correlation measures, a very rough and simple method is to estimate the relationship using projection methods. In this setting, contagion is reflected as a significant coefficient of nonlinear linkages, like the second- and the third- order terms on top of linear linkages, i.e. testing for nonlinearity.

To investigate the nonlinearity in the projection between the changes in the CDS spreads of any two countries, we first consider the simple linear model and then test the null hypothesis of linearity using a simple diagnostic procedure. More formally, we first estimate a Generalized Auto Regressive Conditional Heteroskedasticity (GARCH)(1,1) baseline model:

$$\Delta CDS_{i,t} = \beta_{ij,0} + \beta_{ij,1}\Delta CDS_{j,t} + \gamma'_{ij}X_{t-1} + \sigma_{ij,t}\varepsilon_{ij,t} \quad (3)$$

$$\varepsilon_{ij,t}|I^{t-1} \sim D\left(0,1\right) \quad (4)$$

$$\sigma^2_{ij,t} = \theta_{ij,0} + \theta_{ij,1}e^2_{ij,t-1} + \theta_{ij,2}\sigma^2_{ij,t-1} \quad (5)$$

where i and j are the two country identifiers, X_{t-1} is a vector of lagged covariates that includes changes in Euribor, the spread between Euribor and EONIA, and the risk appetite calculated as the difference between the VSTOXX and the GARCH(1,1) volatility of the EuroStoxx50 index, $e_{ij,t-1} = \sigma_{ij,t}\varepsilon_{ij,t}$.[10] Moreover, the parameters in the GARCH equation (5) must satisfy the constraints leading to variance positivity and covariance stationarity, namely $\theta_{ij,0} > 0$, $\theta_{ij,1} \geq 0$, $\theta_{ij,2} \geq 0$, and , $\theta_{ij,1} + \theta_{ij,2} \leq 1$. The parameters in equation (3) are estimated by quasi-maximum likelihood with robust standard errors. In the rest of the section, we drop the

[10] We have repeated the same analysis using as covariates the variables adopted by Ang and Longstaff (2011), i.e. the daily returns of the DAX index, the daily change in the five-year constant maturity Euro swap rate, the daily change in the VSTOXX volatility index, the daily change in the European ITraxx Index of CDS spreads, the daily change in the CDS contract for Japan, China, and for the CDX Emerging Market (CDX EM) Index of sovereign CDS spreads. The data for these variables are all obtained from the Bloomberg system. The results, again, are unchanged.

subscript ij for the sake of brevity.

We consider a reduced-form approach since we do not impose a priori a specific transmission channel for shocks. Therefore, our estimated equations always involve the ΔCDS of only two countries. The null hypothesis of linearity is tested by the following extended model:

$$\begin{aligned}
\Delta CDS_{i,t} &= \beta_0 + \beta_1 \Delta CDS_{j,t} + \gamma' X_{t-1} + \sum_{l=2}^{p} \beta_l \left(\Delta CDS_{j,t}\right)^l + \sigma_t \varepsilon_t & (6)\\
\varepsilon_t | I^{t-1} &\sim D\left(0,1\right) & (7)\\
\sigma_t^2 &= \theta_0 + \theta_1 e_{t-1}^2 + \theta_2 \sigma_{t-1}^2 & (8)
\end{aligned}$$

where linearity is associated with the null hypothesis $H_0 : \beta_l = 0 \ \forall l = 2, \ldots p$. Given the presence of the GARCH term, we evaluate the null hypothesis using a likelihood ratio test.

Table 3 shows that the coefficients of the powers in equation 6, if singularly considered, are statistically significant in many cases. Specifically, β_2 and β_3 (i.e. the coefficients of the square and cubic terms) are statistically significant, respectively, in 26 and 40 cases out of 56. Moreover, jointly testing their significance shows evidence of their relevance in 41 out of 56 cases. However, if we compare the impact coming from the linear term to the coefficients associated with the squared and cubed changes used to explain the CDS variation, we note that the coefficients are extremely small. This trait is common across countries and is not associated with a specific dependent country nor on a particular country where the ΔCDS movements originated. More specifically, if we calculate the economic relevance of the coefficients by multiplying them by the square and the cubic value of the median of the absolute ΔCDS for country j reported in Table 1 we see that the economic impact of the nonlinearity is extremely small (as shown in Table 4).

We thus face some evidence of nonlinearity albeit with a limited economic impact. The possible sources of this behavior might be identified in the inappropriateness of the linear specification and the fact that such regressions might be subject to omitted variable or simultaneous equations biases. The biases are a nonlinear function of the conditional volatility and these are in generally mistaken for nonlinearities when not properly corrected. These issues will be dealt with below. Thus far, however, whatever evidence of nonlinearity we find implies a very small effect, and therefore supplies a very limited evidence of contagion.

The weakness of the linear and nonlinear specifications also might mask parameter instability that occurs at the extreme realizations of the distribution. During large market movements, the linkage between the ΔCDS of the selected European countries might not follow a linear relationship. In fact, during flight-to-quality episodes, large movements in cross-country dependence might drop, while during contagion events this dependency would be expected to increase. The flight-to-quality case and the potential changes in the linear relationship might also be seen in the exceedence correlations which in most cases are not stable across quantiles. We thus address the problem from a different technical viewpoint and consider quantile regressions between the ΔCDS of any two countries.

3.3 Quantile Regressions

Quantile regressions offer a systematic strategy for examining how variables influence the location, scale, and shape of the entire response distribution and therefore permit to measure shift in the propagation intensity when large shocks occur. The advantage is that quantile regressions are a particularly efficient way to estimate a linear relationship that varies across quantile and therefore to detect the presence of interdependence asymmetries in the data.

Starting from the linear model in equation (3), our purpose is to verify if the coefficient β_1 is changing across quantiles of the dependent variable $\Delta CDS_{i,t}$.[11] As the parameters might be different over quantiles, the overall model is highly nonlinear. The quantile regression parameters are estimated by solving the following minimization problem:

[11] We stress that the coefficient β_1 in equation (3) represents the link between the dependent variable $\Delta CDS_{i,t}$ and the explanatory $\Delta CDS_{j,t}$ and thus represents the impact on country i of shocks originated in country j

$$min_{\Theta_\tau} \sum_{t=1}^{T} \rho_\tau \left(\Delta CDS_{i,t} - \beta_{ij,0} - \beta_{ij,1} \Delta CDS_{j,t} - \gamma'_{ij} X_{t-1} \right) \tag{9}$$

where $\rho_\tau (a)$ is the *check* function for quantile τ of the dependent variable ΔCDS_i. This function is defined as $\rho_\tau (a) = a \times (\tau - I(a < 0))$. Moreover, we collect all quantile-dependent parameters in the set $\Theta_\tau = \{\beta_{0,\tau}, \beta_{1,\tau}, \gamma'_\tau\}$, where again the subscript i and j are dropped for the sake of brevity.

The minimization of equation (9) leads to the estimation of the τ quantile for $\Delta CDS_{i,t}$. This specific quantile linearly depends on $\Delta CDS_{j,t}$ and X_{t-1}, and is thus conditioned to the evolution of the covariates and of the ΔCDS_j. The conditional quantile is denoted as

$$\Delta \widehat{CDS}_{i,t} (\tau) = \widehat{\beta}_{0,\tau} + \widehat{\beta}_{1,\tau} \Delta CDS_{j,t} + \widehat{\gamma}'_\tau X_{t-1} \tag{10}$$

where $\widehat{\Theta}_\tau = \left\{ \widehat{\beta}_{0,\tau}, \widehat{\beta}_{1,\tau}, \widehat{\gamma_\tau}' \right\}$ are the τ quantile estimates of the model parameters. For details on the quantile regressions see Koenker (2005).

The most relevant coefficient in our analysis is $\hat{\beta}_{1,\tau}$, which represents the coefficient of the propagation of shocks in ΔCDS of country j in the ΔCDS of country i, conditional on other information in X, and at a certain quantile τ of the dependent variable. We explain how contagion can be detected using equation (10). We are interested in understanding how the propagation changes when ΔCDS_i occurs in normal periods compared to what happens during turbulent periods. For simplicity consider just two quantiles $\tau = 0.50$ (ΔCDS_i in normal periods) and $\tau = 0.99$ (ΔCDS_i in turbulent times). Then, we statistically compare $\widehat{\beta}_{1,0.50}$ with $\widehat{\beta}_{1,0.99}$ and detect contagion when $\widehat{\beta}_{1,0.99}$ is significantly larger than $\widehat{\beta}_{1,0.50}$; in this case the intensity of the propagation increases during turbulent periods. The contagion hypothesis is rejected when $\widehat{\beta}_{1,\tau}$ is stable over quantiles.

Compared to the evaluation of the coefficient linking CDS_i and CDS_j in a traditional linear regression framework, quantile regression is more flexible and allows a more precise measure of the risk associated with a given country. For example, the absence of contagion might be present among just two quantiles (for example 0.50 versus 0.99) or for a large range of quantile levels (0.50 versus 0.99 but also 0.95 and 0.90), leading to several different designs of the relationships across countries. This measurament flexibility is worthwhile when there is evidence of different $\widehat{\beta}_{1,\tau}$ among the quantiles. If the $\widehat{\beta}_{1,\tau}$ are not statistically different across quantiles, the quantile regression shows evidence of linearity in the intensity of the propagation mechanism between the two countries. These features make quantile regression a particularly good approach to investigating contagion.

To analyse the link between ΔCDS we estimated the quantile regressions in equation (9) across any two ΔCDS variables, also conditioning on the lagged exogenous variables used in equation (3).[12] Given the estimates, we perform the these two evaluations: first, we graphically analyse the variation of the coefficient $\beta_{1,\tau}$ across different quantiles; second, we run the test for quantile stability to verify that the coefficients are statistically stable across quantiles.

Figure 6 reports the values of the $\beta_{1,\tau}$ coefficient for French CDS across different quantile levels for all the possible pairs of countries in our dataset. Each figure shows the coefficient values for several quantiles and for each country. Note that each panel of each figure is obtained from a different quantile regression (we are thus not considering system estimation, or the estimation of quantile regressions with several ΔCDS_j as explanatory variables). Furthermore, the panels report the 95% confidence intervals obtained with the Markov Chain Marginal Bootstrap of Kocherginsky et al. (2005). In drawing the graphs we evaluated the quantile regression for the following quantile: $\tau = 0.01$, 0.015, 0.02, 0.025, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 0.95, 0.975, 0.98, 0.985, 0.99.

From a global evaluation of all the figures, two common features emerge. At first, the coefficients are almost flat across quantiles, suggesting that the dependence between the movements of any two ΔCDS does not change as a function of the size and sign of the movements. In

[12] The introduction of the covariates allows controlling for the impact coming from common information. Lagged CDS changes are not included since we believe that the past information is either already included in the actual δCDS or conveyed by the covariates.

particular, $\widehat{\beta}_{1,\tau}$ around the median ΔCDS (for example $\tau = 0.50$) are very similar to those on the extreme quantiles ($\tau = 0.95$ or $\tau = 0.99$). This indicates that the contagion hypothesis of contagion is hardly acceptable (as we will see later on from the formal test). Instead, there is strong evidence of linearity in the propagation of shocks among the CDS of the different countries, i.e. the linkages among the different countries are the same during normal or turbulent times.[13]

Secondly, as expected, the dispersion of each quantile regression coefficient is much larger for extreme quantiles (below 0.1 and above 0.9). This is associated with the smaller number of events falling in those quantiles. Furthermore, the impact is always statistically significant, as the 95% confidence intervals do not include the zero.

With respect to this study, the most interesting equivalence occurs across upper the quantiles and can easily be tested. Table 5 reports the tests for equivalence across quantiles for the two following null hypotheses: $H_0 : \widehat{\Theta}_{0.90} = \widehat{\Theta}_{0.95} = \widehat{\Theta}_{0.99}$ and $H_0 : \widehat{\Theta}_{0.98} = \widehat{\Theta}_{0.985} = \widehat{\Theta}_{0.99}$.

Note that the test focuses on the entire set of coefficients. The Wald test statistic has a Chi-square density and in the second test we maintain the 95% quantile given that it is estimated on a somewhat larger number of points. Notably, in almost all the cases, the tests suggest the validity of the null hypothesis; that is, the linear interdependence across the changes in the CDS indices is not varying in its slope across the upper quantile.

To summarize, in this subsection we find that the relationship across quantiles is remarkably stable: sovereign risk propagation is largely a linear phenomenon, i.e.we are not able to find significant evidence of contagion among European sovereign risks for the sample considered.

One aspect that we have not considered, however, is the possibility that the quantile regressions could be affected by the presence of heteroskedasticity. We explore this topic in the following section.

[13] Such a result suggests also that the use of linear models to capture the linkages among the different countries is appropriate.

3.4 Bayesian Quantile with Heteroskedasticity

The absence of variability across quantiles suggests a linear interdependence across large changes in the CDS. This difference might be due to the absence of the GARCH component in the quantile regressions used in the previous subsection. Given that the model's computational complexity will sensibly increase, to reduce the estimation problems we resort to Bayesian techniques.

As mentioned before, quantile regression analysis offers a systematic strategy for examining how the explanatory variables influence the location, scale, and shape of the entire response distribution. Such methodologies can account for time-varying effects. However, when such effects are not explicitly modeled in the quantile regression bias, or at the least inefficiencies, may occur and incorrect conclusions may result. This will especially occur at low and high quantile levels, where dynamic changes may be largely influenced by changes in volatility. Therefore, as in Hiemstra and Jones (1994), Koenker and Zhao (1996), and Chen, Gerlack, and Wei (2009), we allow for heteroskedasticity in equation (9).

The changes in the CDS are assumed to follow a linear model with heteroskedasticity as described in equation (3), where the time-varying conditional variance $\sigma^2_{ij,t}$ is modeled as a GARCH(1,1) specifications. Following Chen, Gerlack, and Wei (2009), the quantile effect is estimated using an extension of the usual criterion function in equation (9) and is proposed to minimize the following logical quantile criterion function:

$$min_{\Theta_\tau,\alpha_\tau} \sum_{t=1}^{T} \left(\frac{\rho_\tau\left(\Delta CDS_{i,t} - \beta_{ij,0} - \beta_{ij,1}\Delta CDS_{j,t} - \gamma'_{ij}X_{t-1}\right)}{\sigma_{ij,t}(\tau)} + log(\sigma_{ij,t}(\tau)) \right) \quad (11)$$

where $\sigma_{ij,t}(\tau)$ is the residual time-varying standard deviation computed using quantile τ estimates of the parameters $\Theta_\tau = \{\beta_{0,\tau}, \beta_{1,\tau}, \gamma'_\tau\}$ and $\alpha_\tau = \{\theta_{ij,0,\tau}, \theta_{ij,1,\tau}, \theta_{ij,2,\tau}\}$. For the sake of notational simplicity the index ij has been suppressed in the following paragraphs. The extra logarithmic term in this expression ensures that the parameters α do not converge to infinity.

See Xiao and Koenker (2010) for an alternative criterion function. The volatility parameters α and the causal effect parameters Θ are estimated simultaneously resulting in a vector of parameters $\hat{\Phi}_\tau = \left(\hat{\Theta}_\tau, \hat{\alpha}_\tau\right)$ with τ subscript identified the reference quantile. We choose a Bayesian approach to estimate parameters because we believe this method has several advantages including: (i) accounting for parameter uncertainty through simultaneous inference on all model parameters; (ii) exact inference for finite samples; (iii) efficient and flexible handling of complex model situations and nonstandard parameters; and (iv) efficient and valid inference under parameter constraints.

Bayesian inference requires the specification of prior distributions. We chose weak uninformative priors to allow the data to dominate inference. As is standard, we assume a normal prior for $\Theta_\tau \sim N(\underline{\Theta}_{0,\tau}, \underline{\Sigma})$. $\underline{\Theta}_{0,\tau}$ is set equal to frequentist estimates of model (9); $\underline{\Sigma}$ to be a matrix with sufficiently "large" but finite numbers on the diagonal. The volatility parameters α_τ follow a jointly uniform prior, $p(\alpha_\tau) \propto I(S)$, constrained by the set S that is chosen to ensure covariance stationarity and variance positivity, as in the frequentist case. These are sufficient conditions to ensure that the conditional variance is strictly positive. See Nelson and Cao (1992) for a discussion of sufficient and necessary conditions on GARCH coefficients. Such restrictions reduce the role of the extra logarithmic term in equation (11).

The model is estimated using the Metropolis-within-Gibbs MCMC algorithms. Similarly to Chen, Gerlack, and Wei (2009), we combine Gibbs sampling steps with a random walk Metropolis-Hastings (MH) algorithm to draw the GARCH parameters (see Vrontos, Dellaportas, and Politis (2000) and So, Chen, and Chen (2005)). To speed the convergence and allow an optimal mixing, we employ an adaptive MH-MCMC algorithm that combines a random walk Metropolis (RW-M) and an independent kernel (IK)MH algorithm; see Appendix for estimation details.

The results for France and Germany are shown in figures 7–8. The median values are very similar to the results of the quantile regression presented in the previous section where heteroskedasticity has not been taken into account. Moreover, the uncertainty is lower and the confidence intervals are smaller than those estimated in the previous section, particularly for smaller and larger quantiles, this indicating that linearity cannot be rejected. Therefore, as for the previous analysis, the relationship across quantiles is remarkably stable and linear.

The evidence is similar for the other countries[14], the only exception being Italy where the parameters for France and Germany cases are subject to larger differences over the quantile. Therefore, Italian CDS seems more sensitive to large changes in French and German CDS, see figure 9.

3.5 Testing for Parameter Stability under Omitted Variables and Simultaneous Equations

Having shown that the coefficients are stable through the different quantiles should suggest that the problems of omitted variables and simultaneous equations are not as severe as previously thought. The reason is that the conditional volatility depends on the quantile. If there was a problem in the linear estimation that would have biased the coefficients, such a bias is a function of the relative variances of the shocks, and the bias tends to shift with the heteroskedasticity in the data. This is, however, only merely suggestive evidence. To investigate this issue more deeply, in this section we apply the DCC (Determinant of the Change in the Covariance matrix) test highlighted in Rigobon (2001), and Dungey et al. (2005).

The DCC is a simple test for parameter stability when the model suffers from biases related to simultaneous equations and omitted variables. These are exactly the types of problems that arise in the estimation of contagion and systemic risk. This test, however, only determines if the relationship is stable, not its strength.[15] In order to apply the DCC test, the only necessary assumption is that some of the structural shocks are homoskedastic within a certain

[14]Estimates of all parameters for all countries are available upon request.

[15]For an evaluation of the properties of the DCC as compared to other parameter stability tests see Rigobon (2000).

estimation window. In the case of Europe, it is reasonable to assume that when Greece is heading toward a fiscal crisis and its shocks become more volatile, the shocks in Germany are homoskedastic, which implies that all the observed heteroskedasticity in Germany is coming from the heteroskedasticity in the shocks to the periphery.

Assume that there are N endogenous stationary variables (x_{it}) that are described by the following model:

$$X_t A' = z_t \Gamma' + \varepsilon_t, \tag{12}$$

where $X_t \equiv (x_{1t}, \ldots, x_{Nt})'$, z_t are K unobservable common shocks, and ε_t are the structural shocks. Assume that all shocks are independent, but not necessarily identically distributed:

$$\begin{aligned} E[\varepsilon_t] &= 0 \;\; E[\varepsilon_{i,t}\varepsilon_{j,t}] = 0 \; \forall i \neq j \\ E[z_t] &= 0 \;\; E[z_{i,t} z_{j,t}] = 0 \; \forall i \neq j \\ E[\varepsilon_t z_t] &= 0 \\ E[\varepsilon_t' \varepsilon_t] &= \Omega_t^{\varepsilon} \;\; E[z_t' z_t] = \Omega_t^{z} \end{aligned} \tag{13}$$

where both Ω_t^z and Ω_t^{ε} are diagonal. Assume A and Γ are non triangular matrices that have been normalized as follows:[16]

$$A = \begin{pmatrix} 1 & a_{12} & \cdots & a_{1N} \\ a_{21} & 1 & & \\ \vdots & & \ddots & \vdots \\ a_{N1} & & \cdots & 1 \end{pmatrix}, \tag{14}$$

[16] This normalization is standard in macro applications. The only change is in the units which measure the errors.

$$\Gamma = \begin{pmatrix} 1 & 1 & \cdots & 1 \\ \gamma_{21} & \gamma_{22} & \cdots & \gamma_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{N1} & \gamma_{N2} & \cdots & \gamma_{Nk} \end{pmatrix}. \tag{15}$$

Finally, without loss of generality, assume that X_t has a zero mean and is serially uncorrelated.[17]

The problem of simultaneous equations is embedded in the assumption that A is not block diagonal, the problem of omitted variables is modelled as the unobservable common shocks, and the heteroskedasticity is built into the covariance matrix of both the structural and the common shocks.

In this model, the question of interest is the stability of the parameters (A or/and Γ). However, it is well-known that equation (12) cannot be estimated. Hence, inference on the coefficients cannot be performed without further information. Indeed, from equations (12) to (15) the only statistic that can be computed is the covariance matrix of the reduced form of X_t:

$$\Omega_t = A^{-1}\Gamma\Omega_t^z\Gamma' A'^{-1} + A^{-1}\Omega_t^\varepsilon A'^{-1}. \tag{16}$$

Note that in the lack of heteroskedasticity, changes in the covariance matrix of the reduced form are an indication that a shift in parameters has occurred. However, if the shocks are heteroskedastic, these changes are uninformative regarding the stability of the coefficients.

Assume that there is a shift in the variance of some of the idiosyncratic shocks (those from $\sigma_{\varepsilon,i}^2$ to $\sigma_{\varepsilon,N}^2$). The change in the covariance matrix is

$$\Delta\Omega_t = A^{-1}\Gamma\ \Delta\Omega_t^z\ \Gamma' A'^{-1} + A^{-1}\ \Delta\Omega_t^\varepsilon\ A'^{-1}$$

[17] If X_t is stationary, the results discussed here are independent of these assumptions.

In this example, $\Delta\Omega_t^z = 0$ and $\Delta\Omega_t^\varepsilon$ is

$$\Delta\Omega_t^\varepsilon = \begin{pmatrix} 0 & & & & \\ & \ddots & & & \\ & & \Delta\sigma^2_{\varepsilon,i} & & \\ & & & \ddots & \\ & & & & \Delta\sigma^2_{\varepsilon,N} \end{pmatrix}$$

Then,

$$\det \Delta\Omega_t = \det\left[A^{-1}\ \Delta\Omega_t^\varepsilon\ A'^{-1}\right] = \det\left[A^{-1}\right]\ \det\left[\Delta\Omega_t^\varepsilon\right]\ \det\left[A'^{-1}\right] = 0$$

In fact, the conditions in which the determinant of the change is zero are easier to satisfy for the multivariate case than for the bivariate case: if the heteroskedasticity only occurs in the structural shocks (ε_t), then if there are less than N shifts in their variances, the determinant is zero. Similarly, if the heteroskedasticity is explained by the common shocks (z_t) that reflect the systemic risk, then if there are less than K variances changing, the determinant is also zero.

For the recent eurozone fiscal crisis, it is assumed that either the crisis is driven by shocks to some of the countries – a subset of the structural shocks – or the crisis is driven by the common shocks (the systemic shocks). In the end, however, if neither assumption is satisfied, then the determinant of the change in the covariance matrix is going to be different than zero, not because the parameters are unstable but because the assumption about the structure of the heteroskedasticity is wrong. Therefore, we have the joint hypothesis that the heteroskedasticity is produced by a subset of the structural shocks and that the parameters are stable.

In our data we first estimate a simple VAR(5) where we control for the exogenous variables and lags. We recover the residuals from that regression and estimated the rolling average variance, see Figure 10. We define a threshold for the different "regimes" (high and low volatility) and compute the determinant of the change in the variance-covariancematrix. The idea is to split the data between high and low conditional volatility. One of the advantages of the

DCC is that the test is linear on the covariance matrices, so minor misspecifications on the "regimes" only reduce the power of the test. In order to control for this possibility we try different subsamples and thresholds.

In Table 6 we present the results of the DCC test for several thresholds. We show the implied T-stat from a block-bootstrap, as well as the one-sided test of the DCC. We present the results for several thresholds, defined as the average conditional standard deviation of the change in the CDS. Within each subsample, we bootstrap the residuals to compute the distribution of the covariance matrix. We implement 1000 replications and use blocks of size 5.

As shown in table 6, the results indicate that the parameters are stable and that the heteroskedasticity in the data is the outcome of the heteroskedasticity from a subset of the shocks. The implied Tstats are all well below the 95 percent confidence intervals. Furthermore, the one-sided test shows all the probabilities are larger than 2.5 percent, with the closest one being at 20 percent.

3.6 Bond Spread Analysis

For the purpose of the present analysis, one disadvantage of the data we are using is the fact that all our observations took place during what could be considered a tumultuous time: the world was already experiencing a financial crisis when our data starts, and truly we are comparing bad times to really bad times. It is quite possible that this explains why the propagation mechanism is so stable. One way to address this issue is to use bond spreads instead of CDS and use the methods derived here to study the propagation of shocks on bond spreads.

The advantage of using CDS data is that it captures the sovereign risk and therefore enables a very clean exercise. In contrast, there are drawbacks to using bond spreads. First, unlike CDS bond spreads are affected by many other factors; for example, they are more sensitive to monetary policy and the actions of the central bank and policymakers.

Second, while the CDS spread is observable in the market, it is not obvious how to compute the appropriate government bond spread. We collect 5-year bond yields from Thomson-Reuters for the eight European countries we consider and calculate the bond spreads relative to the 5-year swap rates because interest rate swaps are commonly seen as the market participants' preferred risk-free rate (see Beber et al., 2009). In addition, this approach guarantees a homogeneous benchmark across the euro area.[18]

In this case the data run since 2003 and we perform the exact same exercise that we did for the CDS but considering three different sample periods:(i) the pre-crisis period (2003–2006), (ii) the post-crisis one (2008–2011) and the entire sample (2003–2011). The statistics for the three samples are reported in table 7.

The results for the post-crisis sample (2008–2011) for quantile regressions and Bayesian quantile regressions for France are shown in Figures 11–12. The median values are very similar to the results presented in the previous section on CDS. However, the confidence intervals (the uncertainty) are larger than those estimated for the CDS because the time series are more volatile.

We still find that for smaller and larger quantiles in most cases we cannot reject the hypothesis that the coefficients are equal, an indication that linearity cannot be rejected. Therefore, as for the previous analysis, the relationship across quantiles is remarkably stable and linear. Moreover, the coefficients are rather similar. These results indicate that the propagation of shocks in bond markets is the same as for CDS in the same subsample.[19]

We repeated the analysis for the pre-crisis period (2003–2006). The results for quantile regressions and Bayesian quantile regressions for France are shown in figures 13–14. The parameter values are larger than those estimated on the post-crisis periods. Yet, we still find that for smaller and larger quantiles in most cases we cannot reject that the coefficients are equal (largely for the Bayesian analysis), indicating that linearity again cannot be rejected. It is

[18]Another possible approach is to use the yield-to-maturity of the German Bund. However, this approach has the disadvantage that the bond spread on Germany must be omitted from the analysis. Furthermore, the benchmark role of Bunds may lead to the existence of a significant "convenience yield".

[19]Evidence is similar for the other countries. Results are provided upon request.

important to observe that the coefficients are quite similar among all the different countries except for the United Kingdom where the coefficient is lower. This indicates that in the pre-crises period the market regarded the government bonds issued by eurozone countries as being very similar and a unique block distinct from the UK government bonds. In contrast, for the period 2008–2011 we do show that the UK coefficients are largely different for the different countries. Therefore, the results indicate that there is a change in the intensity of the propagation of shocks between the pre crisis period (2003–2006) and the post crisis one (2008–2011). However, the coefficients actually go down, not up! So there is no evidence of contagion. Moreover, between 2008 and 2011 the propagation is quite stable and surprisingly the coefficients are very similar between bond spreads and CDS.

Despite the certainty that a structural break occurred in 2008, we perform the exact same exercise over the entire sample, 2003–2011. The results for quantile regressions and Bayesian quantile regressions for France are shown in Figures 15–16. We do not find a linear relationship: for smaller and larger quantiles in most of the cases we reject that the coefficients are the same. As we would expect by allowing for heteroscedasticity, the differences among quantiles are larger for Bayesian estimates. The pattern, especially for the Bayesian coefficients, follow a bell-shaped profile that confirms the results we obtain for the two different subsamples: on the tail the coefficients are lower and assume values similar to the post-Lehman period, and for the middle quantiles values are higher and similar to the pre-crisis period.This is particularly evident for the coefficients associated with Greece, Ireland, Italy, Portugal, and Spain, whereas France's relationship with Germany and the United Kingdom is more stable over time, such as we also find in the analysis of the two subperiods. This result is encouraging because it clearly indicates that the (Bayesian) methodology has enough power to reject certain samples. [20]

[20] Our results is robust to different prior values, including priors centered around frequentist estimates with very small variance.

4 Discussion

Recent European events have spurred a new discussion of contagion. In previous crises, the United States in 1987, Mexico in 1994, Thailand in 1997, Russia in 1998, the United States in 2001, etc. the "culprit" propagating the shock was relatively clear. This is not the case in Europe right now. Several countries on the periphery entered a fiscal crisis at roughly the same time and therefore several of the techniques that exist in the contagion literature are inadequate to deal with the present situation. The purpose of this paper is to offer a assessment of contagion risk based on quantile regressions that account for the possibility of heteroskedasticity when extreme events occur.

Our paper uses the definition of contagion as the change in the propagation mechanisms when large shocks occur. We find that there is no change in the intensity of the transmission of shocks among European countries during the onset of the current fiscal crisis — suggesting that so far contagion in Europe has remained subdued. This does not mean that the situation might not change, but indicates that so far the common shift in CDS spreads that we have observed in the data is the outcome of the interdependence that has always been present — the strength of the propagation mechanisms has not changed during the recent fiscal crisis.

This finding has important implications for policymakers. Our methodology could be used as a tool to provide information to policymakers regarding markets view and related risks. In fact, the analysis suggests that the market was viewing the eurozone area as perfectly integrated (living in a dream?) and considering sovereign bonds of the different countries as almost perfect substitutes. Beginning in 2008, but largely after 2009 this view has been radically modified and the market has started to distinguish between weak/peripheral countries and strong/central countries such that transmission effects of country specific risks have been limited. Germany is the only country that has almost the same transmission power as prior to the eurozone fiscal crisis.

This recognition does not mean that since there is no contagion or the transmission of large shocks is lower, strong central European countries can easily ignore the country-specific risk of weak/peripheral countries. Transmission effects still remain present but the strength in the propagation mechanism has not altered during the recent fiscal crisis. Therefore, the strong eurozone countries should worry about risks that may come from large country-specific shocks and perhaps try to mitigate them, but not be concerned about similar shocks propagated with higher intensity across Europe.

From the methodological viewpoint, our procedure has several advantages. First, it is a very flexible method to detect changes in the transmission mechanisms conditional on the size of the shocks. Second, it deals explicitly with heteroskedasticity in the data — a problem that affects the validity of many measures proposed in the literature. Third, it is a reduced-form approach that does not require knowing the specific formulation of the contagion channel before the crisis occurs.

It is important to highlight that our procedure does not predict changes in propagation, but does measure such changes. It is possible that a sovereign default in the region will shift the relationship across CDS, but so far this has not happened. We believe this methodology could offer a vehicle to policymakers and market participants to detect such changes when the data suffers from heteroskedasticity.

Finally, the observed stability across different quantiles opens the door to the use of linear models, like VAR, in the system's analysis of cross-country interdependencies. Moreover, these models could represent a relevant tool in the analysis of the transmission mechanism of shocks. Such an extension is left to ongoing and future researches.

Appendix

The relation between the CDS of country i with country j and other covariates is modelled as:

$$\Delta CDS_{i,t} = \beta_{ij,0} + \beta_{ij,1}\Delta CDS_{j,t} + \gamma'_{ij,}X_{t-1} + \sigma_{ij,t}\varepsilon_{ij,t} \tag{17}$$

$$\varepsilon_{ij,t}|I^{t-1} \sim D(0,1) \tag{18}$$

$$\sigma^2_{ij,t} = \theta_{ij,0} + \theta_{ij,1}e^2_{ij,t-1} + \theta_{ij,2}\sigma^2_{ij,t-1} \tag{19}$$

The subscript ij is dropped for convenience in the the text below. The univariate SL location-scale family $SL(\mu, \delta, \tau)$ has the following density function:

$$f(z) = \frac{\tau(1-\tau)}{\delta} exp\left(-\tau\left(\frac{z-\mu}{\delta}\right)\right)$$

Chen, Gerlack, and Wei (2009) shows that if the residual $\varepsilon_{ij,t-1}$ in equation (17) is assumed to be skewed Laplace distributed, *i.i.d.*, and has been standardized to have variance of one, the likelihood of model (17)-(19) is:

$$l(\Delta CDS_i|\Theta, \alpha) = \sqrt{1-2\tau+2\tau^2}\left(\prod_{t=1}^{T}(\rho_\tau(\sigma_{ij,t}))^{-1}\right)\exp\left(\sum_{t=1}^{T}\frac{\sqrt{1-2\tau+2\tau^2}(\Delta CDS_{i,t}-\beta_{0,\tau}-\beta_{1,\tau}\Delta CDS_{j,t}-\gamma'_\tau X_{t-1})}{\rho_\tau(\sigma_{ij,t})}\right) \tag{20}$$

where $\rho_\tau(a)$ is the *check* function for quantile τ defined as $\rho_\tau(a) = a \times (\tau - I(a<0))$, $\Theta = \{\Theta_\tau\}_\tau = \{\beta_{0,\tau}, \beta_{1,\tau}, \gamma'_\tau\}_\tau$ and $\alpha = \{\alpha_\tau\}_\tau = \{\theta_{ij,0,\tau}, \theta_{ij,1,\tau}, \theta_{ij,2,\tau}\}_\tau$. The maximum likelihood estimates from equation (20) for Θ_τ are mathematically equivalent to the heteroskedastic quantile estimators from equation (11).

Then, define the vector $\Phi_\tau = (\beta_{0,\tau}, \beta_{1,\tau}, \gamma_\tau, \theta_{0,\tau}, \theta_{1,\tau}, \theta_{2,\tau})$ and $\Phi_{j,\tau}$ the j-th element of the vector, the sampling scheme consists of the following iterative steps, where the subscription τ is deleted to simplify the reading:

Step 1: at iteration i, generate a point Φ_j^* from the random walk kernel (RW-M)

$$\Phi_j^* = \Phi_j^{i-1} + \epsilon_j \;\; \epsilon \sim N(0, \Sigma) \tag{21}$$

where Σ is a diagonal matrix and σ_j^2 is its j-th diagonal element, and Φ_j^{i-1} is the $(i-1)$th iteration of Φ_j. We accept Φ_j^* as Φ_j^i with probability $p = min\left[1, f(\Phi_j^*)/f(\Phi_j^{i-1})\right]$, where $f()$ is the likelihood in equation (20) multiplied by the priors. Otherwise, set $\Phi_j^* = \Phi_j^{i-1}$. The elements of Σ are turned by monitoring the acceptance rate to lie between 25% and 50%.

Step 2: After M iterations, we apply the following independent kernel (IK)MH algorithm. Generate Φ_j^* from

$$\Phi_j^* = \mu_{\Phi_j}^{i-1} + \epsilon_j \;\; \epsilon \sim N(0, \Sigma_{\Phi_j}) \tag{22}$$

where μ_{Φ_j} and Σ_{Φ_j} are respectively the sample mean and the sample covariance of the first M iterations for Φ_j. Then accept Φ_j^* as Φ_j^i with probability

$$p = min\left[1, \frac{f(\Phi_j^*)g(\Phi_j^{i-1})}{f(\Phi_j^{i-1})g(\Phi_j^*)}\right] \tag{23}$$

where $g()$ is the Gaussian proposal density in (22).

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Table 1: **Summary Statistics**

	CDS spreads				
	Mean	Standard Deviation	Minimum	Maximum	Median
FRANCE	57.28	24.88	21.00	149.81	55.65
GERMANY	35.93	13.90	17.96	92.50	32.92
GREECE	702.85	729.75	88.00	5398.18	428.15
IRELAND	334.45	228.84	96.92	1191.16	220.62
ITALY	133.43	62.65	48.00	447.22	123.02
PORTUGAL	280.36	264.65	37.00	1217.47	185.86
SPAIN	149.74	71.83	47.00	364.01	144.08
UK	280.36	264.65	37.00	1217.47	185.86
	Conditional variables				
	Mean	Standard Deviation	Minimum	Maximum	Median
D(EURIBOR-EONIA)	0.00	0.02	–0.18	0.14	0.00
D(RISK APPETITE)	0.01	3.59	–28.07	15.49	0.33
D(EURIBOR)	0.00	0.01	–0.12	0.06	0.00
	Changes in CDS spreads				
	Mean	Standard Deviation	Minimum	Maximum	Median(Abs)
FRANCE	0.15	3.12	–17.66	22.19	1.00
GERMANY	0.04	2.28	–13.89	19.02	0.63
GREECE	6.53	64.70	–462.83	764.06	6.36
IRELAND	0.96	16.93	–137.21	101.18	5.00
ITALY	0.46	9.35	–79.98	63.91	2.98
PORTUGAL	1.30	20.76	–199.91	174.71	4.00
SPAIN	0.37	10.14	–75.24	48.80	3.50
UK	0.03	3.25	–18.89	18.00	1.01

Notes: This table presents summary statistics for daily 5 years CDS spreads, daily changes in CDS spreads as well the conditional variables, Euribor, Euribor minus Eonia and Risk appetite, from November 2008 to September 2011. Risk appetite is defined as the difference between VSTOXX and the volatility of the EuroStoxx50 estimated by a GARCH(1,1) model. CDS are expressed in basis points.

Table 2: **Correlations**

	Correlation Matrix						
	FRANCE	GERMANY	GREECE	IRELAND	ITALY	PORTUGAL	SPAIN
GERMANY	0.573						
GREECE	0.283	0.190					
IRELAND	0.495	0.378	0.399				
ITALY	0.641	0.446	0.391	0.602			
PORTUGAL	0.498	0.374	0.490	0.741	0.701		
SPAIN	0.606	0.456	0.361	0.629	0.857	0.730	
UK	0.537	0.515	0.230	0.450	0.569	0.398	0.520

Notes: This table reports the correlation matrix of daily five-year CDS spread changes. The sample consists of daily observations for November 2008 to September 2011 period.

Table 3: **Likelihood Ratio Test for Linearity**

i	j	P-value	β_1	β_2	β_3
FRANCE	GERMANY	1.000	0.898	—	—
FRANCE	GREECE	0.000	0.036	0.000	0.000
FRANCE	IRELAND	0.015	0.102	—	0.000
FRANCE	ITALY	0.008	0.226	0.001	—
FRANCE	PORTUGAL	1.000	0.083	—	0.000
FRANCE	SPAIN	0.005	0.201	0.001	0.000
FRANCE	UK	0.654	0.358	—	—
GERMANY	FRANCE	0.000	0.539	—	–0.001
GERMANY	GREECE	0.000	0.018	—	0.000
GERMANY	IRELAND	0.004	0.059	—	0.000
GERMANY	ITALY	0.001	0.144	—	0.000
GERMANY	PORTUGAL	0.000	0.063	—	0.000
GERMANY	SPAIN	0.050	0.119	—	0.000
GERMANY	UK	0.955	0.370	—	—
GREECE	FRANCE	0.570	2.783	—	—
GREECE	GERMANY	0.000	3.251	—	–0.022
GREECE	IRELAND	0.000	0.541	–0.008	0.000
GREECE	ITALY	0.000	1.155	–0.010	0.000
GREECE	PORTUGAL	0.062	1.423	–0.002	0.000
GREECE	SPAIN	0.000	1.157	—	0.000
GREECE	UK	0.000	1.624	—	–0.004
IRELAND	FRANCE	0.088	2.176	–0.039	—
IRELAND	GERMANY	0.000	3.234	—	–0.013
IRELAND	GREECE	0.000	0.223	—	0.000
IRELAND	ITALY	0.009	1.004	–0.004	0.000
IRELAND	PORTUGAL	0.000	0.610	—	0.000
IRELAND	SPAIN	0.000	0.885	—	0.000
IRELAND	UK	0.455	1.726	—	—

Notes: This table reports the likelihood ratio test for linear relationship between the change in the CDS of country i and country j. P-Value denotes the P-Value of the likelihood ratio test and β_1, β_2, β_3 are the significant estimated coefficient of equation (6) at the 5 percent level.

Table 3: continued

i	j	P-value	β_1	β_2	β_3
ITALY	FRANCE	0.242	1.771	–0.022	—
ITALY	GERMANY	0.000	2.158	—	–0.008
ITALY	GREECE	0.000	0.125	0.000	0.000
ITALY	IRELAND	0.003	0.354	0.000	0.000
ITALY	PORTUGAL	0.000	0.438	–0.001	0.000
ITALY	SPAIN	0.000	0.669	0.001	0.000
ITALY	UK	0.001	1.158	–0.012	–0.002
PORTUGAL	FRANCE	0.162	1.346	–0.030	—
PORTUGAL	GERMANY	0.000	1.644	–0.022	–0.014
PORTUGAL	GREECE	0.000	0.306	0.000	0.000
PORTUGAL	IRELAND	0.000	0.280	–0.003	0.000
PORTUGAL	ITALY	0.000	0.658	–0.003	0.000
PORTUGAL	SPAIN	0.000	0.732	0.005	0.000
PORTUGAL	UK	0.328	0.791	—	—
SPAIN	FRANCE	0.587	1.885	—	—
SPAIN	GERMANY	0.000	2.265	—	–0.010
SPAIN	GREECE	0.000	0.143	0.000	0.000
SPAIN	IRELAND	0.015	0.387	—	0.000
SPAIN	ITALY	0.001	0.883	–0.003	—
SPAIN	PORTUGAL	1.000	0.447	—	—
SPAIN	UK	1.000	0.996	—	—
UK	FRANCE	0.001	0.520	–0.006	0.000
UK	GERMANY	0.000	1.015	—	–0.004
UK	GREECE	0.000	0.018	0.000	—
UK	IRELAND	0.000	0.088	—	0.000
UK	ITALY	0.001	0.211	–0.001	0.000
UK	PORTUGAL	0.003	0.064	0.000	0.000
UK	SPAIN	0.803	0.133	—	—

Notes: This table reports the likelihood ratio test for linear relationship between the change in the CDS of country i and country j. P-Value denotes the P-Value of the likelihood ratio test and β_1, β_2, β_3 are the significant estimated coefficient of equation (6) at the 5 percent level.

Table 4: **Economic Impact of Nonlinear Terms**

	quadratic f2 * DCDS2	cubic f3 * DCDS3	quadratic f2 * DCDS2	cubic f3 * DCDS3	quadratic f2 * DCDS2	cubic f3 * DCDS3	quadratic f2 * DCDS2	cubic f3 * DCDS3
	France		Germany		Greece		Ireland	
FRANCE	—	—	—	0.00	—	—	–0.04	—
GERMANY	—	—	—	—	—	–0.01	—	0.00
GREECE	0.00	0.00	—	0.00	—	—	—	0.00
IRELAND	—	0.00	—	0.00	–0.12	0.01	—	—
ITALY	0.008	—	—	0.00	–0.02	0.00	0.00	0.00
PORTUGAL	—	0.00	—	0.00	–0.10	0.04	—	–0.01
SPAIN	0.01	0.00	—	0.00	—	–0.24	—	–0.08
UK	—	—	—	—	—	0.15	—	0.16
	Italy		Portugal		Spain		UK	
FRANCE	–0.02	—	–0.03	—	—	—	–0.01	0.00
GERMANY	—	0.00	–0.01	0.00	—	0.00	—	0.00
GREECE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	—
IRELAND	–0.01	0.00	–0.03	0.00	—	0.00	—	0.00
ITALY	—	—	–0.03	0.01	–0.03	—	–0.01	0.00
PORTUGAL	0.04	0.01	—	—	—	—	0.00	0.00
SPAIN	–0.19	–0.12	0.07	–0.05	—	—	—	—
UK	–1.20	0.65	—	—	—	—	—	—

Notes: This table presents the economic impact of the quadratic and cubic factors.

Table 5: **Test for Stability Across Quintile**

		$H_0 : \widehat{\Theta}_{0.90} = \widehat{\Theta}_{0.95} = \widehat{\Theta}_{0.99}$		$H_0 : \widehat{\Theta}_{0.98} = \widehat{\Theta}_{0.985} = \widehat{\Theta}_{0.99}$	
Dependent	Explanatory	Test-stat	P-value	Test-stat	P-value
FRANCE	GERMANY	10.074	0.260	5.668	0.932
FRANCE	UK	18.293	0.019	2.650	0.998
FRANCE	SPAIN	2.400	0.966	4.364	0.976
FRANCE	ITALY	2.565	0.959	2.570	0.998
FRANCE	IRELAND	3.064	0.930	0.784	0.999
FRANCE	PORTUGAL	2.848	0.944	3.171	0.994
FRANCE	GREECE	4.634	0.796	1.712	0.999
GERMANY	FRANCE	2.708	0.951	3.827	0.986
GERMANY	UK	12.136	0.145	8.391	0.754
GERMANY	SPAIN	2.323	0.969	1.512	0.999
GERMANY	ITALY	8.631	0.374	3.257	0.993
GERMANY	IRELAND	4.469	0.813	4.346	0.976
GERMANY	PORTUGAL	3.817	0.873	1.357	0.999
GERMANY	GREECE	4.805	0.778	6.362	0.897
UK	FRANCE	6.205	0.624	7.836	0.798
UK	GERMANY	10.328	0.243	5.954	0.918
UK	SPAIN	9.090	0.335	4.200	0.980
UK	ITALY	13.614	0.092	6.959	0.860
UK	IRELAND	8.609	0.376	4.402	0.975
UK	PORTUGAL	11.985	0.152	6.189	0.906
UK	GREECE	3.932	0.863	6.961	0.860
SPAIN	FRANCE	7.893	0.444	1.748	0.999
SPAIN	GERMANY	1.620	0.991	2.796	0.997
SPAIN	UK	17.924	0.022	6.421	0.893
SPAIN	ITALY	6.473	0.594	5.495	0.939
SPAIN	IRELAND	1.759	0.988	0.936	0.999
SPAIN	PORTUGAL	3.675	0.885	2.111	0.999
SPAIN	GREECE	5.294	0.726	4.098	0.982

Notes: This table presents the test for stability across quintile in the relation between the CDS of country i and country j.

Table 5: continued

		$H_0 : \widehat{\Theta}_{0.90} = \widehat{\Theta}_{0.95} = \widehat{\Theta}_{0.99}$		$H_0 : \widehat{\Theta}_{0.98} = \widehat{\Theta}_{0.985} = \widehat{\Theta}_{0.99}$	
Dependent	Explanatory	Test-stat	P-value	Test-stat	P-value
ITALY	FRANCE	9.692	0.287	3.011	0.995
ITALY	GERMANY	3.961	0.861	2.397	0.999
ITALY	UK	18.560	0.017	3.569	0.990
ITALY	SPAIN	3.990	0.858	7.585	0.817
ITALY	IRELAND	0.526	0.999	2.371	0.999
ITALY	PORTUGAL	2.805	0.946	1.459	0.999
ITALY	GREECE	1.760	0.988	4.341	0.976
IRELAND	FRANCE	2.892	0.941	4.955	0.959
IRELAND	GERMANY	4.376	0.822	3.933	0.985
IRELAND	UK	2.262	0.972	4.664	0.968
IRELAND	SPAIN	10.546	0.229	5.828	0.924
IRELAND	ITALY	2.059	0.979	6.083	0.912
IRELAND	PORTUGAL	29.008	0.001	15.913	0.195
IRELAND	GREECE	6.202	0.625	3.695	0.988
PORTUGAL	FRANCE	1.165	0.997	3.065	0.995
PORTUGAL	GERMANY	6.576	0.583	1.897	0.999
PORTUGAL	UK	28.371	0.000	9.553	0.655
PORTUGAL	SPAIN	6.952	0.542	12.66	0.394
PORTUGAL	ITALY	3.984	0.859	6.008	0.916
PORTUGAL	IRELAND	6.410	0.601	1.827	0.999
PORTUGAL	GREECE	7.723	0.461	7.442	0.827
GREECE	FRANCE	4.053	0.852	3.478	0.991
GREECE	GERMANY	5.18	0.738	17.613	0.128
GREECE	UK	9.762	0.282	4.449	0.974
GREECE	SPAIN	6.338	0.609	2.711	0.997
GREECE	ITALY	15.941	0.043	8.082	0.779
GREECE	IRELAND	4.490	0.810	2.241	0.999
GREECE	PORTUGAL	8.298	0.405	2.921	0.996

Notes: This table presents the test for stability across quintile in the relation between the CDS of country i and country j.

Table 6: DCC Test

Threshold	Tstat	Mass > 0
12.00	0.96	0.32
13.00	0.83	0.30
14.00	1.39	0.20
15.00	0.53	0.32
16.00	0.62	0.39
17.00	0.69	0.29
18.00	1.27	0.21
19.00	1.41	0.28
20.00	1.77	0.40
21.00	1.72	0.39
22.00	0.96	0.42
23.00	0.58	0.43
24.00	0.09	0.39

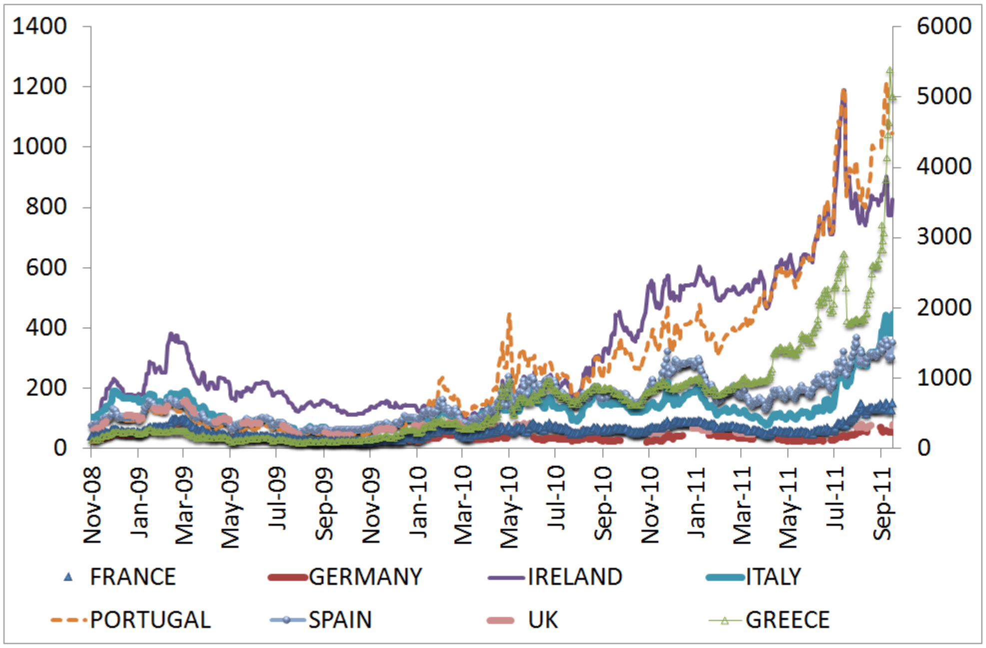
Notes: This table includes the DCC test across different threshold values.

Table 7: **Summary Statistics Bond Spreads**

Changes in bond spreads				
	Mean	Standard Deviation	Minimum	Maximum
		Full sample 2003–2011		
France	0.01	4.16	–20.75	23.23
Germany	–0.03	4.14	–22.05	26.14
Greece	1.20	25.48	–650.83	400.86
Ireland	0.28	11.00	–139.00	97.94
Italy	0.15	5.66	–91.46	61.23
Portugal	0.55	14.08	–315.65	253.74
Spain	0.12	5.96	–107.86	43.16
U.K.	–0.02	4.57	–32.27	48.07
		pre-crisis 2003–2006		
France	0.017	2.612	–18.873	15.975
Germany	0.015	2.298	–12.877	13.383
Greece	0.023	2.727	–20.373	29.483
Ireland	–0.009	2.972	–17.929	37.100
Italy	0.011	2.522	–15.973	22.799
Portugal	0.008	2.832	–17.773	52.283
Spain	0.014	2.517	–14.473	34.883
U.K.	0.004	1.708	–7.073	7.734
		post-Lehman 2008–2011		
France	0.05	5.66	–20.75	23.23
Germany	–0.03	5.75	–22.05	19.44
Greece	3.48	44.04	–650.83	400.86
Ireland	0.81	17.48	–139.00	97.94
Italy	0.39	8.73	–91.46	61.23
Portugal	1.65	24.03	–315.65	253.74
Spain	0.38	9.36	–107.86	43.16
U.K.	0.01	7.04	–19.66	48.07

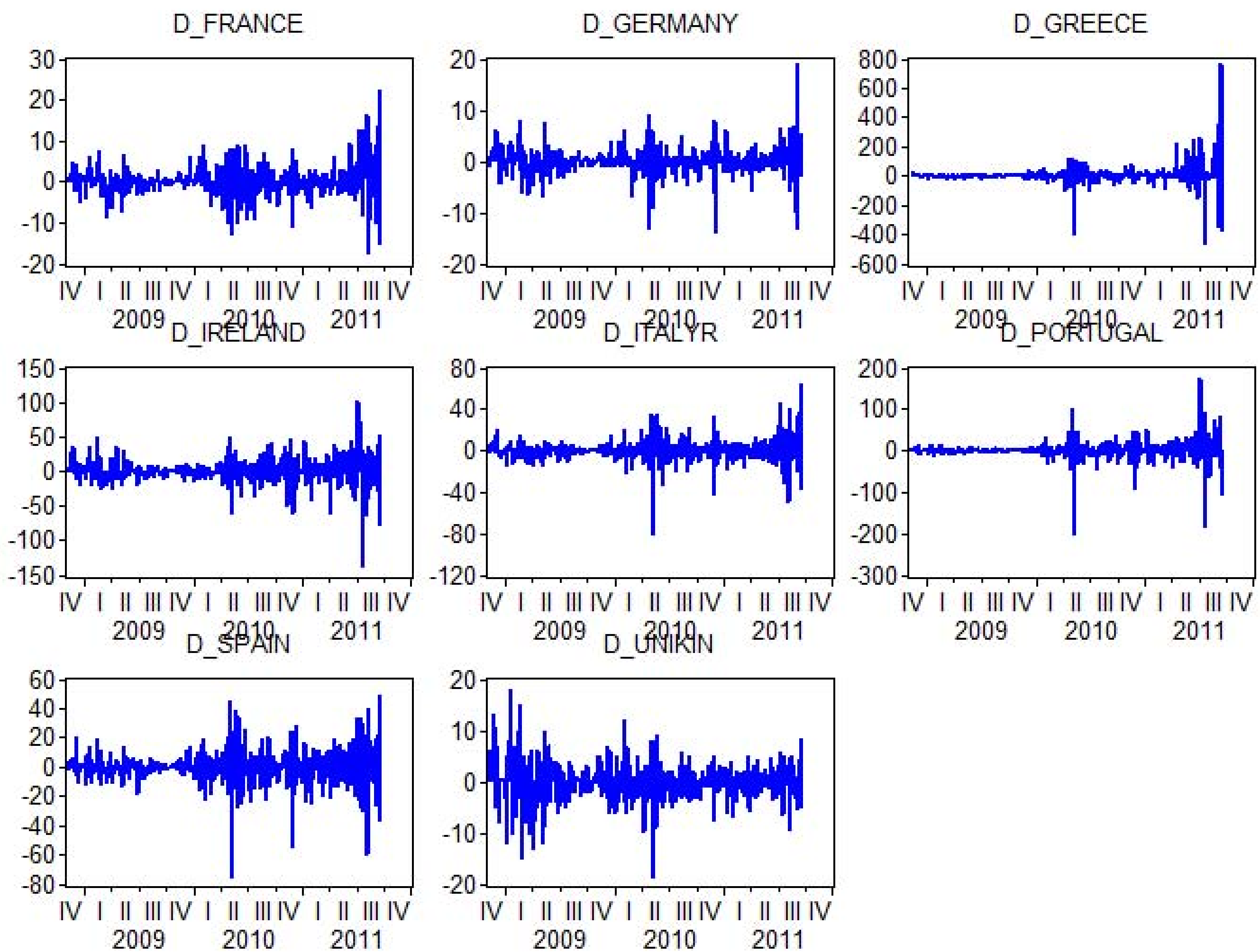
Notes: This table presents the summary statistics for daily bond spreads for different samples.

Figure 1: **CDS Spreads (Levels)**



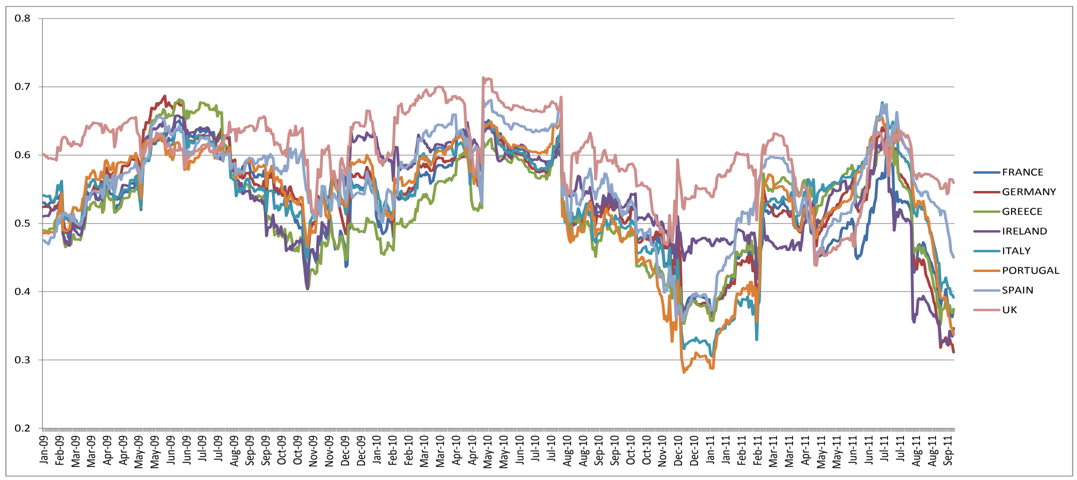
Notes: This figure shows the levels of the CDS spreads. Left axes for all series apart Greece which is reported on the right axes.

Figure 2: **Changes in CDS Spreads**



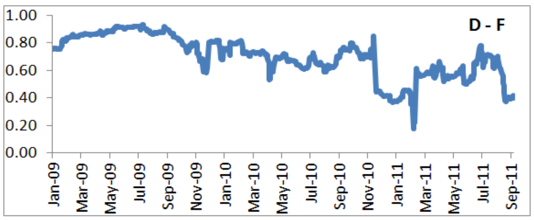
Notes: This figure shows the changes in CDS spreads.

Figure 3: **CDS Average Rolling Correlation Among Countries**

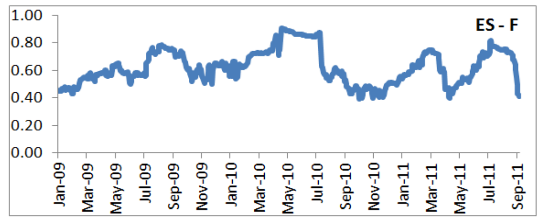


Notes: This figure depicts a 60-days rolling window average correlation among CDS spreads.

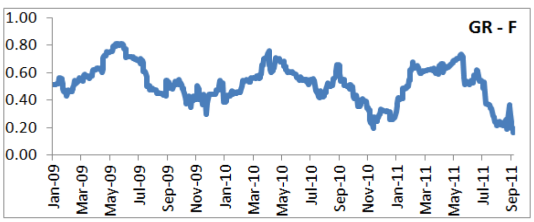
Figure 4: **CDS Rolling Correlations between France and the Other Countries**



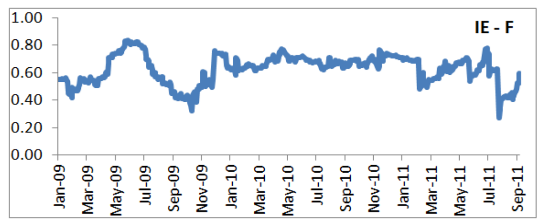
(a) D: GERMANY



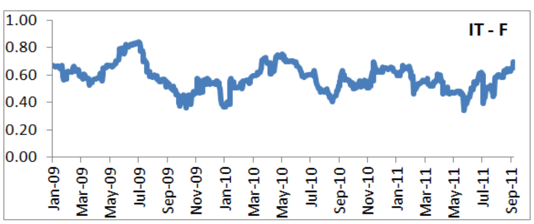
(b) ES: SPAIN



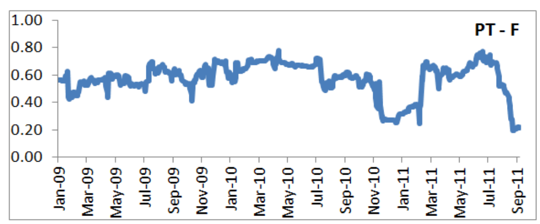
(c) GR: GREECE



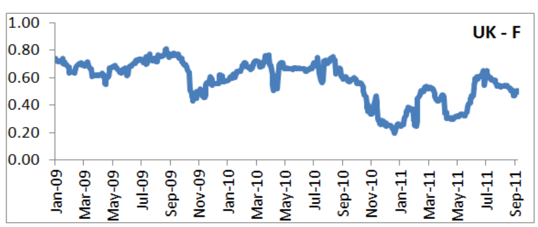
(d) IR: IRELAND



(e) IT: ITALY



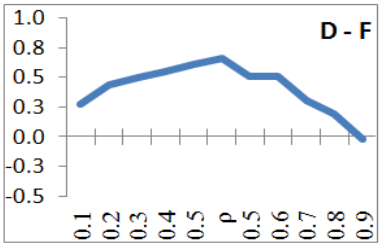
(f) PT: PORTUGAL



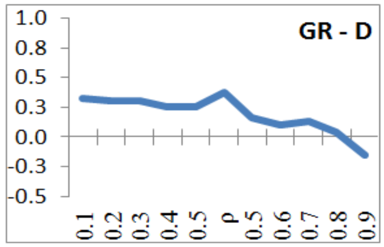
(g) UK: UNITED KINGDOM

Notes: This figure depicts a 60-days rolling window average correlation between the (F) French CDS spreads those of the other countries.

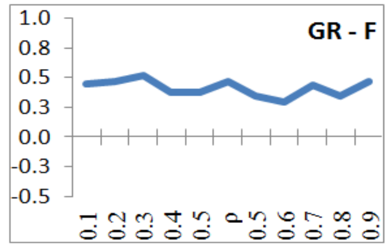
Figure 5: **Exceedence Correlations (60-days)**



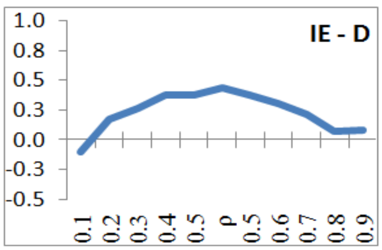
(a) D & F



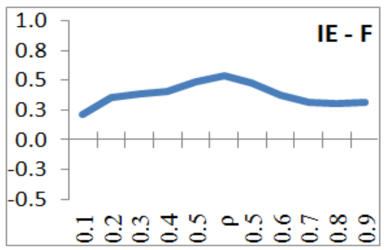
(b) GR & D



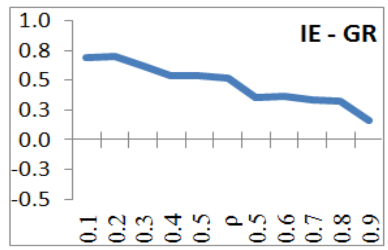
(c) GR & F



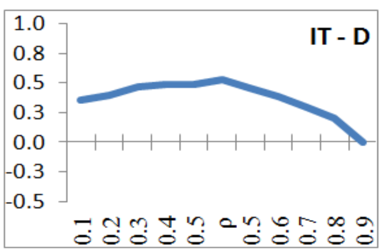
(d) IE & D



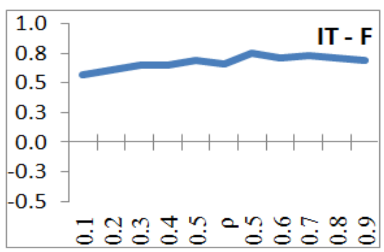
(e) IE & F



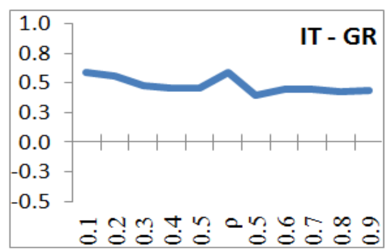
(f) IE & GR



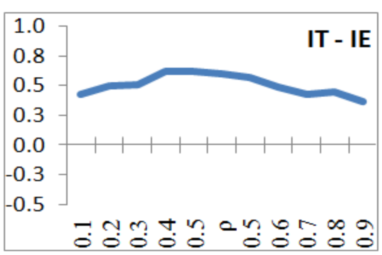
(g) IT & D



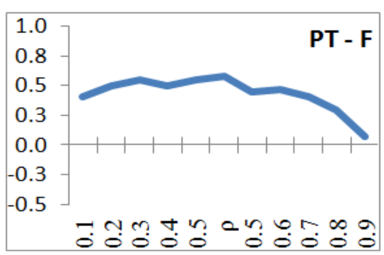
(h) IT & F



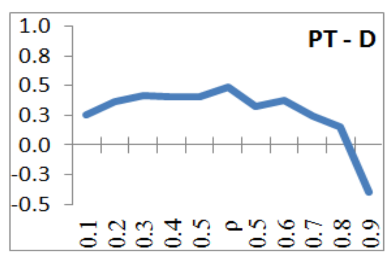
(i) IT & GR



(j) IT & IE



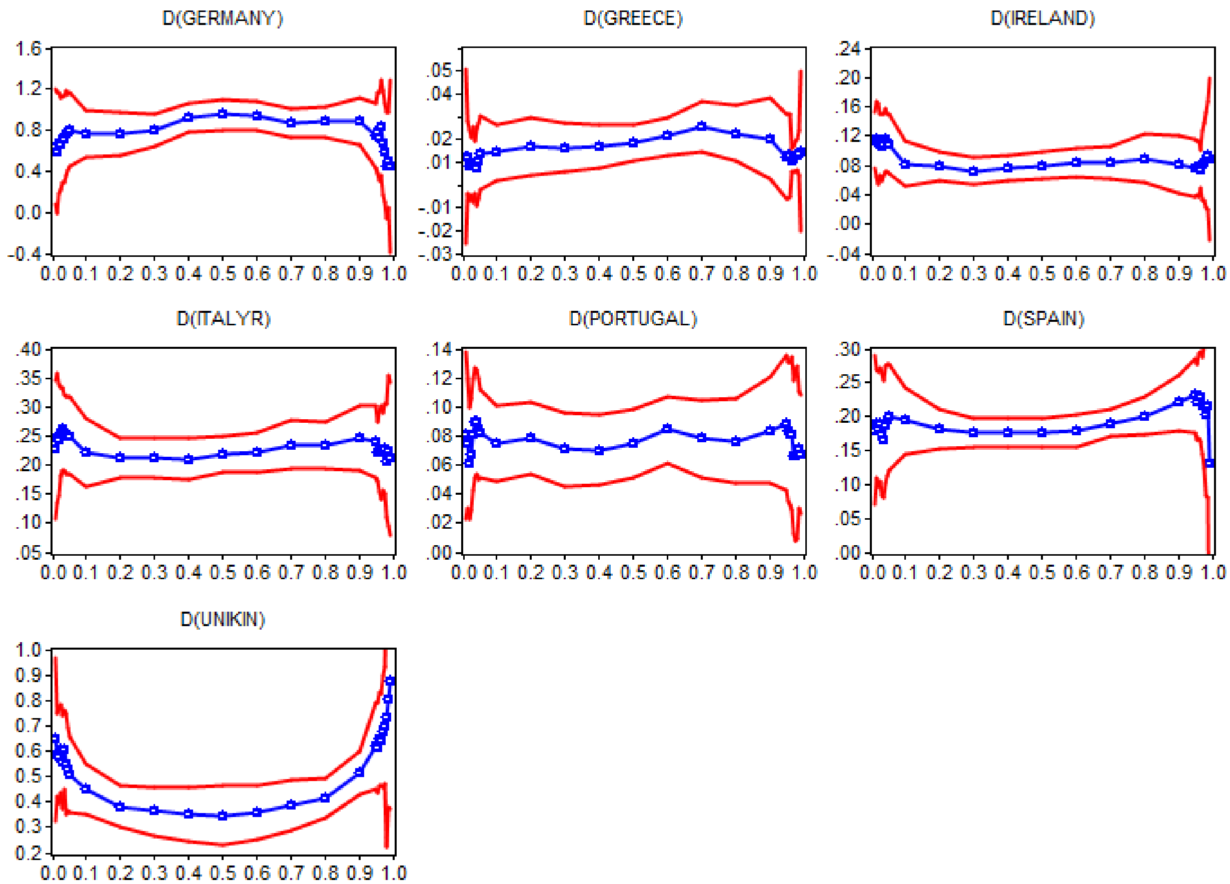
(k) PT & F



(l) PT & D

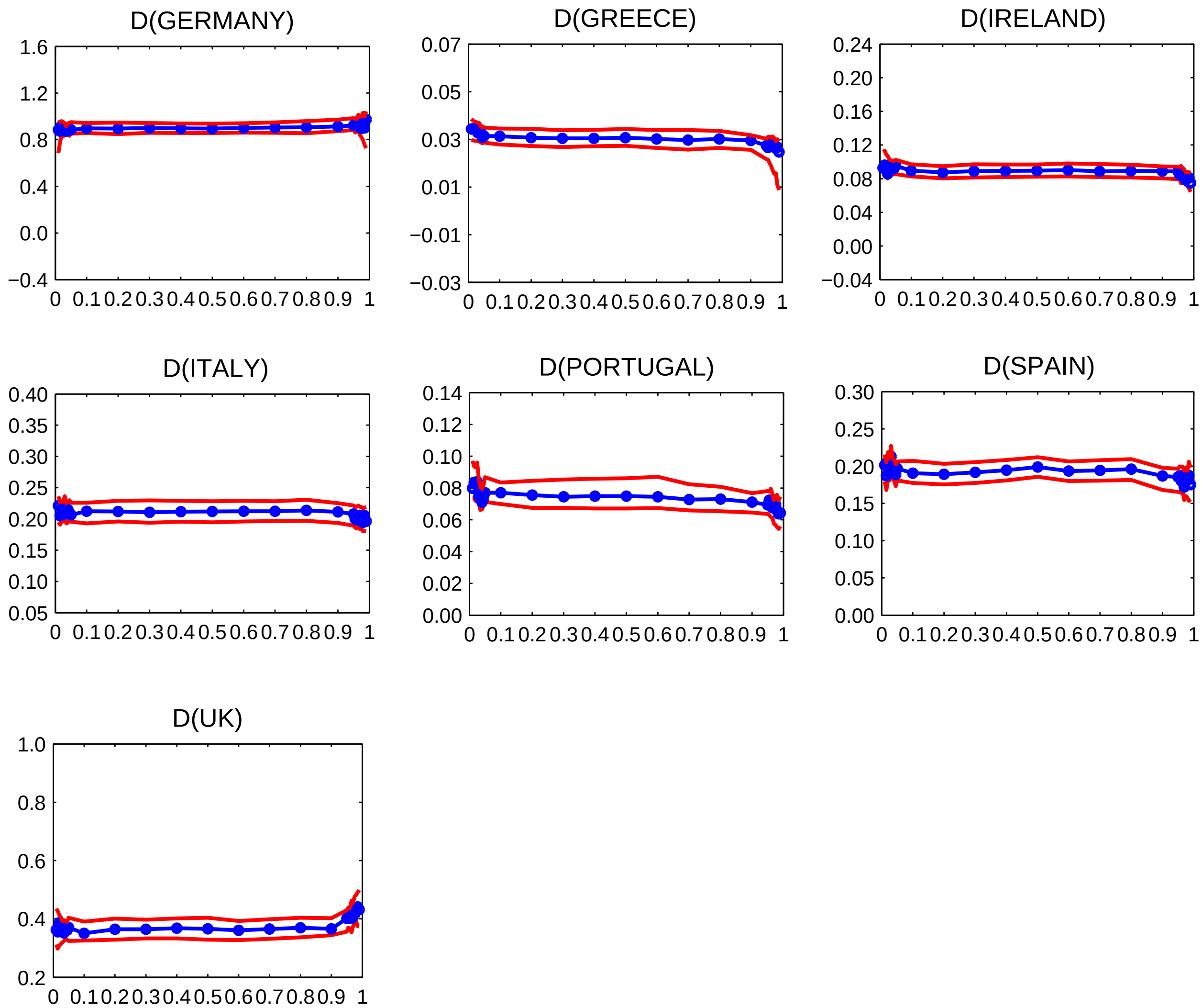
Notes: This figure shows the 60-days exceedence correlations

Figure 6: **Quantile Regression Coefficients for French CDS**



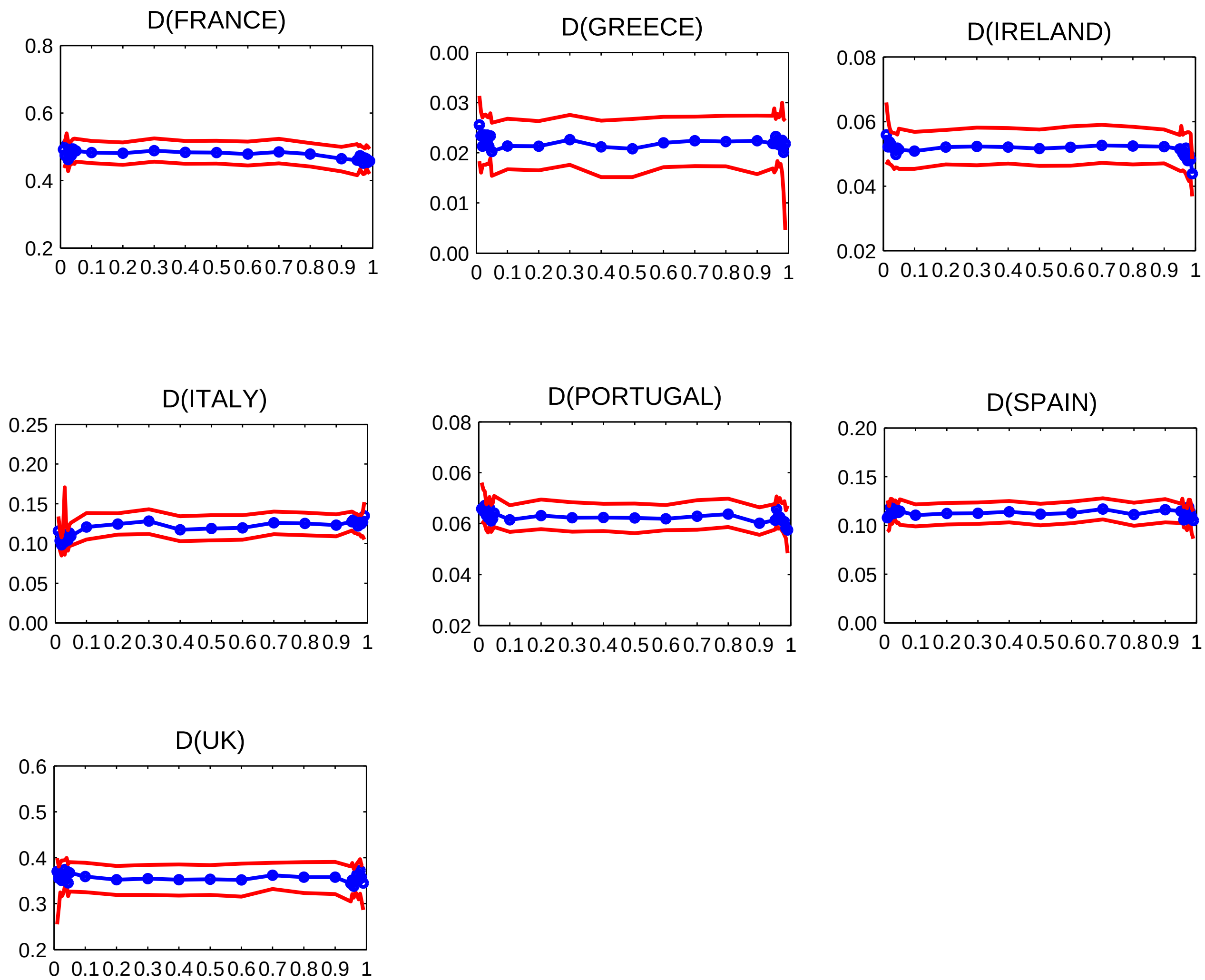
Notes: This figure shows the quantile regression coefficients for France.

Figure 7: **Quantile Regression Coefficients with Heteroskedasticity for French CDS**



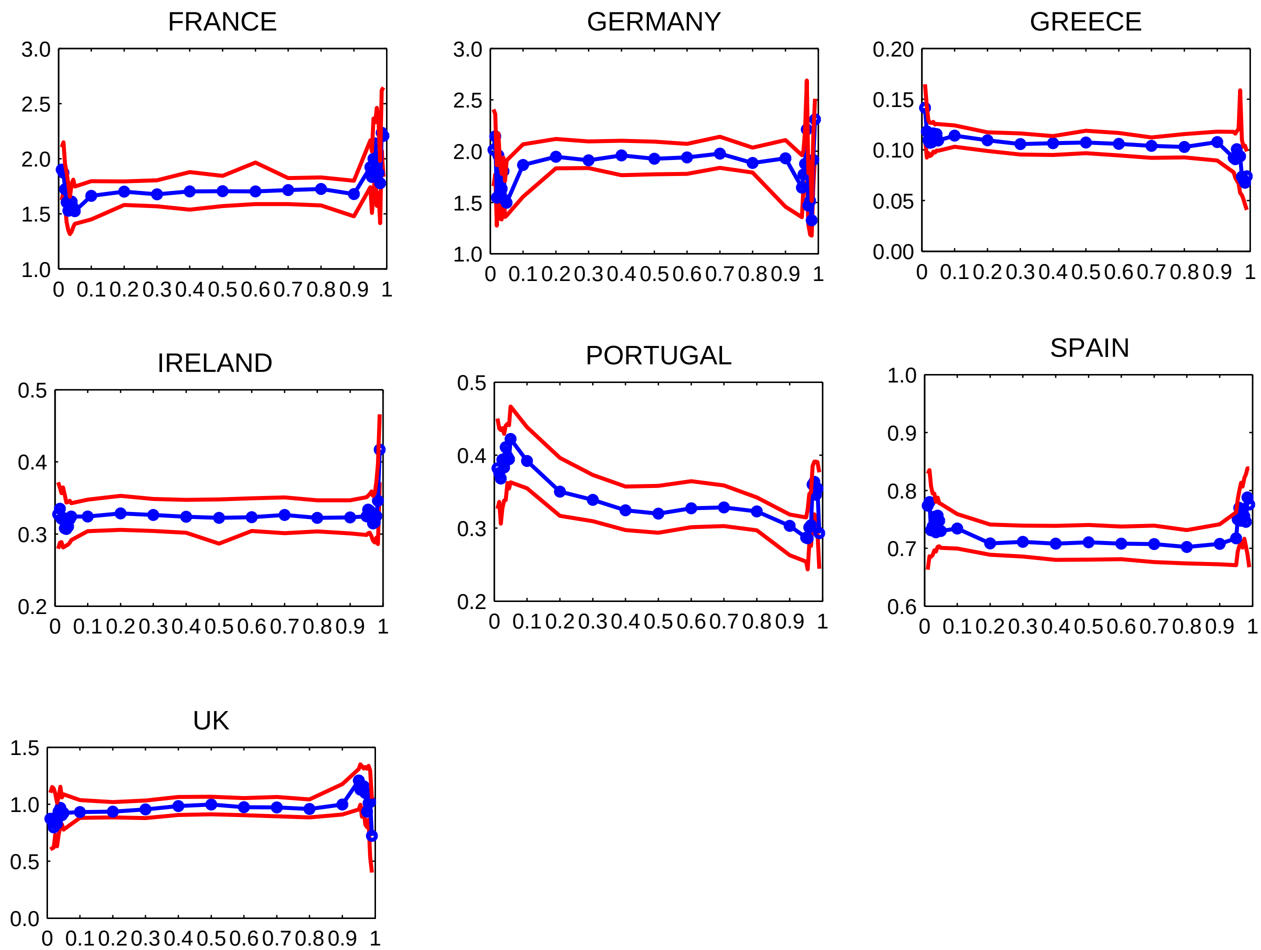
Notes: This figure shows the quantile regression coefficients with heteroskedasticity for France.

Figure 8: **Quantile Regression Coefficients with Heteroskedasticity for German CDS**



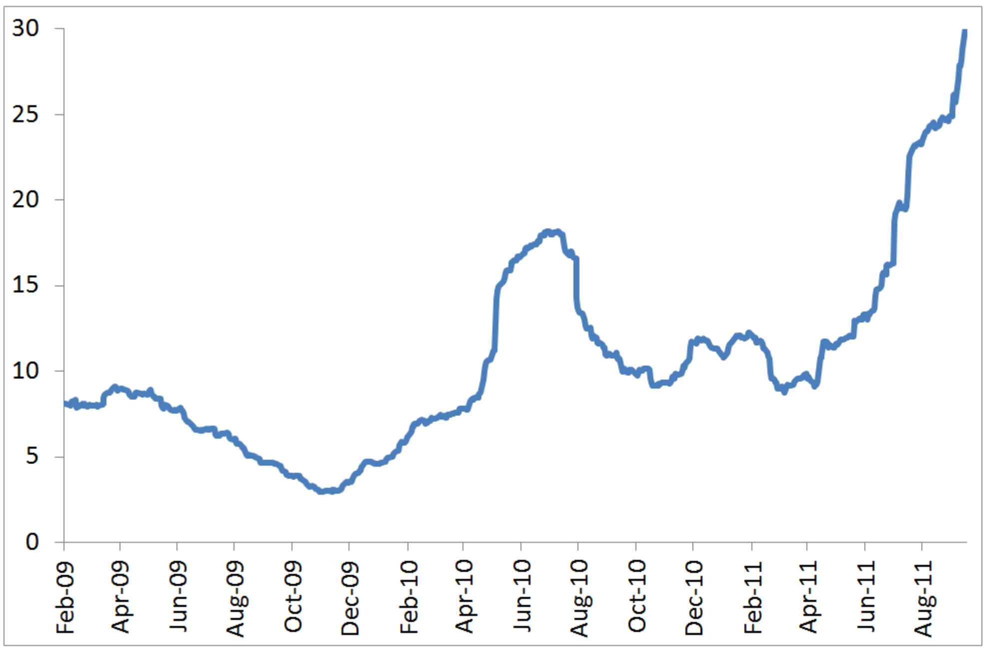
Notes: This Figure shows the quantile regression coefficients with heteroskedasticity for Germany.

Figure 9: **Quantile Regression Coefficients with Heteroskedasticity for Italian CDS**



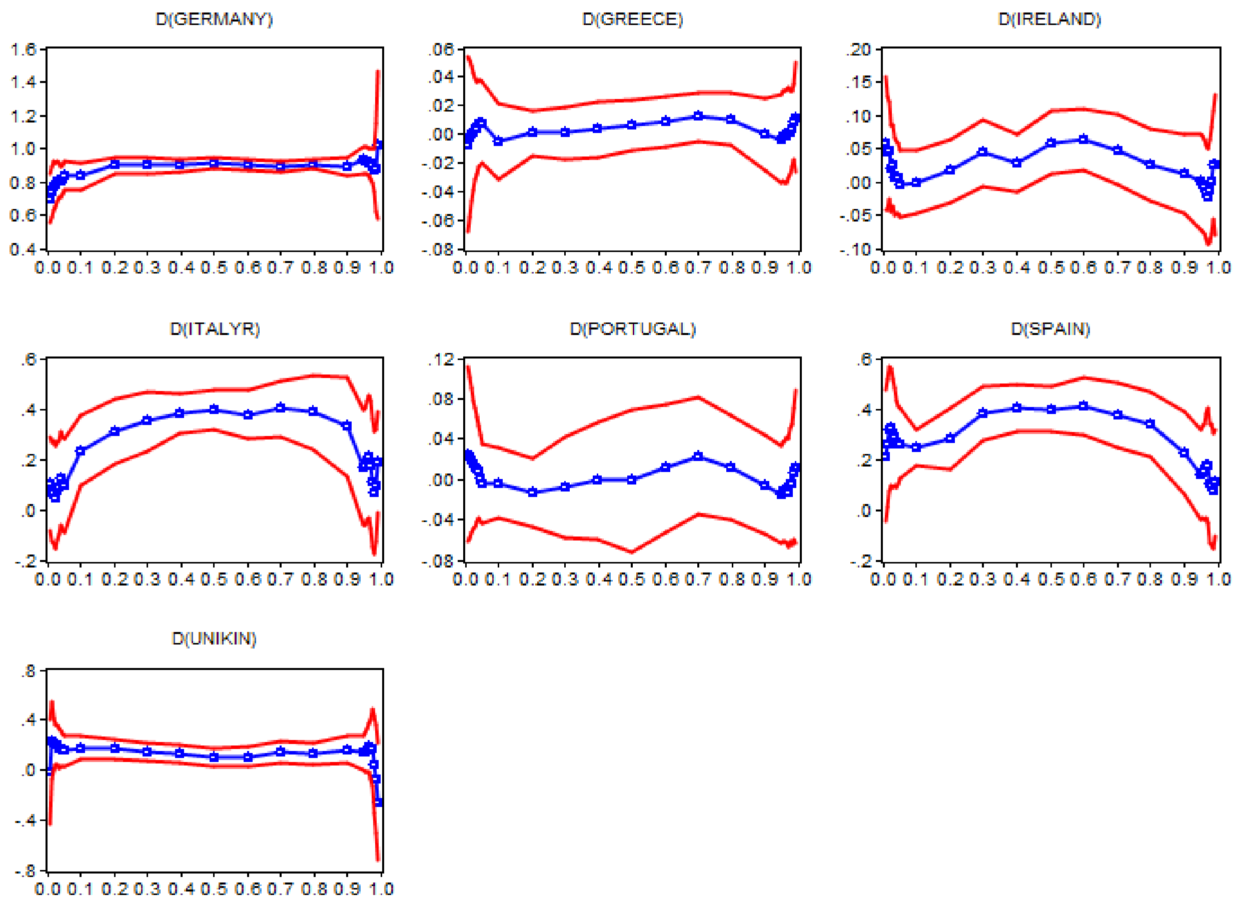
Notes: This figure shows the quantile regression coefficients with heteroskedasticity for Italy.

Figure 10: **Average Rolling Variance**



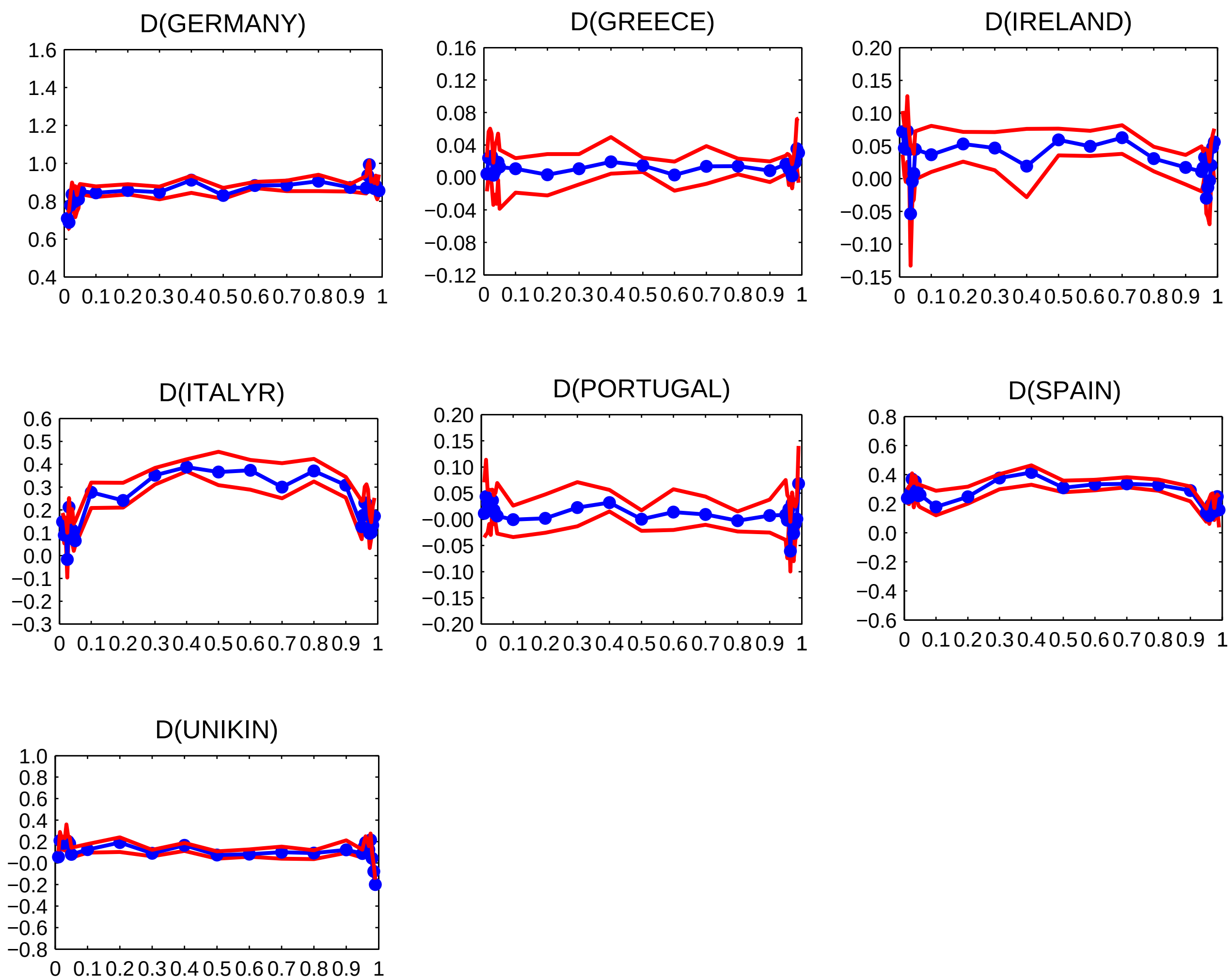
Notes: This figure reports the average rolling variance

Figure 11: **Quantile regression coefficients for French Bond Spreads, 2008–2011**



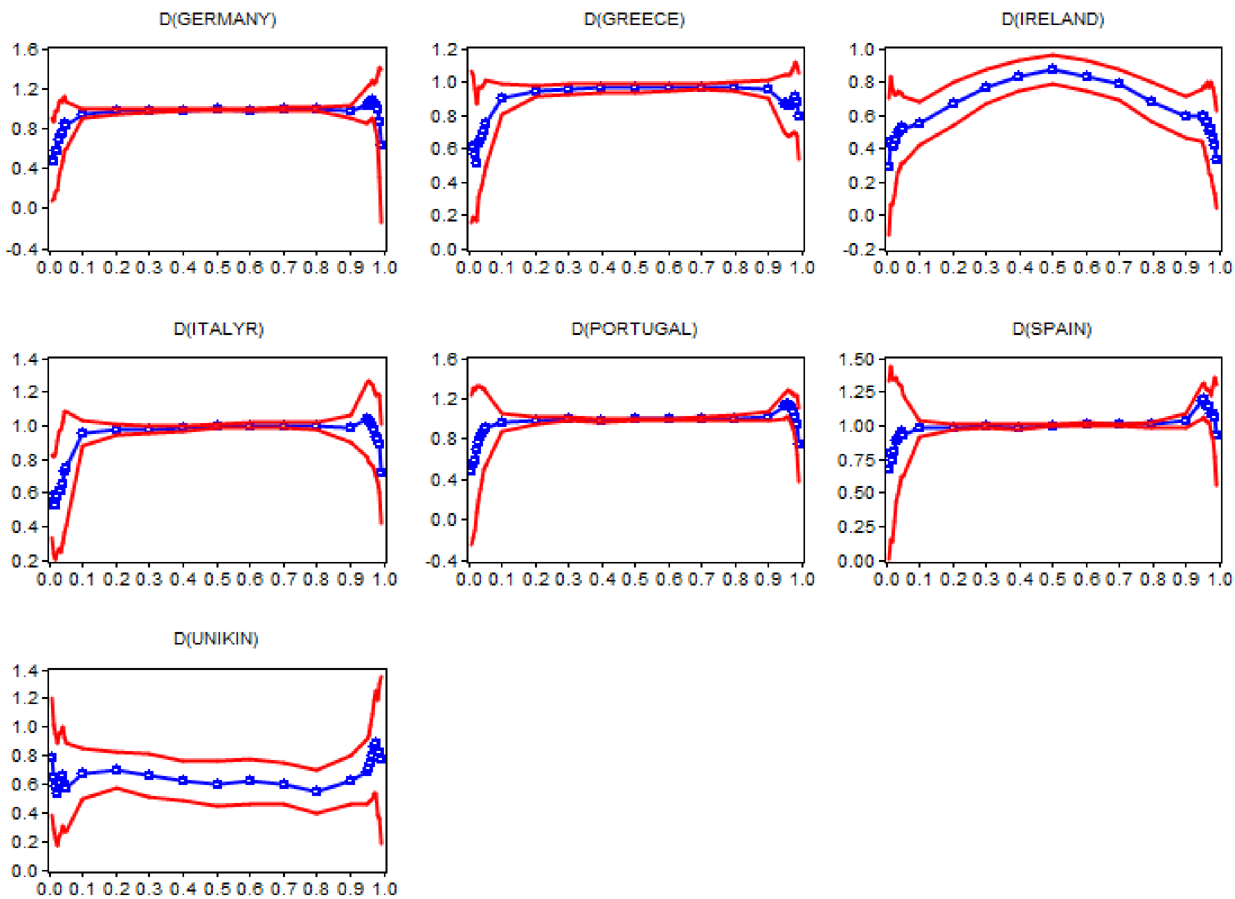
Notes: This figure shows the quantile regression coefficients for French bond spreads over the sample 2008–2011.

Figure 12: **Quantile Regression Coefficients with Heteroskedasticity for French Bond Spreads, 2008–2011**



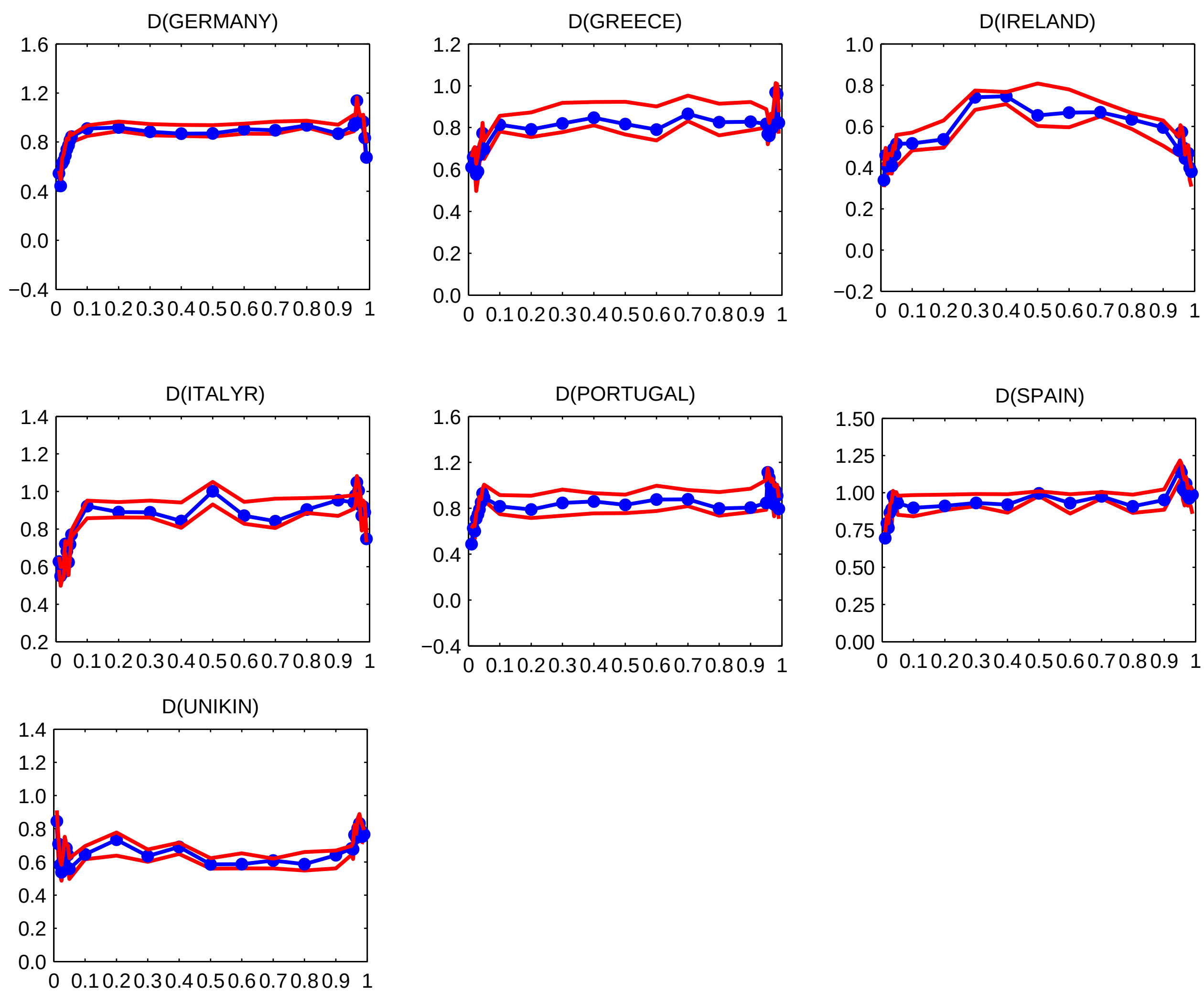
Notes: This figure shows the quantile regression coefficients with heteroskedasticity for Italian bond spreads over the sample 2008–2011.

Figure 13: **Quantile Regression Coefficients for French Bond Spreads, 2003–2006**



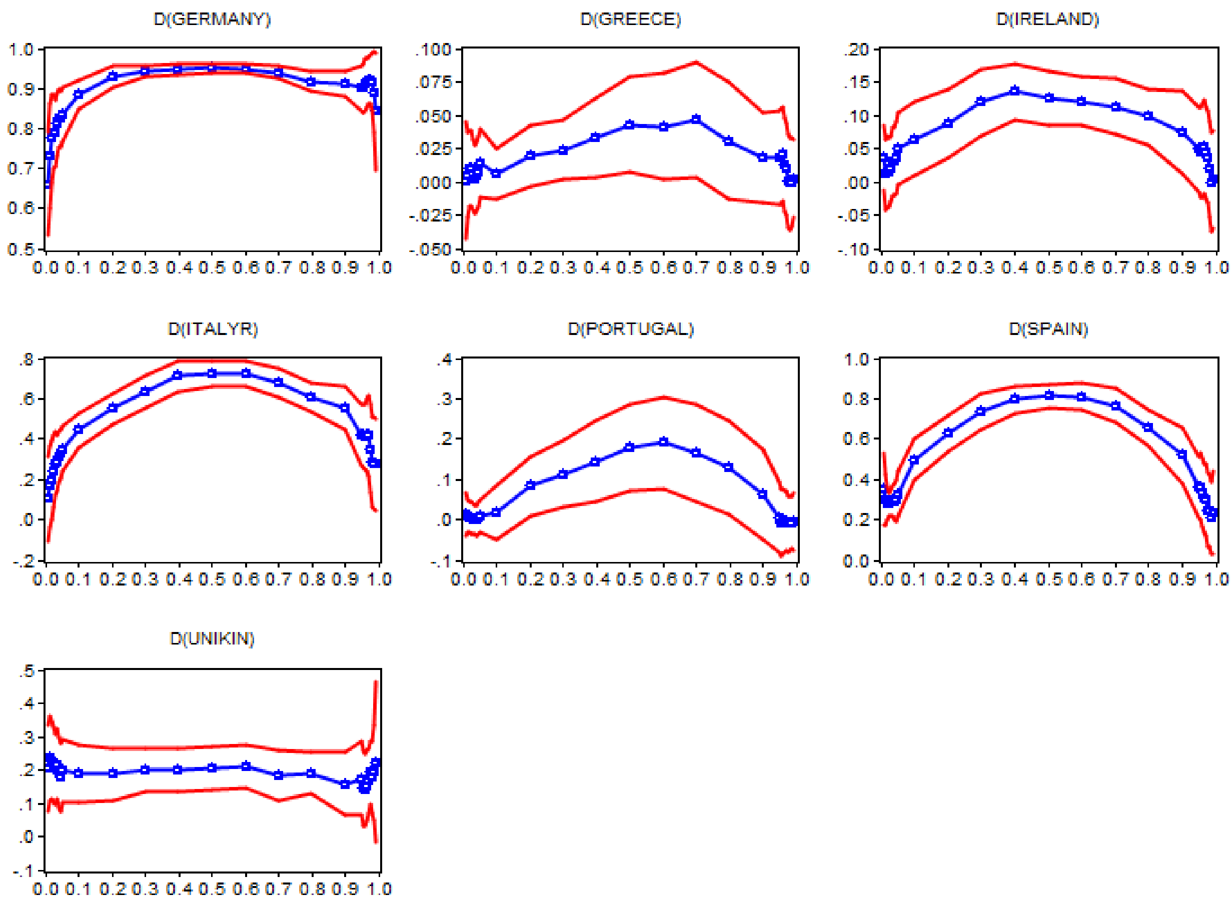
Notes: This Figure shows the quantile regression coefficients for French bond spreads over the sample 2003–2006.

Figure 14: **Quantile Regression Coefficients with Heteroskedasticity for French Bond Spreads, 2003–2006**



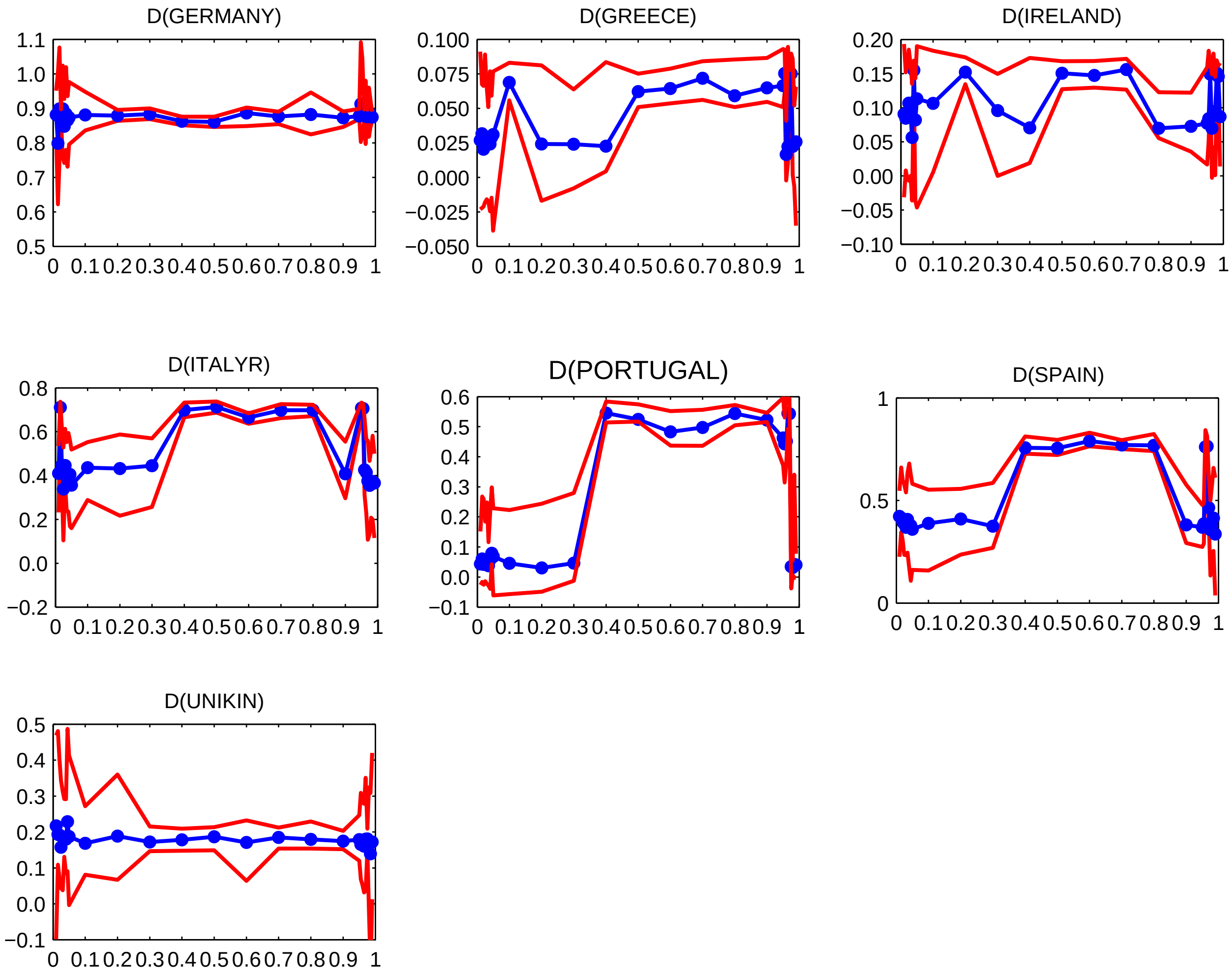
Notes: This figure shows the quantile regression coefficients with heteroskedasticity for Italian bond spreads over the sample 2003–2006.

Figure 15: **Quantile Regression Coefficients for French Bond Spreads, 2003–2011**



Notes: This figure shows the quantile regression coefficients for French bond spreads over the sample 2003–2011.

Figure 16: **Quantile Regression Coefficients with Heteroskedasticity for French Bond Spreads, 2003–2011**



Notes: This figure shows the quantile regression coefficients with heteroskedasticity for Italian bond spreads over the sample 2003–2011.