Measuring Sovereign Contagion in Europe*

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Abstract

This paper analyzes the sovereign risk contagion using CDS and bond spread for the major euro area countries. Using several econometric approaches (non linear regression, quantile regression and Bayesian quantile regression with heteroskedasticity) we show that propagation of shocks in Europe's CDS's has been remarkably constant for the period 2008-2011 even though in 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 countries is stable, and the risk spillover among countries is not affected by the size of the shock. Results for the same sample are confirmed by bond spreads. However, the analysis on bond data shows that there is a change in the intensity of the propagation of shocks in the pre crisis period (2003-2006) and the post Lehman one (2008-2011) and the coefficients actually come down, not up! All the increases in correlation we have witnessed in the last two years is coming from larger shocks and the heteroskedasticity in the data, and not from similar shocks propagated with higher intensity across Europe. This is the first paper, to our knowledge, where a Bayesian quantile regression approach is used to measure contagion. This methodology is particularly good to deal with non-linear and unstable transmission mechanisms.

JEL Classification: E58, F34, F36, G12, G15.

Keywords: Sovereign Risk, Contagion

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1 Introduction

The 2010 sovereign debt crisis in Europe 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 France and Germany are going to be affected? How about countries outside the European Union? Through which channel is the shock going to be transmitted? etc. Clearly these are important questions for economists, policy makers, and practitioners. However, the empirical challenges to address these questions are extraordinary.[1]

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

Some literature tends to define contagion as the comovement that takes place under extreme conditions – or tail events[3]–while another sizeable proportion of the literature compares how different the propagation of shocks is after normal and rare events. The first definition concentrates on the measurement of the transmission after a bad shock takes place, while the second one measures how different the propagation is after a negative shock appears. It is impossible to solve this "semantic" problem in this paper, but 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 contagion exists within the sovereign debts in Europe– where contagion is defined as how different the propagation is after a large negative realization has taken place.

The second challenge is an empirical one. Contagion is an unobservable shock and therefore most empirical techniques have problems dealing with omitted variables and simultaneous

[1]For a survey indicating the shortcomings of most empirical methods see 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.

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 crisis times, how can we be sure that this is the outcome of a shift in the propagation and not the result of the fact that correlations are not neutral to shifts in volatility? Crisis times 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, again, 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 variable 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 channel of transmission of the Russian crisis in 1998 was going to be LTCM. Furthermore, even though several economists anticipated the US 2008 crisis, none described the transmission from the subprime, to insurances, to AIG, and then to the rest of the world. The profession is extremely good at describing the channels through which shocks are transmitted internationally right after the contagion has taken place. This puts a significant constraint on structural estimation. Structural estimations of contagion have the problem 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 existence of contagion that was not fully taken into account before the shock occurs.

In this paper we first evaluate the extent of contagion in the credit default swaps (CDS) in the euro region using a reduced form approach based on quantile regressions. As mentioned, contagion is measured as a shift in the propagation when large shocks occur – i.e. comparing the highest quantile and the middle ones. In this methodology when the coefficients are the same

[4]See Forbes and Rigobon (2002).

it means that the underlying transmission mechanisms are the same, and that the econometric problems such as omitted variables and endogeneity are not significantly enough to provide a rejection. This is indeed the result we find: for every pair of countries in our data, the contagion at the extreme quantile is not statistically different from the contagion that exists in the mid-quantile. We examine sovereign CDS in the period from November 2008 to September 2011 of seven European countries on the euro area: France, Germany, Greece, Ireland, Italy, Portugal, Spain, and a European Country that is not on the euro area: The United Kingdom.

The biggest drawback the CDS data has is that it starts in November of 2008 – well into the US financial crisis. So, the comparison we perform is between two different crisis periods: the Lehman meltdown (started in September 2008) and the fiscal crisis in Europe started after 2009. The advantage of the CDS data is that it captures the sovereign risk and therefore it is a very clean exercise. To deal with the weaknesses in the data we also measure the extent of contagion in bond spreads. In this case the data runs since 2003. When we perform the exact same exercise that we did for the CDS we find two main results. First, there is a change in the intensity of the propagation of shocks in the pre crisis period (2003-2006) and the post crisis one (2008-2011). However, the coefficients actually come down, not up! This is encouraging from the methodological perspective because it clearly indicates that it has enough power to find a rejection in certain samples. Second, the propagation between 2008-2011 is stable and quite surprisingly the coefficients are very similar between bonds and CDS's.

All our results offer a consistent message: propagation of shocks in Europe's CDS's and Bonds has been remarkably constant between 2008-2011 even though in 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 is coming from larger shocks, and not from similar shocks propagated with higher intensity across Europe. Finally, the only evidence of parameter instability we find is in the bond market, and actually points to a weakening of the contagion channel between 2003-2006 and 2008 onwards.

We start by measuring pair of correlations across time and show that it shifts all over the place. In this particular case the Forbes and Rigobon (2002) correction cannot be used because that procedure needs to know which country or variable is the one that causes the increase in volatility. For several of our pairs this is impossible.[5] The next step is to directly test for non-linearity using a polynomial specification within a time-series regression framework. We estimate allowing for second and third order terms and test for the significance of non-linearity. In fact, in our regressions we find a large number of significant coefficients (73%) but when we evaluate their economic impact we find that the non-linearity is small. The problem of these regressions is that they impose too much structure and might be underestimating the transmission of extreme events.

Finally, we measure contagion using quantile regressions. The main advantage of using the quantile regression is that is a very natural and powerful way to deal with possible non-linearities or parameter instability in the data. By conditioning on the size of the shocks and evaluating the propagation mechanisms via the interdependence between the dependent variable and the explanatory ones, this methodology allows to understand and to estimate the extent of asymmetries — such as the transmission of positive and negative shocks.

We start with a standard quantile regression to highlight the main point. We show that the transmission of shocks is the same across different quantile. This methodology although allows for changes in the conditional densities across time, if such changes are not specifically modelled the estimates might be inefficient. This leads us to the estimation of quantile regressions allowing for heteroskedasticity.

We follow Chen, Gerlack and Wei (2009) and assume 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 on all model parameters. Moreover, the methodology used is efficient and flexible in handling the non-standard likelihood

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

and is based on the use of prior information. We choose weak uninformative prior to allow the data to dominate inference. Again the results show that sovereign risk contagion is largely a linear phenomenon. Moreover, posterior distributions of the parameters show lower uncertainty than the standard quantile regression, in particular for extreme quantile.

There is an extensive literature on contagion and it is impossible to review it here. We direct the interested reader to the multiple reviews that 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's.

In particular, some recent research on this topic concentrates on the relantion 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, Pan, Pedersen, and Singleton (2011) and Ang and Lonstaff (2011). These works show that the most significant variables for CDS credit spreads are the U.S. stock and high-yield market returns as well as the volatility risk premium embedded in the VIX index. Moreover, Acharya, Drechsler and Schnabl (2011) concentrate on the financial sector bailouts and, using a broad panel of bank and sovereign CDS data, show that bank and sovereign credit risk are intimately linked. Our paper complements and extends this literature by investigating the degree of co-movement among sovereign CDS (and bond spreads) after controlling common factors that explain credit spreads, 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.

2 The data

A CDS contract obliges the seller of the CDS to compensate the buyer in the event of loan default, see definitions in Duffie (1999), Longstaff, Mithal, and Neis (2005), Pan and Singleton (2008), Longstaff, Pan, Pedersen, and Singleton (2011), and others. It is generally a swap agreement because in the event of 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 from Datastream. We consider the euro denominated CDS of seven European countries on the euro area: France, Germany, Greece, Ireland, Italy, Portugal, Spain, and a Eurpean Country that is not on the euro area: The United Kingdom. Therefore, our sample considers periphery countries (Greece, Ireland, Italy, Portugal and Spain) such as the three largest economies in the European Community area: France, Germany and the United Kingdom. The sample covers the period from November 2008 to September 2011. The beginning of this sample period is dictated by the availability of CDS data for all of the countries in the study. Figure 1 reports the evolution of the CDS levels in the sample considered.

Table 1 provides summary information for the daily sovereign CDS premiums[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 sovereign CDS premiums present significant time-series variation. In Figure 2 we reports the dynamic of the changes in the CDS spreads through time. One aspect that it is important to observe is that the magnitude of the changes is rather different through time indicating the presence of heteroskedasticity.

Since we focus on the co-movement in CDS spreads among the different countries on top of common changes due to a set of global common factors we have considered also the variables that the previuos literature has identified as the most significant for CDS credit spreads. We

[6]All CDS premiums are denominated in basis points.

have therefore considered 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 summary statistics of these variables as well as the summary statistics of the daily changes in sovereign CDS premiums.

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 8 sovereigns is 0.502.

3 Methodology and Results

3.1 Non parametric inference

As a first evaluation of the linearity of the relationship across CDS and its stability we consider the rolling evaluation of the linear correlation. We calculate correlation among changes in CDS spreads considering 60 observations, roughly equivalent to one quarter.[7] The rolling correlation is plotted in Figure 3 from January 2009 through September 2011. This figure shows overall high values of the correlation between changes in the CDS national indices (generally between 0.3 and 0.7). Furthermore, we observe that the correlations across the countries changes largely through the sample. Looking to the last part of the sample it seems that the averall 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 and all the other countries. As Figure 4 shows, in the last part of the sample the correlation with almost all the other countries

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

decreases but, with Italy and Ireland increases[8].

To evaluate the possible presence of non-linearities in the relationships 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 follow:

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

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

where i and j denote any two different countries, while F_i and F_j are the cumulative density functions of the corresponding CDS variations. Therefore, the exceedence correlation ρ^- measure 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^+ are the more interesting. Figure 5 presents the results for France.[9] We graphically represent the exceedence correlations by reporting in the middle 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 the correlation across countries. This is not the case for the opposite: for large negative CDS changes, the correlation across countries tends to increase (in most cases).

This measure, despite being interesting, has a drawback: it is affected by the changes in the marginal density. Moreover, it suffers of the problem highlighted by Forbes and Rigobon (2002), the ΔCDS volatility might differ during market turbulence compared to the volatility during tranquil market periods and these changes may bias the correlation measure. This

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

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

clearly emerges when looking at figure Figure 2, where the volatility tends to increase during 2010. For this reason these measures cannot be used to investigate the sovereign risk spillover among countries

The adjustment proposed in Forbes and Rigobon (2002) cannot be used in this case. The primarily reason is that such adjustment requires the knowledge of the source of the increase in volatility. For instance, during the Tequila Crisis (Mexico 94) the origin of the crisis is Mexico and therefore the adjustment can be implemented. During the European Sovereign Debt crises there are several countries in crisis. This leaves the correlation measures uninformative of the degree of co-movement in the data.

3.2 Parametric inference

An alternative to deal with the problem that arises from the heteroskedasticity in the data and the bias it produces in correlation measures, is to estimate the relation using projection methods. In this setting, contagion is reflected as a larger coefficient after a crisis has taken place. This is equivalent to a non-linearity. To investigate the linearity in the projection between the changes in the CDS indices of any two countries we have to consider first the simple linear model and then test the null hypothesis of linearity using a simple diagnostic procedures. More formally, we estimate first a Generalized AutoRegressive Conditional Heteroskedasticity (GARCH)(1,1) baseline model:

$$\Delta CDS_{i,t} = \beta_0 + \beta_1 \Delta CDS_{j,t} + \gamma' X_{t-1} + \sigma_t \varepsilon_t \tag{3}$$

$$\varepsilon_t | I^{t-1} \sim D(0,1) \tag{4}$$

$$\sigma_t^2 = \theta_0 + \theta_1 \varepsilon_{t-1}^2 + \theta_2 \sigma_{t-1}^2 \tag{5}$$

where i and j are 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.[10] Moreover, the parameters in the GARCH equation (5) must satisfy the constraints leading to variance positivity and covariance stationarity, namely $\theta_0 > 0$, $\theta_1 \geq 0$, $\theta_2 \geq 0$, and , $\theta_1 + \theta_2 \leq 1$.

Furthermore, the parameters in the model (3) are estimated by quasi maximum likelihood with robust standard errors. The null hypothesis of linearity is tested by means of simple diagnostic procedures. As first, we might consider the following extended model:

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

where linearity is associated with the null hypothesis $H_0 : \phi_l = 0 \forall l = 2, \ldots p$. 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 26 and 40 cases out of 56. Moreover, jointly testing their significance shows evidence of their relevance in 41 cases out of 56. However, if we compare the impact coming from the linear term to the coefficients associated with the squared and cubed changes in the explanatory CDS variation, we note that the coefficients are extremely small. This is common across countries and it not associated with a specific

[10]We have repeated the same analysis using as covariates the same variables used in Ang and Longstaff, 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.

dependent country neither on a peculiar country where CDS movements are 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 changes in the CDS for country j reported in Table1 we have that the economic impact of the nonlinearity is extremely small (as shown in Table 4).

We thus faces some evidence of non-linearity but 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 they are in general mistaken by non-linearities when not properly corrected. These issues will be dealt bellow. Thus far, however, whatever evidence of non-linearity we find it implies a very small effect.

The weakness of the linear and non-linear 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, in case of flight-to-quality occurrences, during large movements the dependence across countries would drop, while during contagion events this is expected to increase. The flight-to-quality case and the potential changes in the linear relations might also be seen in the Exceedence correlations which are in most cases not stable across quantile. We thus take the problem from a different technical viewpoint and consider Quantile Regressions between the CDS changes of any two countries.

The overall analysis above indicates that the relation among the different countries is the same for small and large changes in the CDS spread. However, this may come just because the OLS is assuming linear mean relationships while the non-linearity might be more complex. Therefore, our specification will not be flexible enough to detect the contagion in the data. For this reason, we recur to a quantile regression next.

3.3 Quantile Regression

Quantile regression offers a systematic strategy for examining how variables influence the location, scale, and shape of the entire response distribution. The advantage is that quantile regressions is a particularly efficient way to estimate a linear relation that vary across quantile and therefore to detect the presence of interdependence asymmetries in the data. In fact, the coefficients capture the "interdependence" relation between the dependent variable and the explanatory ones. In absence of covariates, for the dependent variable Y in the quantile regression over a constant, the β_0 coefficient at quantile τ is the quantile of the variable Y, and thus β_0 with $\tau = 0.5$ is the median, and with $\tau = 0.05$ is the 5% Value at Risk (VaR). If we add covariates, we are computing Conditional quantile analysis, thus Conditional VaR but where coefficients leading to the estimation of the Conditional VaR are quantile-specific. If the coefficients β_1 and γ are constant across quantile, the VaR estimated from a linear regression and the Conditional VaR estimated from quantile regression are identical. Differently, if the dependence between the Y and the covariates changes across quantile, coefficients will also change, and the VaR computed from a linear regression conditioning on covariates, and the Conditional VaR computed from quantile regression will be different. However, only quantile regression will allow to detect the differences across quantile.

Starting from the linear model in 3, the Quantile Regression is determined by solving the following problem

$$min_{\Theta} \sum_{t=1}^{T} \rho_{\tau} \left(\Delta CDS_{i,t} - \beta_0 - \beta_1 \Delta CDS_{j,t} - \gamma' X_{t-1} \right) \tag{9}$$

where $\rho_{\tau}(a)$ is the *check* function for quantile τ defined as $\rho_{\tau}(a) = a \times (\tau - I(a < 0))$ and $\Theta = \{\beta_0, \beta_1, \gamma'\}$. Note that the minimization of (9) lead to the identification of the τ conditional quantile for $\Delta CDS_{i,t}$ which we denote as

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

where the hat denotes estimated values while the τ subscript identified the reference quantile. For details on the Quantile Regression see Koenker (2005). The introduction of the covariates allows controlling for the impact coming from common information. Analyzing the coefficients across different quantile values τ we can infer the stability of the linear relantion between the dependent variable and the explanatory ones. We are in particular interested by the relation between the two changes in CDS, and we would like to verify if the dependence of $\Delta CDS_{i,t}$ on $\Delta CDS_{j,t}$ is stable across quantile with a special focus on the upper quantile (that correspond to increased in the CDS levels).

The most relevant coefficient is thus β_1 which identifies the dependence, at a given quantile, between the two ΔCDS. If this coefficient is equal to 1, a change in the CDS of country j is replicated in the CDS of country i. Coefficients larger than 1 leads to an amplification of the effect, while coefficients smaller than 1 can be read as a limited interdependence between the CDS of country j and the CDS of country i. If we observe large differences in the coefficients among the different quantile this means that the connections among the two countries are changing and different relations might be detected. In particular, if the coefficients $\beta_{\tau,1}$ on the upper tail (τ larger than 0.9) are statistically larger than the coefficient estimated on the median, we are in presence of a contagion occurrence. In fact, when the ΔCDS of country i is in its upper quantile (and thus associated with increases in the CDS level), an increase in the ΔCDS of country j provides larger effects compared to what we observe in the median, and thus might have an amplification effect on the increase in the ΔCDS of country i. Note that a similar interpretation is at the basis of the $\Delta CoVaR$ measure of Adrian and Brunnermeier (2011). Conversely, if at the upper quantile the coefficient $\beta_{1,\tau}$ decreases compared to the median, the two countries are becoming less interdependent when large movements take place in country i. Moreover, if we focus at lower quantile of the ΔCDS (τ lower than 0.1), larger coefficients might still be associated with contagion occurrences, but in this case the contagion has a positive connotation since a decrease in the risk of country j (a decrease in the ΔCDS) is transmitted to country i with an impact that is larger than what we observe in the median. Compared to the evaluation of quantile (or VaR) in a traditional linear regression framework, quantile regression is more flexible and would allow a more precise measure of the risk associated with a given country. Clearly, the absence of contagion, or better, the absence of interdependence, might be present at single quantile or at different quantile levels, leading to several different designs of the relationships across countries. In addition, the coefficients $\beta_{\tau,1}$ might also change over time, with possible increases (decreases) in the interdependence or contagion across countries.

If the coefficient is statistically larger than before, we are in presence of contagion on the tails, i.e. a large increase in the CDS of country generates a significant increase of the CDS of country. Note that contagion exists if the coefficients in the extreme quantile are statistically different and larger than those in the middle quantile. The absence of contagion might be present in single quantile, or for different quantile levels. Finally, the decrease over time of the β_1 coefficient might be associated with a decrease in the interdependence of the different countries for all the levels of changes in CDS.

To analyse the link between $\Delta CDSs$ we estimated the quantile regressions in (9) across any two ΔCDS variables, conditioning also on the lagged exogenous variables used in (3). Given the estimates, we perform the two following evaluations: first, we graphically analyse the variation of the coefficient β_1 across different quantile; second, we run the test for quantile stability to verify that coefficients are statistically stable across quantile.

Figure 6 reports the values of the β_1 coefficient across different quantile levels for all the possible pairs of countries in our dataset. Each Figure shows the coefficient values for several quantile and for each other country. Note that each panel of each figure is obtained from a different quantile regression (we are thus not considering system estimation, not the estimation of quantile regressions with several ΔCDS as explanatory variables). Furthermore, the figures 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: 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 Figures, two common features emerge. At first, and as expected, the dispersion of each quantile regression coefficient is much larger for extreme quantile (below 0.1 and above 0.9). This is associated with the smaller number of events falling in those quantile. Secondly, the coefficients are almost flat across quantile, suggesting that the dependence between the movements of any two ΔCDS is not changing as a function of the size and sign of the movements. Furthermore, the impact is always statistically significant as the 95% confidence intervals do not include the zero. The equivalence across upper quantile, the most interesting with respect to the purposes of this study, might be easily tested.

Table 5 reports the tests for equivalence across quantile for the two following null hypothesis: v $H_0 : \widehat{\Theta}_{0.90} = \widehat{\Theta}_{0.95} = \widehat{\Theta}_{0.99}$ 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 we maintained in the second test 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.

In summary, in this subsection we find that the relation across quantile is remarkably stable. One aspect that we have not considered, however, is the possibility that the quantile regression could be affected by the presence of heteroskedasticity. This is the topic of the following section.

3.4 Bayesian quantile with heteroskedasticity

The absence of variability across quantile 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 Regression in the previous subsection. Given that the computational complexity of the model will sensibly increase, to reduce the estimation problems we resort to Bayesian techniques.

As mentioned before, quantile regression 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 inefficiency may occur and incorrect conclusions may result. This will especially happen in 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 is assumed to follow a linear model with heteroskedasticity as described in equation (3), where the time-varying conditional variance σ^2 is modeled as a GARCH(1,1) specifications. The quantile effects is estimated using an extension of the usual criterion function in (9) such as:

$$min_{\Theta,\alpha} \sum_{t=1}^{T} \left(\rho_\tau \left(\frac{\Delta CDS_{i,t} - \beta_0 - \beta_1 \Delta CDS_{j,t} - \gamma' X_{t-1}}{\sigma(\tau)} \right) + log(\sigma_t(\tau)) \right) \tag{11}$$

where $\alpha = (\theta_0, \theta_1, \theta_2)$. The extra logarithmic term in this expression ensures that the parameters α do not converge to infinity. The volatility parameters α and the causal effect parameters $\Theta = (\beta_0, \beta_1, \gamma)$ are estimated simultaneously resulting in a vector of parameters $\Phi_\tau = \left(\hat{\Theta}_\tau, \hat{\alpha}_\tau\right)$ with $\Theta_\tau = \left(\hat{\beta}_{\tau,0}, \hat{\beta}_{\tau,1}, \hat{\gamma}_\tau\right)$ and $\alpha_\tau = \left(\hat{\theta}_{\tau,0}, \hat{\theta}_{\tau,1}, \hat{\theta}_{\tau,2}\right)$ and the τ subscript identified the reference quantile. Chen, Gerlack and Wei (2009) shows that the residuals of the equation (11) follows a skewed-Laplace distribution (SLD). The univariate SL location-scale family $SL(\mu, \delta, \tau)$ has the following density function:

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

The above density is standardised to have variance 1, so that σ_t is the conditional variance of $\Delta CDS_{i,t}$ as required. The likelihood of the model (11) has not a standard form solution and estimation of the model via frequentist inference might be difficult. Therefore, we choose a Bayesian approach which 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 non-standard 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 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, 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 on sufficient and necessary conditions on GARCH coefficients. Such restrictions reduce the role of the extra logarithmic term in (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.

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 be taken into account. Moreover, the uncertainty is lower, the confidence intervals are smaller than those estimated in the previous section, in particular, for smaller and larger quantile, indicating that linearity cannot be rejected. Therefore, as for the previous analysis, the relation across quantile is remarkably stable and linear.

Evidence is similar for the other countries[11], the only exception is Italy where parameters for France and Germany cases are subject to larger differences over the quantile. Therefore, Italian CDS's seem more sensitive to large changes in France and Germany CDS's, 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 quantile should be a suggestion 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, and if there was a problem in the linear estimation that would have biased the coefficients, such 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, suggestive evidence. 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 simultaneous equations and omitted variable bias. This is exactly the type of problems that arise in the estimation of contagion and systemic risk. This test, however, only determines if the relation is stable, not its strength.[12] In order to apply the DCC the only needed assumption is that some of the structural shocks are homoskedastic within certain window. In the case of Europe, assuming that when Greece is heading toward the fiscal crisis and its shocks become more volatile, that the shocks in Germany are homoskedastic is a reasonable assumption and implies

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

[12] For an evaluation of the properties of the DCC comparing it to other parameter stability tests see Rigobon (2000).

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 shock, and ε_t are the structural shocks. Assume that all shocks are independent, but not necessarily identically distributed.

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

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[13]:

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

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

[13] This normalization is standard in macro applications. It is only changing the units in which the errors are measured.

Finally, without loss of generality, assume that X_t has mean zero and that is serially uncorrelated.[14]

The problem of simultaneous equations is summarized 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, at least, are indication that a shift in parameter has occurred. However, if the shocks are heteroskedastic, these changes are uninformative about the stability of the coefficients.

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

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

[14] 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

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

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, in the multivariate case, the conditions in which the determinant of the change is zero are easier to satisfy than in 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) which reflects the systemic risk, then if there are less than K variances changing, the determinant is also zero.

For the European recent fiscal crisis the assumptions are that either the crisis is driven by shocks to some of the countries – a sub set of the structural shocks – or the crisis is driven by the common shocks (the systemic shocks). In the end, however, if this assumption is not satisfied, then the determinant of the change in the covariance matrix is going to be different from zero, not because the parameters are unstable but because the assumption on the structure of the heteroskedasticity is wrong. Therefore, we have the join 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 defined a threshold for the different "regimes" (high and low volatility) and computed the determinant of the change in the variance covariance matrix. 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 reduces the power of the test. In order to control for this possibility we try different subsamples/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 bootstrapped the residuals to compute the distribution of the covariance matrix. We implemented 1000 replications and used blocks of size 5.

As can be seen, the results indicate that the parameters are stable and that the heterokedasticity in the data is the outcome of the heteroskedasticity of a subset of the shocks. The implied Tstats are all well bellow the 95 confidence intervals. Furthermore, the one sided test shows all probabilities that are larger than 2.5 percent, with the closest one being at 20 percent.

3.6 Bond spreads Analysis

One disadvantage of the data we are using – for the purpose of the present analysis – is the fact that all our observations are already in what could be considered a tumultuous time: the world is already in 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 is so stable. One way to address this issue is to use bonds spreads instead of CDS and use the methods here derived to study the propagation of shocks on bond spreads.

The advantage of the CDS data is that it captures the sovereign risk and therefore it is a very clean exercise. Instead, bond spreads show a series of drawbacks. First, they are affected by many other factors than CDS, for example they are more related to monetary policy and the actions of the central bank and policy makers.

Second, while the CDS spread is observable in the market, it is not obvious how to compute the appropriate government bond spread. We collected benchmark bond yields on 5 years from Thomson-Reuters for the 8 European countries considered and we calculate the bond spreads relative to the 5-year swap rate because interest rate swap are commonly see as the market participant preferred risk-free rate (see Beber et al., 2009). In addition, this approach guarantees a homogeneous benchmark across the euro area.[15]

In this case the data runs since 2003 and we performed the exact same exercise that we did for the CDS but considering three different samples: (i) the pre crisis period (2003-2006), (ii) the post crisis one (2008-2011) and all the sample (2003-2011). Statistics for the three samples are reported in the Table 7.

Results for the post crisis sample (2008-2011) for quantile regression and Bayesian Quantile regression 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 quantile we cannot reject in most of the cases the coefficients are equal, indicating that linearity cannot be rejected. Therefore, as for the previous analysis, the relation across quantile is remarkably stable and linear. Moreover, the coefficients are rather similar. These results indicate that propagation in bonds is the same as in CDS for the same subsample.[16]

We repeated the analysis for the pre crisis period (2003-2006). Results for quantile regression and Bayesian Quantile regression for France are shown in Figures 13–14. The values are larger to those estimated on the post crisis periods. We still find that for smaller and larger quantile we cannot reject in most of the cases the coefficients are equal (largely for the Bayesian analysis), indicating that linearity cannot be rejected again. It is important to oberserve that

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

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

the coefficients are quite similar among all the different countries except for UK where the coefficient is lower. This indicates that the market is in this period looking to the government bonds issued by Euro countries as very similar, distinguishing slightly with UK government bonds. For the period 2008-2011 instead we do have that the coefficients for UK are largely different among 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 come down, not up! So there is not evidence of contagion. Moreover, the propagation between 2008-2011 is stable and quite surprisingly the coefficients are very similar between bonds and CDS's.

Even if it is clear that there is a structural break in 2008, we performed the exact same exercise in all the sample (2003-2011). Results for quantile regression and Bayesian Quantile regression for France are shown in Figures 15–16. We do not find a linear relation: for smaller and larger quantile we reject in most of the cases that the coefficients are the same. Differences among quantile are larger for Bayesian estimates as we would expect by allowing for heteroscedasticity. The pattern, above all for the Bayesian coefficients, follow a bell-shape profile confirming the results we obtained for the two different subsamples: coefficients are lower and with values similar to the post-Lehman period on the tails and higher and with similar values to the pre-crisis period for the central part of the distribution. This is particular evident for coefficients associated to Greece, Ireland, Italy, Portugal and Spain, whether the relation of France with Germany and UK is more stable over time, such as we also find in the two subperiods analysis. This result is encouraging from the (Bayesian) methodological perspective because it clearly indicates that it has enough power to find a rejection in certain samples.[17]

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

4 Discussion

Recent events in Europe have spurred a new discussion of contagion. In previous circumstances, USA 87, Mexico 94, Thailand 97, Russia 98, USA 2001, etc. the "culprit" of the shock is relatively clear. This is not the case in Europe right now. Several countries in the periphery entered into a fiscal crisis roughly at the same time and therefore several of the techniques that exist in the contagion literature have become inadequate to deal with the present situation. The purpose of this paper is to offer a measurement of contagion based on quantile regressions that deal with 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 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 contagion in Europe has remained subdue so far. This does not mean that the situation might not changed, but it means that so far the common shift in CDS spreads that we have observed in the data is the outcome of interdependence that has been present all the time – the strength in the propagation mechanisms has not changed during the recent fiscal crisis.

This has important implications for policy makers. Our methodology could be considered a policy tool to provide information to the policy makers on the markets view and related risks. The analysis suggest in fact that the market was looking to the Euro area as a perfectly integrated area (leaving in a dream?) and consider sovereign bonds of all the different countries as almost substitutes. From 2008 and largely after 2009 this view has been radically modified and the market has started to distinguish between weak/periphery countries and strong/central countries such that transmission effects of country specific risks have been limited. The only country that still has almost the same power of transmission as before is Germany.

This does not mean that, since there is no contagion or that the transmission of large shocks is lower, strong central countries could easily ignore country specific risk of weak/periphery countries. Transmission effects still exist and are present but the strength in the propagation mechanisms has not changed during the recent fiscal crisis. Therefore, Eurozone countries should be worried of risks that are coming from large shocks of the other countries that are country specific (and maybe try to mitigate them), and not from similar shocks propagated with higher intensity across Europe. From the methodological point of view, our procedure has several advantages; First, it is a very flexible procedure 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 the specific formulation of the channel of contagion before the crisis takes place.

Finally, it is important to highlight that our procedure does not predict changes in propagation, but measure such changes. It is possible that a default in the region shifts the relation across CDS's and that hasn't taken place. We believe this methodology could offer a vehicle to policy makers and market participants to detect such changes when the data suffers from heteroskedasticy.

Appendix

The Bayesian quantile regression with GARCH residuals takes the following form:

$$min_{\Theta,\alpha} \sum_{t=1}^{T} \left(\rho_\tau \left(\frac{\Delta CDS_{i,t} - \beta_0 - \beta_1 \Delta CDS_{j,t} - \gamma' X_{t-1}}{\sigma(\tau)} \right) + log(\sigma_t(\tau)) \right) \tag{17}$$

$$\sigma_t^2 = \theta_0 + \theta_1 \varepsilon_{t-1}^2 + \theta_2 \sigma_{t-1}^2 \tag{18}$$

Define the vector $\Phi_\tau = \left(\hat{\beta}_{\tau,0}, \hat{\beta}_{\tau,1}, \hat{\gamma}_\tau, \hat{\theta}_{\tau,0}, \hat{\theta}_{\tau,1}, \hat{\theta}_{\tau,2} \right)$ and $\Phi_{\tau,j}$ the j-th element of it, the sampling scheme consists of the following iterative steps where the subscription τ is deleted for simplifying the reading:

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

$$\Phi_j^* = \Phi_j^{i-1} + \epsilon_j \;\; \epsilon \sim N(0, \Sigma) \tag{19}$$

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 iterate of Φ_j. The 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 of model (17) conditional on all quantile times 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

$$\Phi_j^* = \mu_{\Phi_j}^{i-1} + \epsilon_j \;\; \epsilon \sim N(0, \Sigma_{\Phi_j}) \tag{20}$$

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

$$p = min\left[1, \frac{f(\Phi_j^*)g(\Phi_j^{i-1})}{f(\Phi_j^{i-1})g(\Phi_j^*)}\right] \tag{21}$$

where $g()$ is the Gaussian proposal density in (20).

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Table 1: **Summary Statistics**

	Mean	Standard Deviation	Minimum	Maximum	Median
		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 linearity relation 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 Model (6) at the 5% 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: See footnote in Table 3

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 quantile**

		$H_0 : \widehat{\Theta}_{0.90} = \widehat{\Theta}_{0.95} = \widehat{\Theta}_{0.99}$		$H_0 : \widehat{\Theta}_{0.98} = \widehat{\Theta}_{0.985} = \widehat{\Theta}_{0.99}$	
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 quantile 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: See footnote in Table 3

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

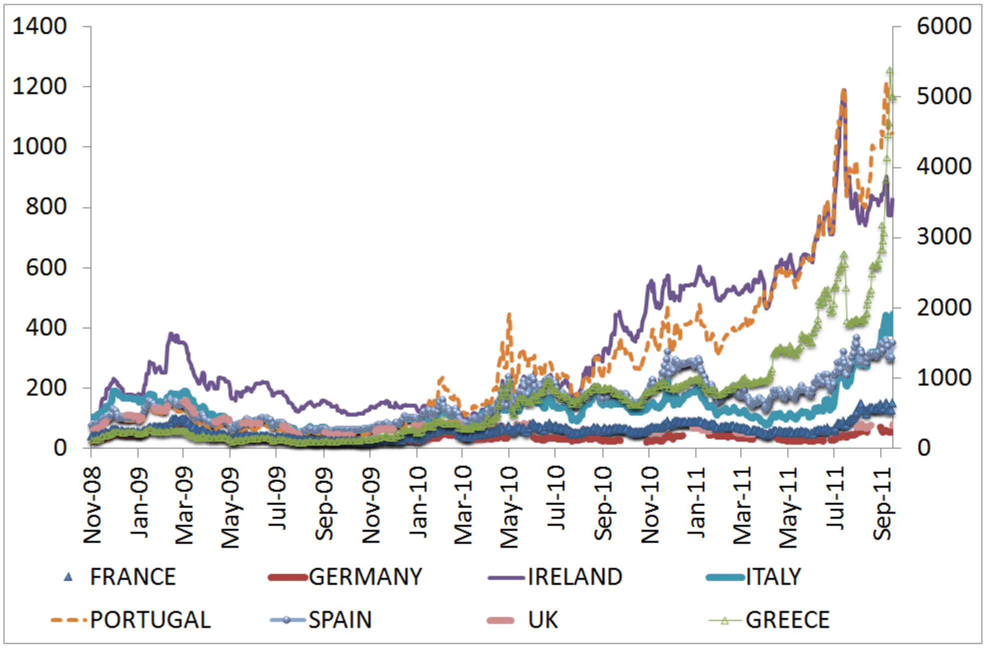
Notes: This Table includes the DCC test across different threshold values.

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
	precrisis - 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

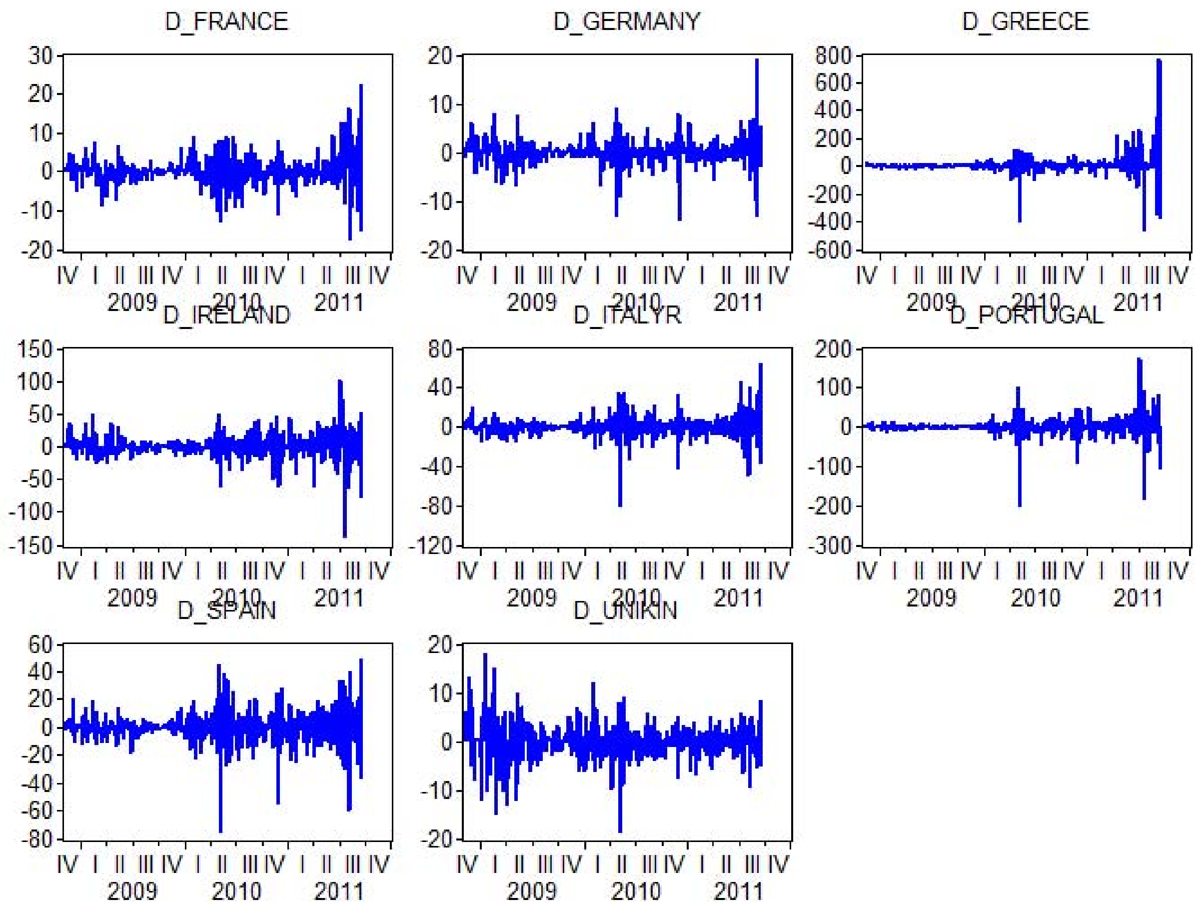
Notes: This table presents summary statistics for daily bond spreads for different samples.

Figure 1: **CDS spreads (levels)**



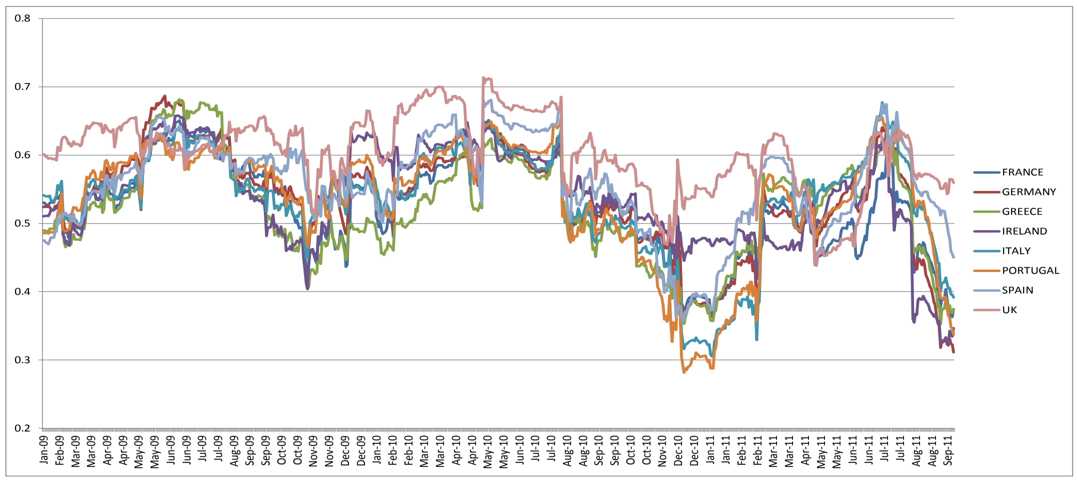
Notes: This Figure shows the levels of the CDS spreads. Left axes for all series apart Greece which is reported on the right axes.

Figure 2: **Changes in CDS spreads**



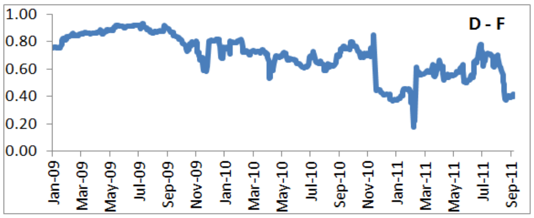
Notes: This Figure shows the changes in CDS spreads.

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

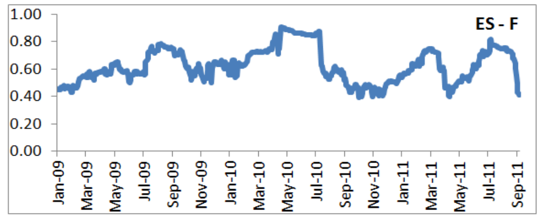


Notes: This Figure depicts a 60-days rolling window average correlation among CDS spreads.

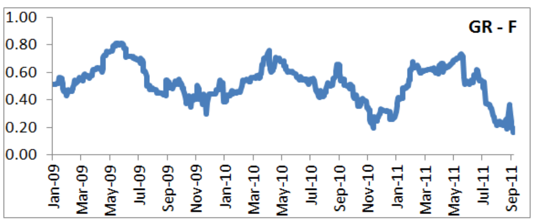
Figure 4: **CDS Rolling Correlation between France and the other Countries**



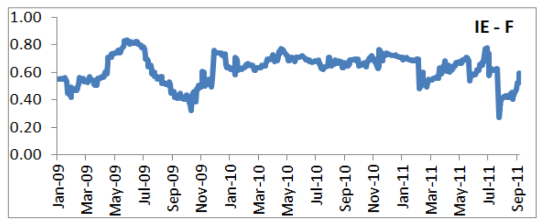
(a) D & F



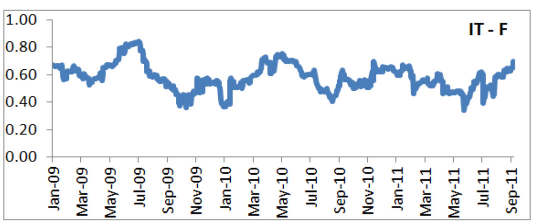
(b) ES & F



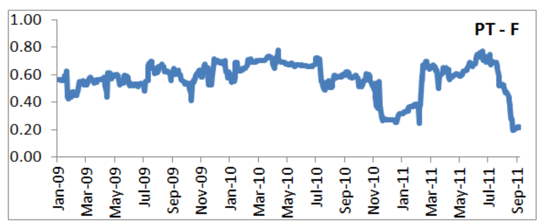
(c) GR & F



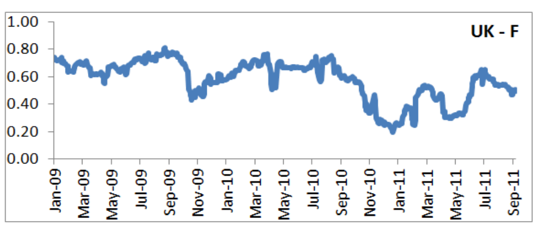
(d) IE & F



(e) IT & F



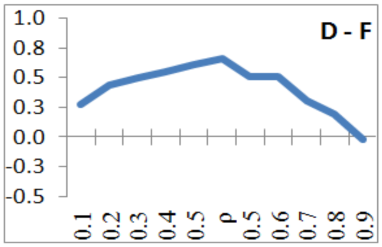
(f) PT & F



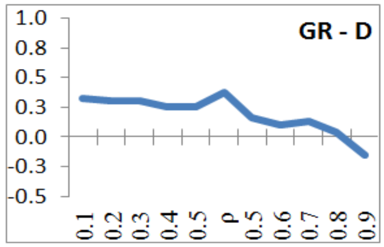
(g) UK & F

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

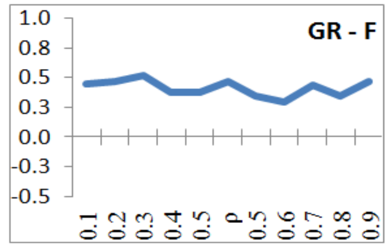
Figure 5: **Exceedence correlations (60-days)**



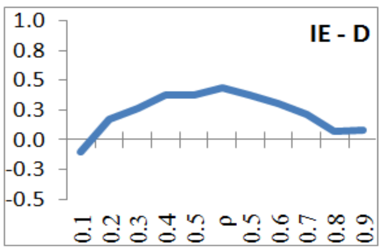
(a) D & F



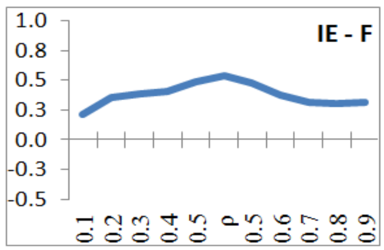
(b) GR & D



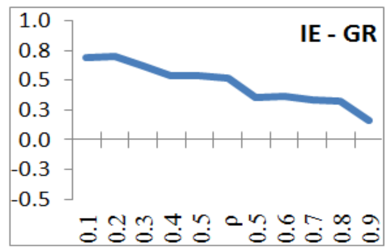
(c) GR & F



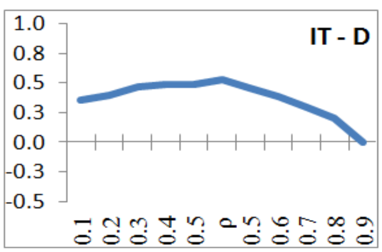
(d) IE & D



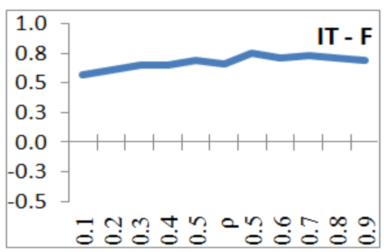
(e) IE & F



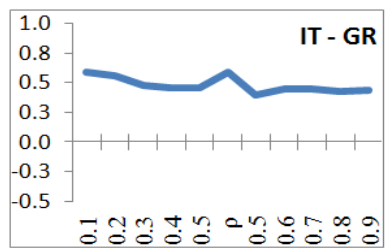
(f) IE & GR



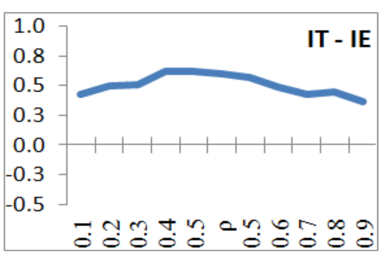
(g) IT & D



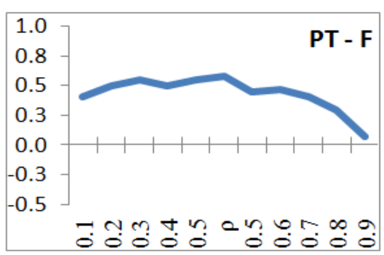
(h) IT & F



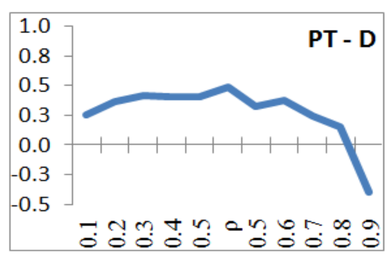
(i) IT & GR



(j) IT & IE



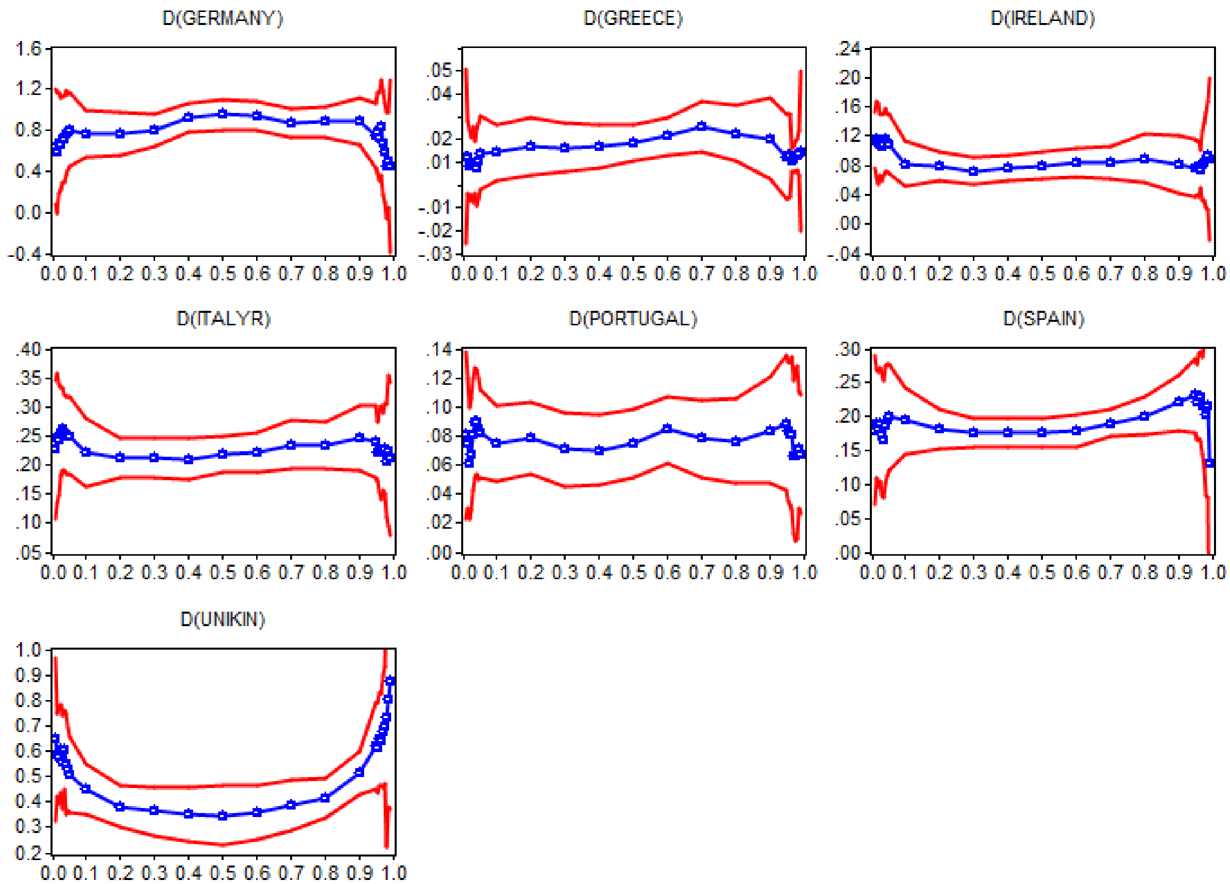
(k) PT & F



(l) PT & D

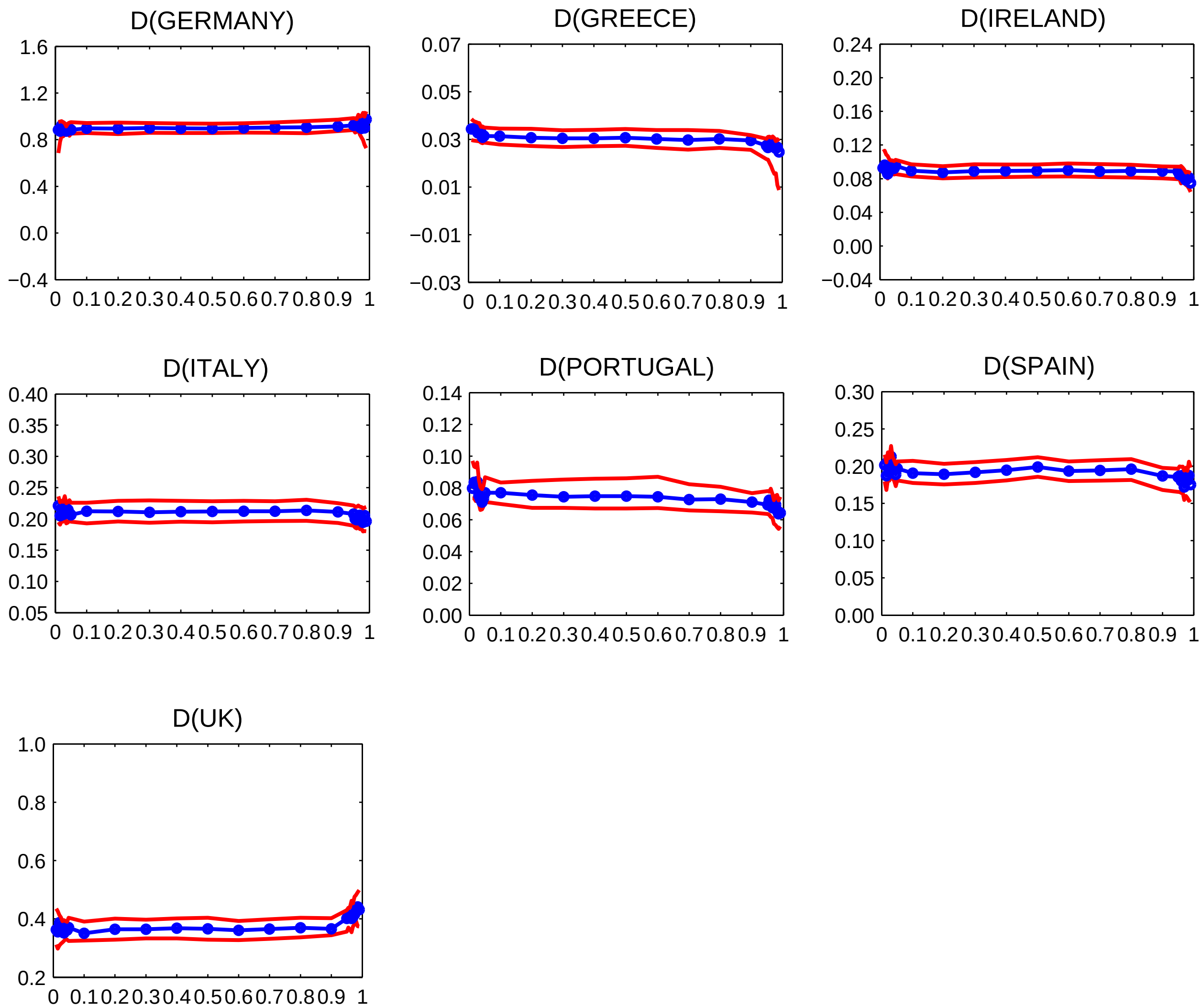
Notes: This Figure shows the 60-days exceedence correlations

Figure 6: **Quantile regression coefficients for French cds**



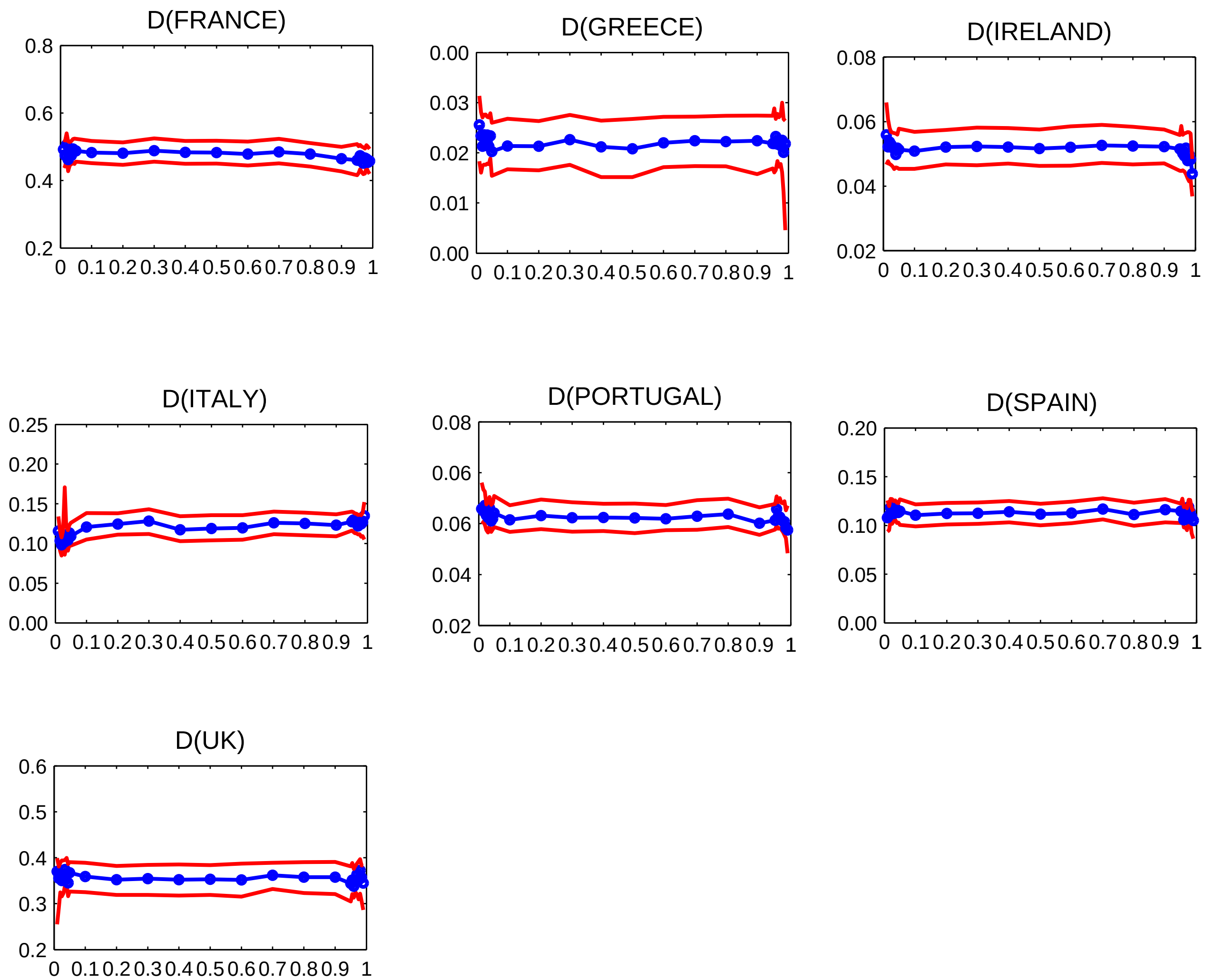
Notes: This Figure shows the quantile regression coefficients for France.

Figure 7: **Quantile regression coefficients with heteroskedasticity for French cds**



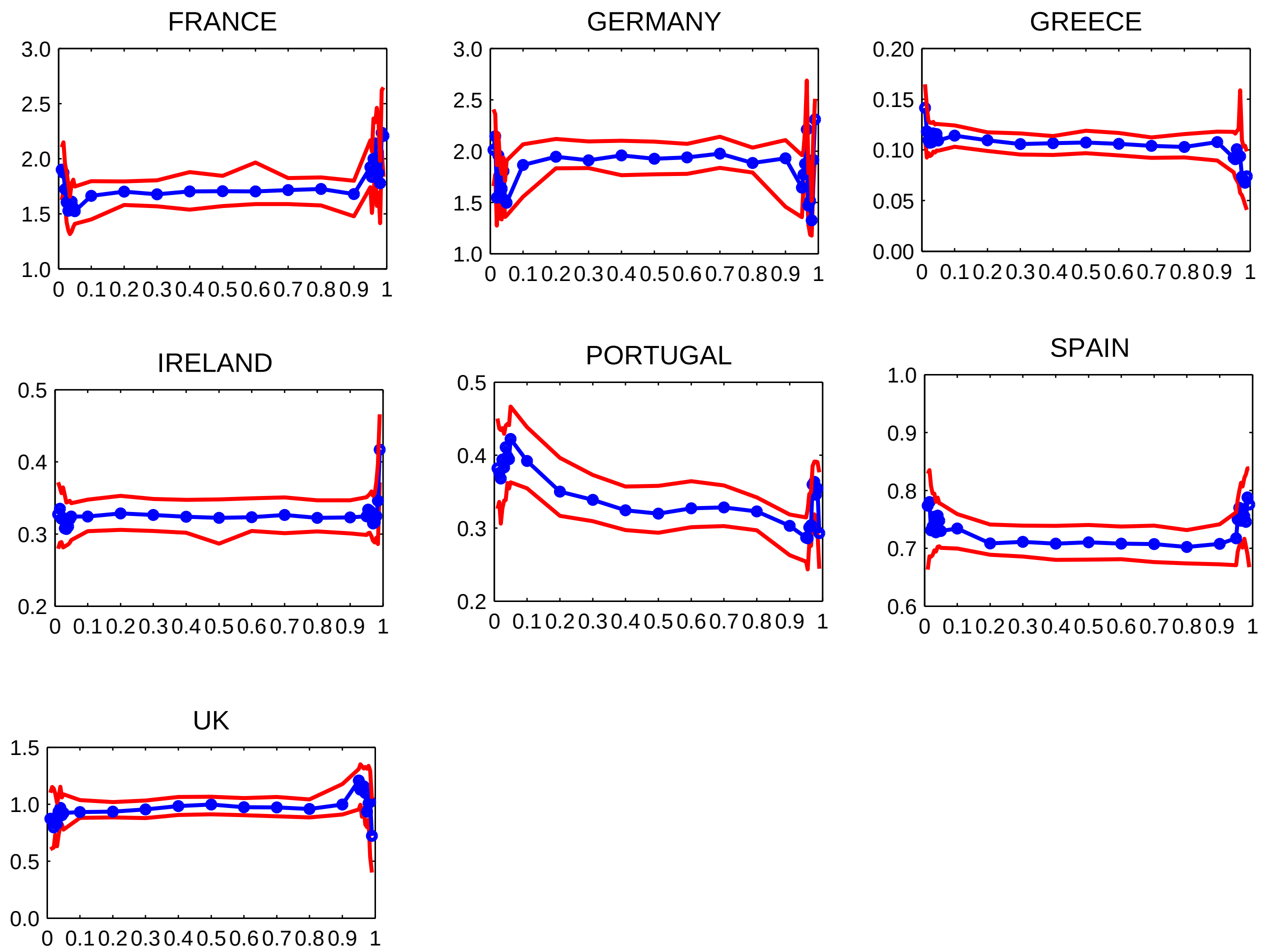
Notes: This Figure shows the quantile regression coefficients with heteroskedasticity for France.

Figure 8: **Quantile regression coefficients with heteroskedasticity for German cds**



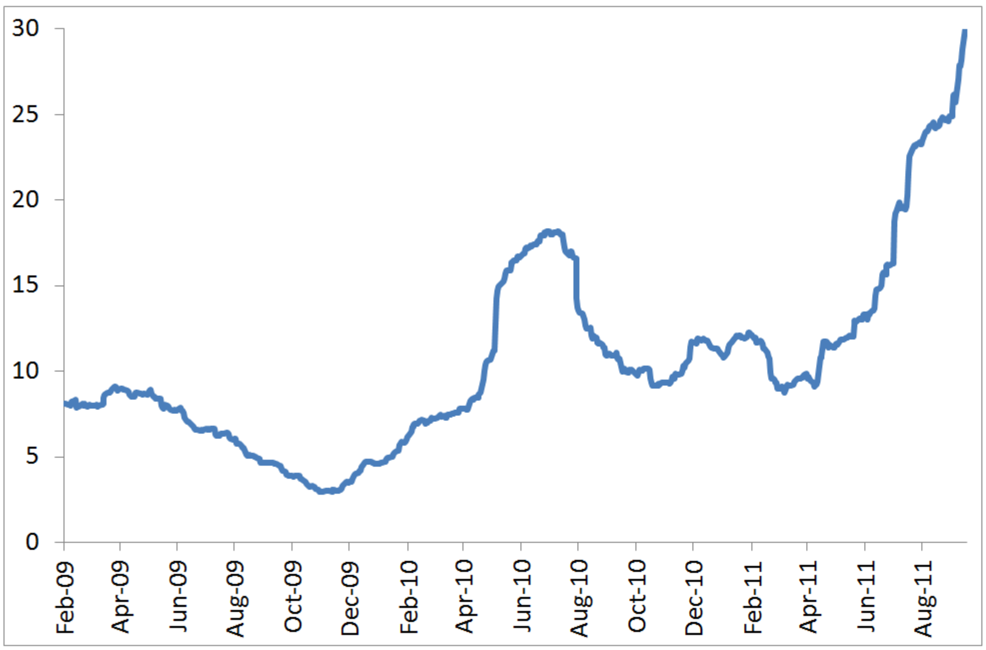
Notes: This Figure shows the quantile regression coefficients with heteroskedasticity for Germany.

Figure 9: **Quantile regression coefficients with heteroskedasticity for Italian cds**



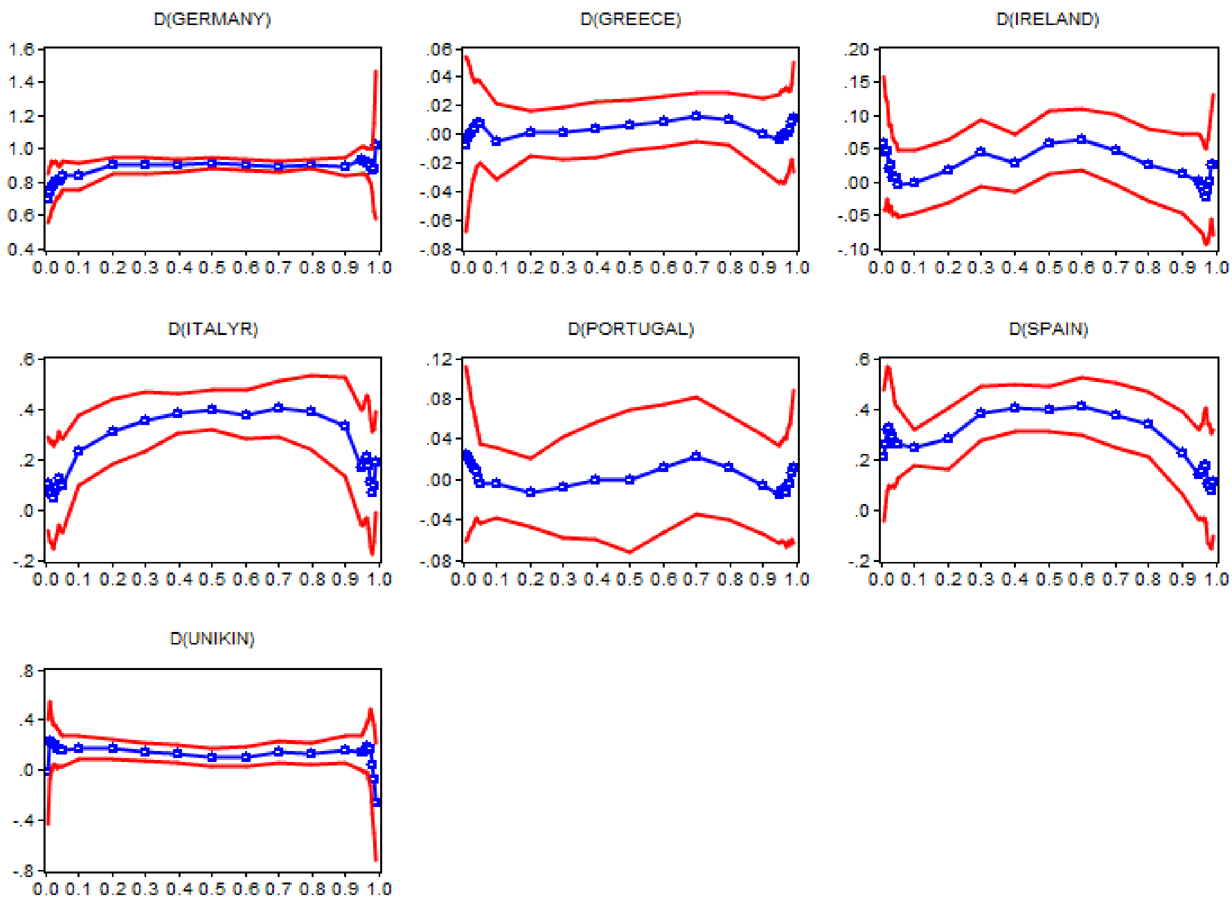
Notes: This Figure shows the quantile regression coefficients with heteroskedasticity for Italy.

Figure 10: **Average rolling variance**



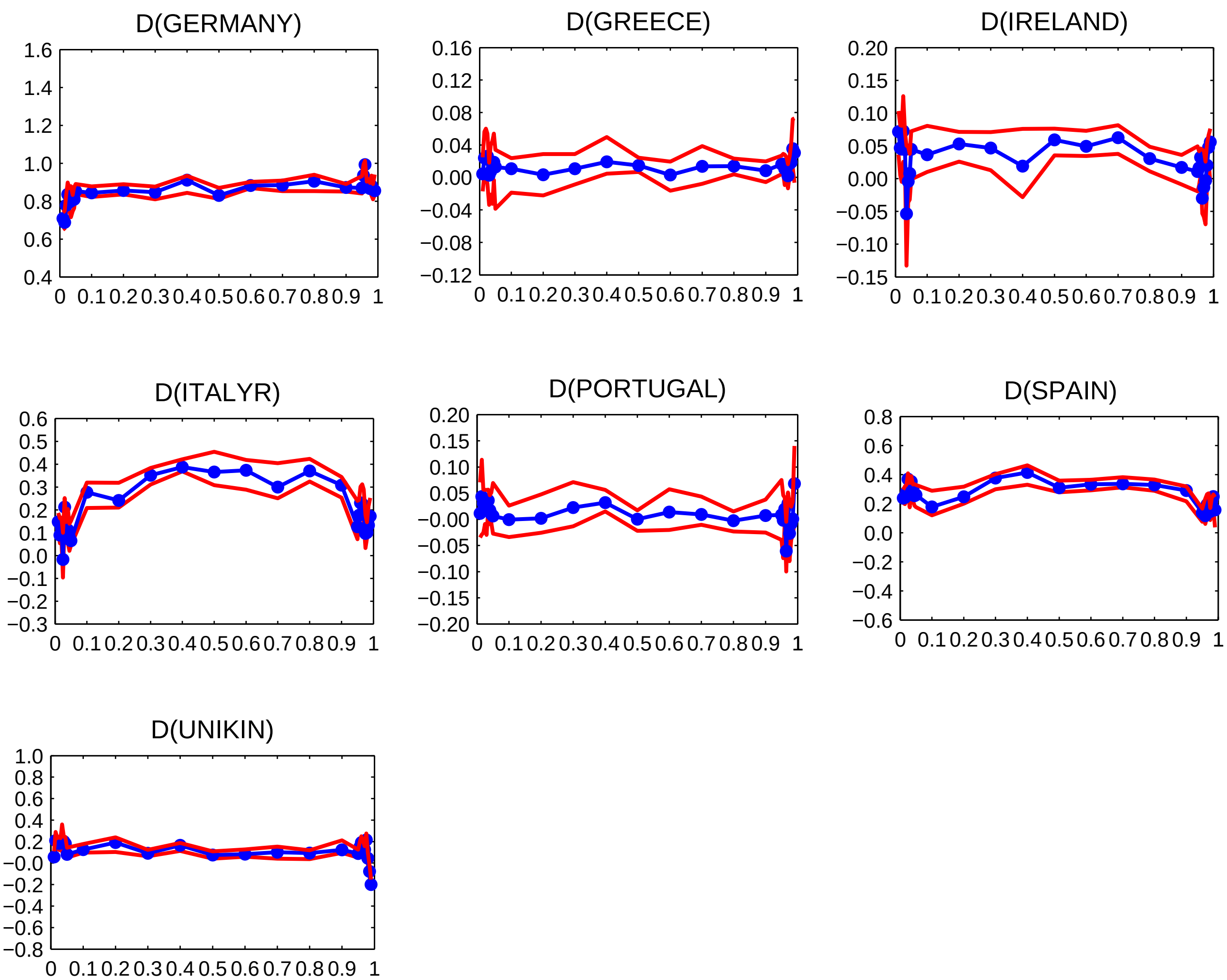
Notes: This Figure reports the average rolling variance

Figure 11: **Quantile regression coefficients for French bond spreads, 2008-2011**



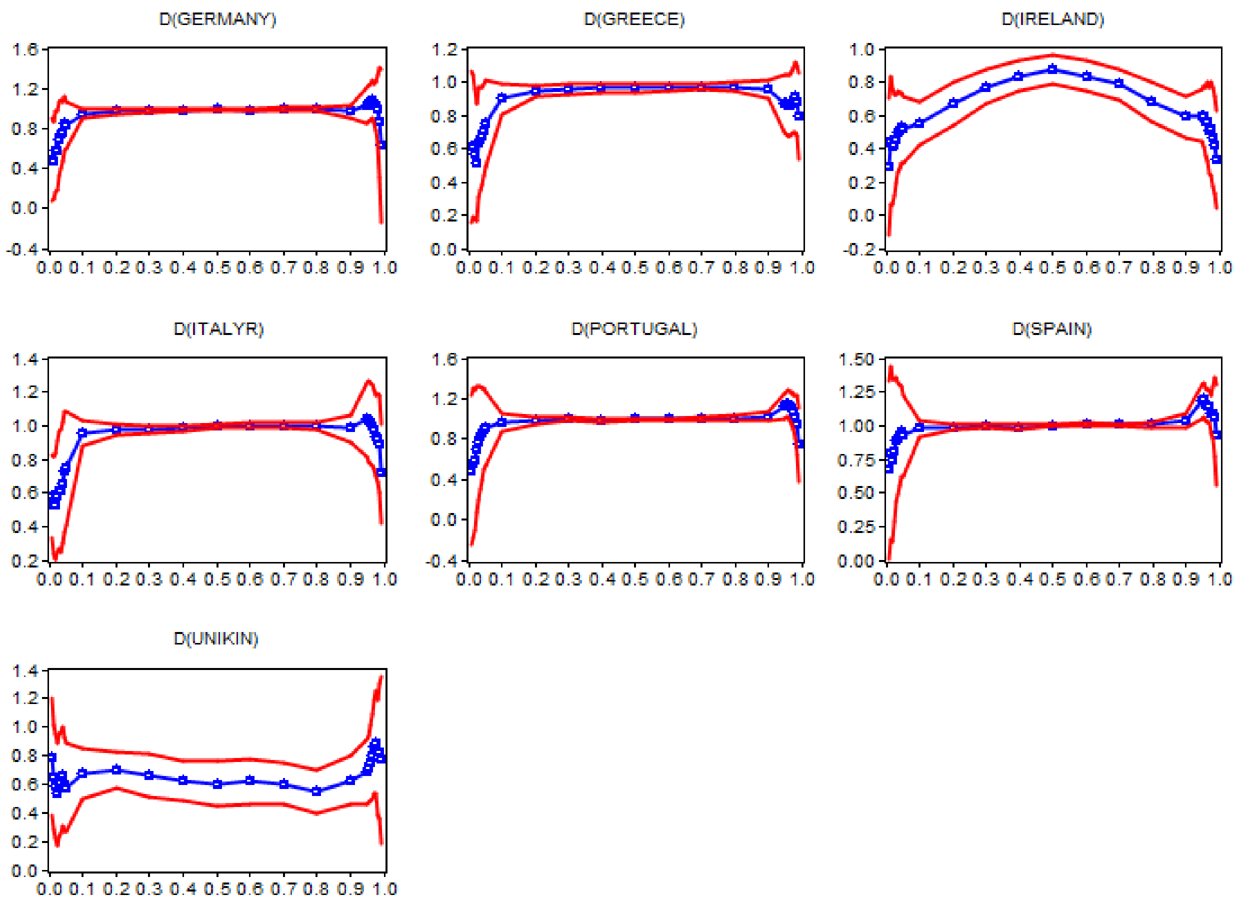
Notes: This Figure shows the quantile regression coefficients for French bond spreads over the sample 2008-2011.

Figure 12: **Quantile regression coefficients with heteroskedasticity for French bond spreads, 2008-2011**



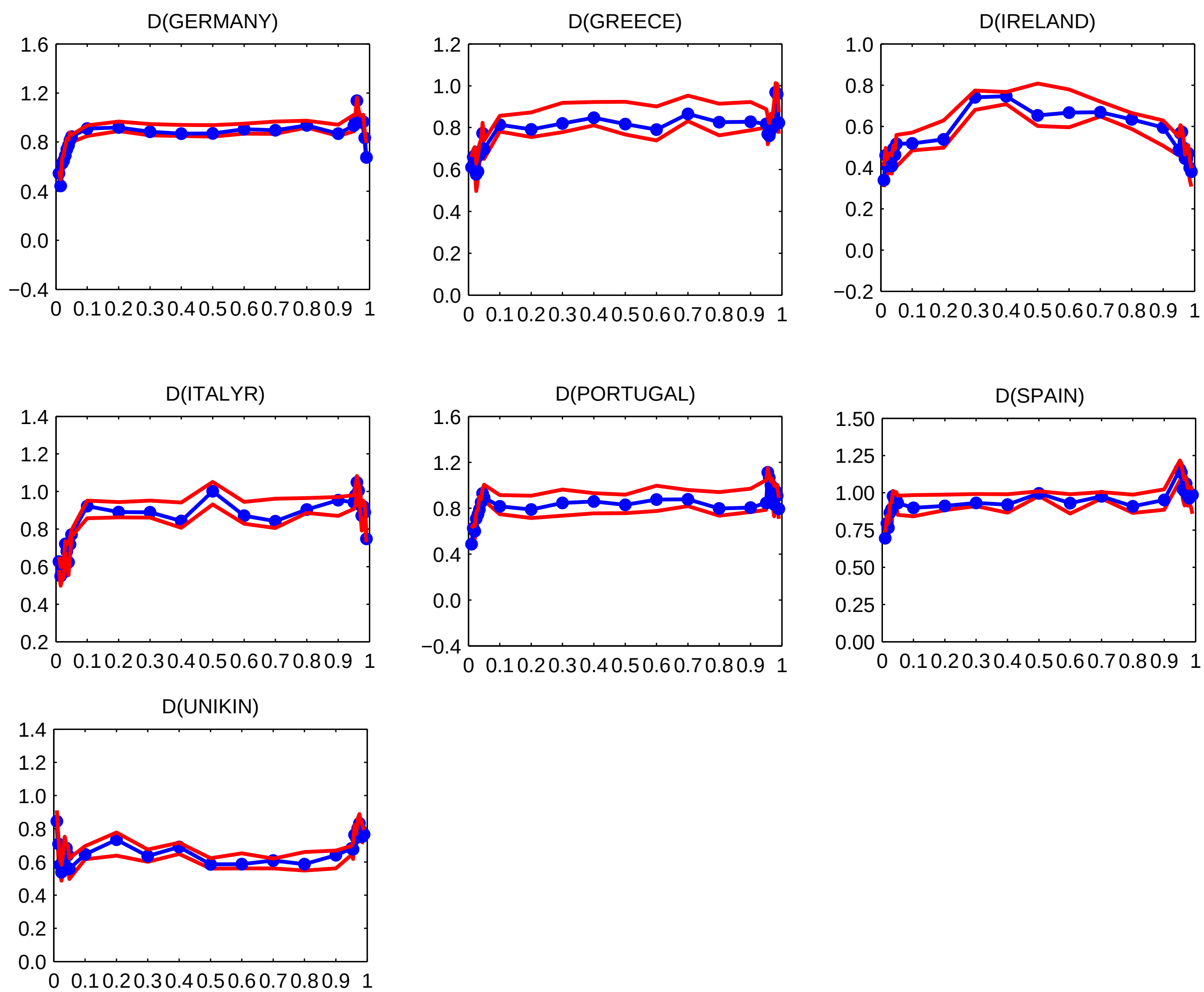
Notes: This Figure shows the quantile regression coefficients with heteroskedasticity for Italian bond spreads over the sample 2008-2011.

Figure 13: **Quantile regression coefficients for French bond spreads, 2003-2006**



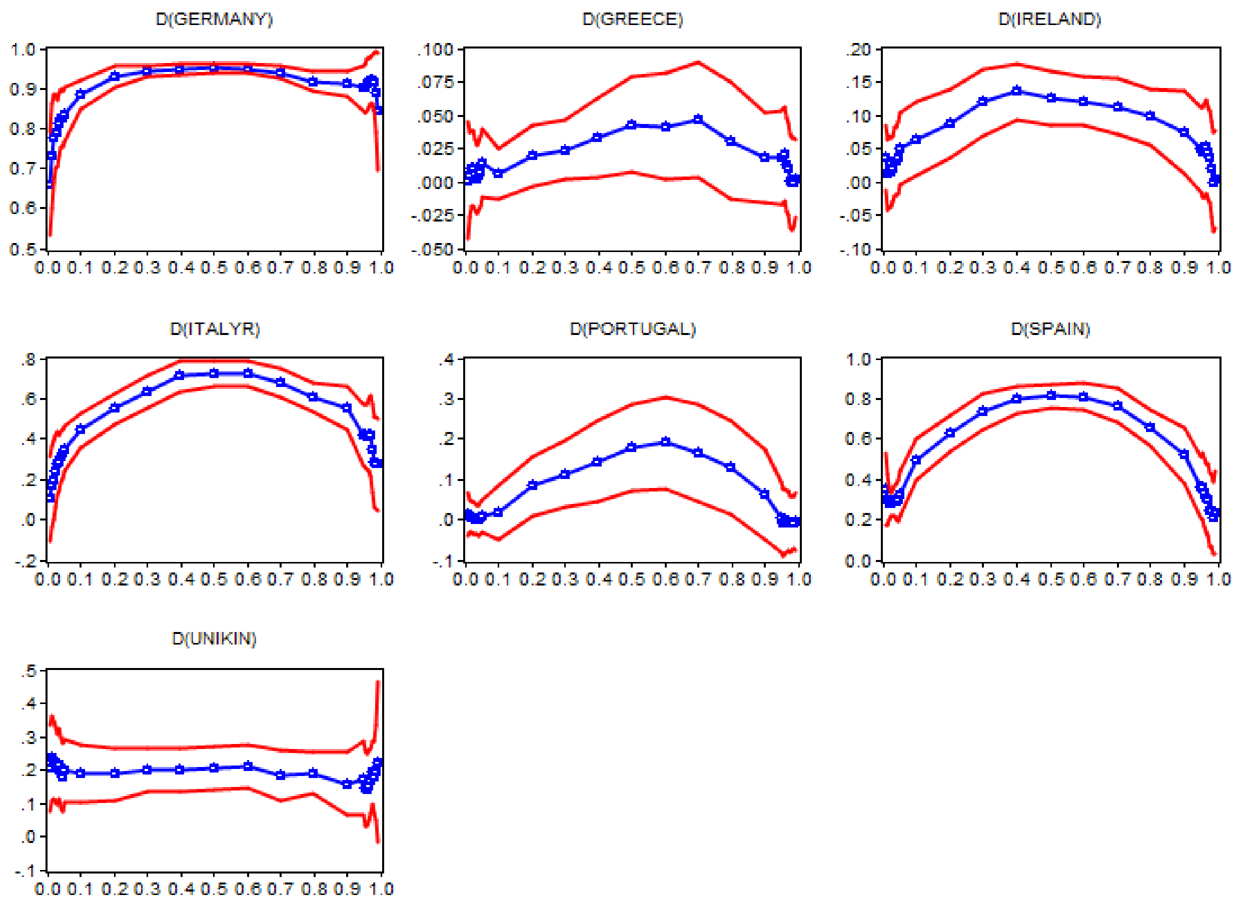
Notes: This Figure shows the quantile regression coefficients for French bond spreads over the sample 2003-2006.

Figure 14: **Quantile regression coefficients with heteroskedasticity for French bond spreads, 2003-2006**



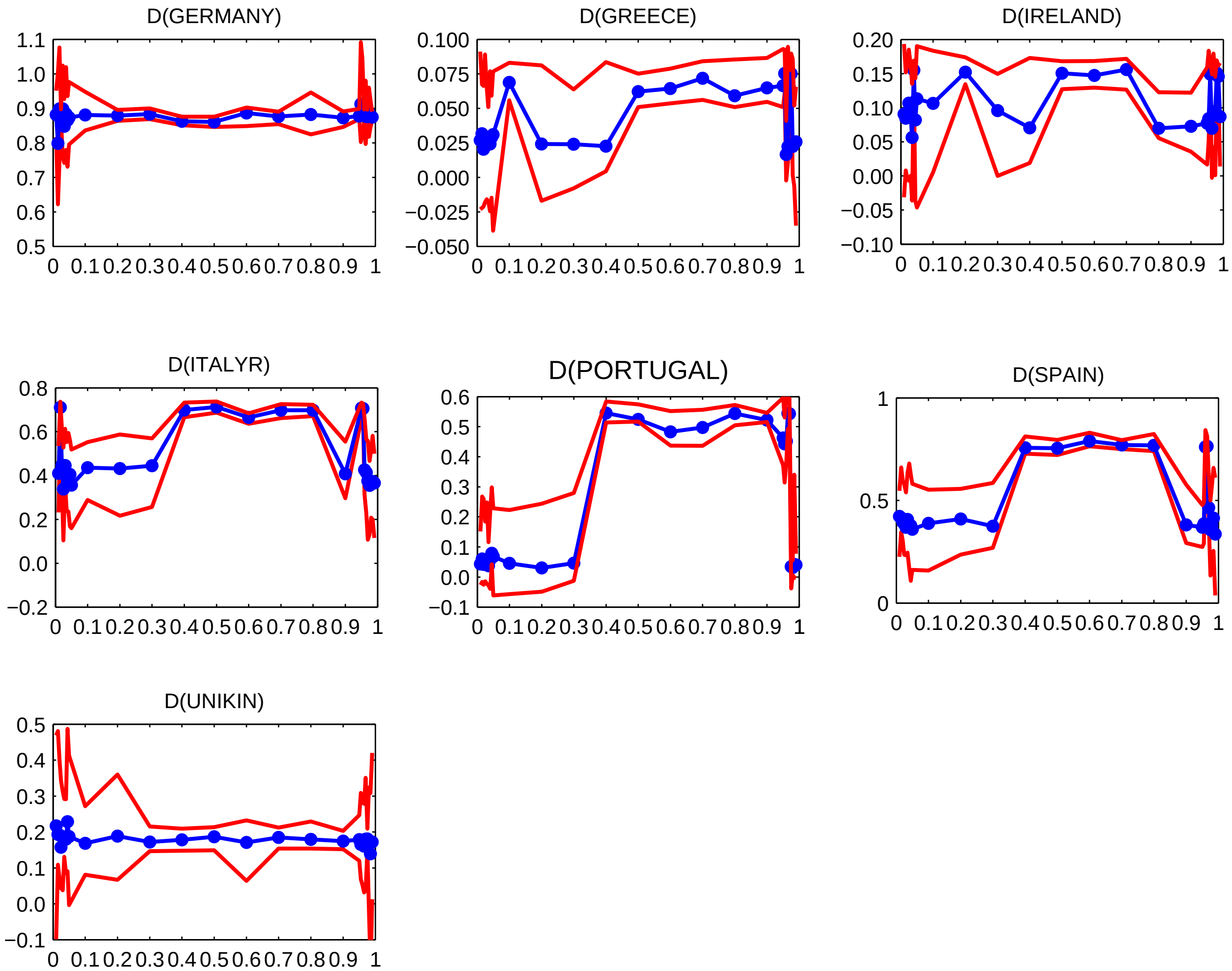
Notes: This Figure shows the quantile regression coefficients with heteroskedasticity for Italian bond spreads over the sample 2003-2006.

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.