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Measuring Sovereign Contagion in Europe

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Measuring Sovereign Contagion in Europe*

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Abstract

This paper analyzes sovereign risk contagion using bond yield spreads and credit default swaps for the major Eurozone countries. By emphasizing several econometric approaches (nonlinear regression, quantile regression and Bayesian quantile regression with heteroskedasticity) we show that the propagation of shocks in Europe Euro's bond yield spreads shows almost no presence of contagion in the sample periods considered (2003-2006, 2008-Nov2011, Dec2011-Apr2013). Shock transmission is no different on days with big spread changes and small changes. This is the case even though a significant number of the countries in our sample have been extremely affected by their sovereign debt and fiscal situations. The risk spillover among these countries is not affected by the size or sign of the shock, implying that so far contagion has remained subdued. However, the US crisis, does generate a change in the intensity of the propagation of shocks in the Eurozone between 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. These surprising, but robust, results emerge because this is the first paper, to our knowledge, in which a Bayesian quantile regression approach allowing for heteroskedasticity is used to measure contagion. This methodology is particularly well-suited to deal with nonlinear and unstable transmission mechanisms especially when asymmetric responses to sign and size are suspected.

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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 (EMU) could be expected as a result of a possible credit event in Greece, Italy or Spain? How much would France and Germany be affected? How about countries outside the European Union? Through which channel should the shock be transmitted? Clearly, these are important questions for economists, policymakers, and practitioners. However, addressing these questions requires the surmounting of 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 significant 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 would be 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 the amount of potential contagion that exists within the European sovereign debt market, where contagion is defined as the size of the difference in the propagation after a large negative realization has taken place, compared to the propagation after an average realization.

The second challenge is an empirical one: how to measure contagion from an unobservable shock. It is common to compare the intuitions about financial contagion to the notions of

[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 defined by the copula approach to measuring contagion (Rodriguez, 2007)

contagion in the medical literature. In medicine, however, there are two approaches: a direct measurement of contagion, and an indirect one. In fact, how do we measure the degree of contagion of a particular virus? One procedure relies on blood tests to detect the presence of the virus. This method evaluates contagion directly, but it requires knowledge of the virus. The second method concentrates on the transmission of symptoms: fever, pain, etc. During most financial crises, the "virus" is unknown. Most of the time, the econometrician observes which countries are affected, and by how much, but rarely the extent of the disease. For instance, most observers were surprised by the magnitude of the Lehman crisis in the US, mainly because very little information about the underlying contracts existed – and still exists. The literature, therefore, treats financial contagion as an unobservable shock, meaning that most empirical techniques have to deal with omitted variables and simultaneous equations. The problem is even more complicated because the data suffer from heteroskedasticity — which implies that if the conditional volatility in the sample changes 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, rather than because the omitted variables and simultaneous equation biases are not neutral to changes in the volatility? This empirical challenge has spurred a very large empirical literature trying to measure contagion.

Finally, the third challenge is that the channel through which contagion spreads is rarely understood before the crisis occurs. For example, very few ever have predicted that the transmission channel of the 1998 Russian crisis was going to be Long Term Capital Management.

[4]See Forbes and Rigobon (2002).

Furthermore, even though several economists anticipated the 2008 US 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 sovereign bonds. We examine sovereign bonds yield spread for seven European countries in the Euro area: France, Germany, Greece, Ireland, Italy, Portugal, and Spain, plus a European country that is not in the EMU: the United Kingdom (UK). We consider a sample period from January 2003 to April 2013, divided into three subsamples: the *pre-crisis* period, 2003-2006, the *crisis* period of 2008-Nov2011 and the European Central Bank *ECB intervention* period of Dec2011-Apr2013. We investigate the following questions:

a) Is there any presence of contagion in the sample periods considered? How is shock transmission different on days with big spread changes rather than small ones, most of which are during the turmoil of the debt crisis?

b) Has shock transmission in the Eurozone changed because of the debt crisis or the US crisis?

We propose quantile regressions as a powerful methodology for measuring contagion and use them to investigate the above questions. The main advantage of using the quantile regressions is that this is a very natural and powerful way to deal with the measurement of different propagation mechanisms, namely, during normal conditions and after a negative shock appears, i.e. to investigate possible parameter instability in the data for small and large, and negative and positive innovations. By conditioning on the size and sign of the shocks and evaluating the propagation mechanisms via the reduced-form model-based coefficients linking the dependent variable and the explanatory ones, this methodology allows us to understand and to estimate the extent of the asymmetries. We define contagion as a shift in the intensity of propagation when large positive shocks in the bond yield spread occur compared to normal shocks. Thus, we compare the coefficient of the propagation of shocks between two countries that show values belonging to, respectively, the highest quantiles (easily associated with turbulent times) and the middle ones (that belong to normal times). When the coefficients are stable over quantiles (i.e. they are not statistically different) we reject the contagion hypothesis. We apply a standard quantile regression and, also, a heteroskedastic version where the conditional variance of the residuals follows a Generalized Auto Regressive Conditional Heteroskedasticity (GARCH)(1,1) specification.

We have two main results: First, for almost every pair of countries in our data the transmission mechanisms is constant across the 2008-Nov2011 and Dec2011-Apr 2013 samples (the few exceptions are from France to Ireland, from France to Italy and from Spain to Italy in the *crisis* period of 2008-Nov2011 using the quantile regression with heteroskedasticity). This is the case for both bond yields and CDS.[5] This result challenges the ongoing discussion about contagion in the Eurozone countries. It implies that the fiscal crises in the periphery countries mostly increased variances without changing the propagation of shocks.[6] Second, using exactly the same methodology, we find that there is a change in the propagation mechanisms between the 2003-2006 and the 2008-Nov2011 samples.[7] However, we find that the coefficients actually fall as opposed to increasing. This implies that what changed the coefficients was the Lehman crisis, and that market participants, if anything, understood that Euro countries bond yields

[5]Exceptions for CDS are Greece and Portugal that present evidence of contagion from almost all the other countries when applying the quantile regression with heteroskedasticity. The difference with bond spread results can be potentially due to liquidity issues in the CDS market.

[6]Indeed, as has been documented even in the public press, volatilities increased dramatically; hence, correlations increased for spurious reasons.

[7]This result could only be tested in the bond yields given that CDSs were not available

were going to be less synchronized than before, and not more.

At a first glance, both results are surprising. A simple explanation, however, can rationalize them. The US crisis changed market views or perceptions of how synchronized bond yields could be within the Eurozone countries, and that it was mostly the fiscal crises in the periphery that caused the shocks that increased overall volatility. In other words, the US crisis could have led market participants to realize that countries within the Euro were going to follow a divergent path – hence the reduction in the coefficients – and the fiscal crisis was the expression of such a divergence. Of course we do not have direct evidence of this mechanisms, except for the fact that it is consistent with the observed behavior.

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 bond spreads and 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.[8] Few papers concentrate instead on the determinants of sovereign spreads in the EMU and the issue of contagion among sovereign securities within the EMU.[9] Our paper complements and extends this literature by investigating the degree of co-movement

[8]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 Longstaff (2011). This body of works shows that the most significant variables for CDS spreads are the US 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 that which can be explained by exposure to common factors.

[9]In particular, Caceres and Segoviano (2010) investigate the effect on the sovereign spread of the default probabilityof country i conditional on the default of the other countries (extracted from CDS). Similarly, Hondroyiannis, Kelejian, and Tavlas (2012) analyze the impact on the sovereign spread of a "contagion variable", defined as a weighted combination of other countries'spreads. Giordano, Pericoli and Tommasino (2013) investigate whether the sharp increase in the sovereign spreads of Euro area countries with respect to Germany is due to deteriorating macroeconomic and fiscal fundamentals or to some form of financial contagion. They concentrate on the explanation of the levels of the sovereign spreads rather than on the degree of co-movement of sovereign bond spreads.

among sovereign bond spreads (and sovereign CDSs) 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 problems involved in measuring contagion. Section 3 describes the data. Section 4 presents the different approaches used to investigate the relationship across bond spreads and the results. Section 5 provides robustness results. Section 6 concludes by discussing the implications of our paper.

2 Contagion, Nonlinearities, and Measurement

It is quite usual to compare the measurement and intuitions of financial contagion to the notions of contagion that we have developed and understood from the medical literature. This is indeed a quite useful exercise because in medicine there are two approaches: a direct measurement of contagion, and an indirect one. In fact, one procedure used to measure the degree of contagion of a particular virus relies on blood tests to detect the presence of the virus, while the other concentrates on the symptoms.

In the direct measurement, the speed and intensity at which the virus is transmitted from one individual to another is directly evaluated by the concentration of the virus in the bloodstream. This procedure, however, requires the presence of the virus to be measured. In the financial markets this is equivalent to observing the fundamentals, that is, to measuring risk appetite, contingent contracts, direct linkages in the banking sector, incentives, the information each agent possess, etc, directly. In practice, in the case of financial contagion, this methodology is hard to implement for two reasons: first, it is almost impossible to measure the fundamentals. For example, we can observe interest rates or average default rates, but not perceptions, heterogeneity, risk preferences, etc. Second, the literature rarely agrees on what needs to be measured. In other words, even if we were able to measure a particular fundamental determining interest rates across countries, it is not clear that such channel would be the one most of the literature would agree upon. Therefore, even after a financial contagion has occurred we rarely agree on or observe the exact "virus".

The second procedure is to observe and evaluate the symptoms. Assume that one of the symptoms of the virus is a high fever (a temperature more than 104). In a population within a city and not suffering from the virus, the frequency of the event "high temperature" will be relatively low. In fact, the likelihood that one person has a temperature of 104, given that another person in the population has a temperature of 104 is relatively low as well. In "normal" times, then, high temperatures are rare, and such events are almost independent. They are not totally independent because high fever in a particular city could be caused by pollution, climate, food, etc, shocks that indeed affect the whole population. This condition is what is defined as "normal" times. If a virus is introduced into the city it is conceivable that the frequency of 104 degree temperatures will increase, and the conditional probabilities are likely to increase as well. In other words, the propagation of the event "high temperature" increases with the presence of the virus. This is the typical problem we have in finance. There are factors that create co-movement in "normal" times that are intensified during a "contagious" period. The idea, therefore, is to evaluate how different the propagation is during a contagious event, from the propagation that exists in normal times. The problems of the indirect procedure are several: Firstly what defines "normal"? Furthermore, given (i) the changes in volatility during the "contagion" period and (ii) the presence of omitted variables and (iii) problems with simultaneous equations (i.e. endogeneity) that are likely to appear, which econometric procedure should be used to evaluate the propagation in "contagious" times?

Let us formalize the econometric problems of measurement in a simple framework. Assume the changes in the bond yield spreads of two different countries (or equally two asset returns), $y_{i,t}$ and $y_{j,t}$, are explained by two common factors and some idiosyncratic shocks. Assume the factors are unobservable.

$$y_{j,t} = z_t + v_t + \epsilon_t \tag{1}$$

$$y_{i,t} = \alpha z_t + \delta v_t + \eta_t \tag{2}$$

where z_t is the factor in "normal" times; while v_t is the factor that appears during a "contagious" event, meaning that it is zero during normal times and different from zero in crisis times, and where ϵ_t and η_t are stock-specific assets.[10] In other words, z_t is the factor that explains "high temperature" appearing in two individuals during normal times, while v_t is the virus. We assume that the variance of the virus is larger than the variance of the "nomal-times" shock: $\sigma_v^2 > \sigma_z^2$. In other words, we assume that contagious events are accompanied by higher volatility. In fact, this is a very reasonable assumption. Crises are usually associated with higher variances. Also, we assume that, conditional on events having the same variance, contagious events are propagated with higher intensity – which means that $\delta > \alpha$. Finally, we assume that idiosyncratic and common shocks are all uncorrelated.

In this environment, correlations are a bad measure of comovement. In fact, in this simple model there are two factors that create high correlation. One, the interesting one, is the larger coefficient in the contagious variable – which mostly answers the question of how much larger is δ than α; and the second, uninteresting, one is due to the heteroskedasticity in the data. In fact, if we assume that $\delta = \alpha$ it is still the case that the correlation increases in "contagious" times even though the propagation of the shock is identical by construction; see Forbes and Rigobon (2002). Conditional probabilities suffer from exactly the same problem. Sometimes the conditional probabilities increase not because the propagation is larger, but just because the shocks during crisis times are larger.

Assume we were to estimate a simple regression of $y_{i,t}$ on $y_{j,t}$ – which we know produces a bi-

[10] In this formulation the nuisance variables (z_t and v_t) are the unobservable factors. They can be normalized to have a coefficient or loading of one on the first asset. Conversely, they could be normalized to have a variance of one with the loadings on the shocks different from one for both assets.

ased estimate due to the omitted variable and endogeneity problems in the model. However, the movements of the biases are interesting in several ways. The estimates during "normal" times assume the absence of the "virus" – which is equivalent to assuming that $v_t = 0$. Therefore, the moments of the asset returns are

$$
\begin{aligned}
var(y_{j,t}) &= \sigma_z^2 + \sigma_\epsilon^2 \\
var(y_{i,t}) &= \alpha^2\sigma_z^2 + \sigma_\eta^2 \\
covar(y_{j,t}, y_{i,t}) &= \alpha\sigma_z^2
\end{aligned}
$$

Therefore, if we were to estimate a regression of $y_{i,t}$ on $y_{j,t}$ the estimated coefficient would be

$$
\begin{aligned}
\beta_{normal} &= \frac{\alpha\sigma_z^2}{\sigma_z^2 + \sigma_\epsilon^2} \\
&= \alpha - \alpha\frac{\sigma_\epsilon^2}{\sigma_z^2 + \sigma_\epsilon^2}
\end{aligned}
$$

Notice that the OLS coefficient is biased downward by the relative importance of the common shock and the idiosyncratic one.

Assume the virus appears. Hence, the two shocks are present. In this case, the moments are

$$
\begin{aligned}
var(y_{j,t}) &= \sigma_z^2 + \sigma_v^2 + \sigma_\epsilon^2 \\
var(y_{i,t}) &= \alpha^2\sigma_z^2 + \delta^2\sigma_v^2 + \sigma_\eta^2 \\
covar(y_{j,t}, y_{i,t}) &= \alpha\sigma_z^2 + \delta\sigma_v^2
\end{aligned}
$$

The OLS coefficient is now

$$\begin{aligned}
\beta_{crisis} &= \frac{\alpha\sigma_z^2 + \delta\sigma_v^2}{\sigma_z^2 + \sigma_v^2 + \sigma_\epsilon^2} \\
&= \alpha + (\delta - \alpha)\frac{\sigma_v^2 + \sigma_\epsilon^2}{\sigma_z^2 + \sigma_v^2 + \sigma_\epsilon^2} - \delta\frac{\sigma_\epsilon^2}{\sigma_z^2 + \sigma_v^2 + \sigma_\epsilon^2}
\end{aligned}$$

The propagation in crisis times is larger than the "normal-times" coefficient due to the second term. We have assumed that $\delta > \alpha$. On the other hand, the coefficient is still biased downward due to the presence of idiosyncratic shocks. However, in percentage terms this bias is always smaller because the noise-to-signal ratio is smaller in crisis times. If we assume that $\sigma_v^2 \gg \sigma_z^2$ and that $\delta > \alpha$ then

$$\begin{aligned}
\frac{\alpha\sigma_z^2 + \delta\sigma_v^2}{\sigma_z^2 + \sigma_v^2 + \sigma_\epsilon^2} &\approx \frac{\delta\sigma_v^2}{\sigma_v^2 + \sigma_\epsilon^2} \\
\beta_{crisis} &\approx \delta - \delta\frac{\sigma_\epsilon^2}{\sigma_v^2 + \sigma_\epsilon^2}
\end{aligned}$$

which is also biased. However, because $\sigma_v^2 \gg \sigma_z^2$, the bias coming from the relative variances in β_{crisis} is smaller than in β_{normal} (in percentage terms, or course).

This simple exercise highlights the underpinnings of our approach. Contagion creates a significant difference in the β-coefficients that capture the relationship between bond-yield spread changes in country $y_{i,t}$ vs country $y_{j,t}$ on days with big spread changes compared to days with small changes during the debt crisis. This will generate a nonlinearity in the OLS estimates. In other words, conditional on a contagious event – meaning larger volatility and larger propagation – the biases in the simple OLS estimates differ between normal and contagious times. On the other hand, if the coefficients are similar the propagation must be very similar as well. We test for this difference in the β-coefficients and therefore in the nonlinearity of the relationship between bond spread changes in country i versus country j in at least three different ways. The results of these tests allow us to answer our first question, i.e. how is shock transmission different on days with big spread changes compared to small changes, the former occurring mostly during the turmoil of the debt crisis. In other words, is there any presence of contagion? Notice that we tests for non-linearities, and this can lead to contagion if the beta coefficients are higher during turmoil times compared to a stable market phase. On the contrary, if the beta coefficients go down, we can interpret this as an evidence of loss of interdependence across markets, or, in other words, when dealing with the Euro sovereign bond spread, as an evidence of disintegration.[11]

The first way we test the difference is to use series estimators in the OLS formulation. This is limited because it imposes a particular form of bias. Although limited, however, it is quite intuitive. The presence of contagion could be associated with a convex relationship between shocks in country j and changes in the bond spread in country i. We thus consider a linear regression of $y_{i,t}$ on the level and powers of the explanatory $y_{j,t}$. The relevance of the coefficients can here be verified from a statistical viewpoint as well as in economic terms. In this framework, evidence of nonlinearity is associated with statistically significant coefficients of the powers of the explanatory.[12] Therefore, significant and positive coefficients linking the powers of the explanatory to the dependent would be a symptom of contagion.

Our second procedure relies on quantile regressions (QR). In this case, the purpose is to evaluate the linear coefficient β conditional on the different realizations of $y_{i,t}$ and investigate whether they are different among the different realizations of $y_{i,t}$ (i.e. in the presence of large

[11] The simplified model we adopt in this section is similar to Corsetti, Pericoli and Sbracia (2005). However, in our model the presence of contagion is associated with a common factor that appears only during contagion occurrences and whose propagation is higher than that of a first common factor. The model of Corsetti, Pericoli and Sbracia (2005) describes interdependence by means of a single common factor. They also describe in footnote (see footnote 9 and equation 6) a model equivalent to the one we adopt, but which is used under the null of presence of a regional common factor affecting only one country. As a consequence, our approach, despite being similar to Corsetti, Pericoli and Sbracia (2005) is more general and associates contagion to the higher propagation of a shock during crises. A similar idea of contagion measured as a change in the exposure has been proposed by Bekaert, Harvey and Ng (2005) and Bekaert, Ehrmann, Fratzscher and Mehl (2012). However, their model is based on observed factors and therefore differs from our approach based on latent factors.

[12] We might consider alternative forms of nonlinearity, such as step dummies capturing the additional impact of large versus small values of the explanatory variable. In this alternative representation, nonlinearities are associated with the significance of the coefficients related to the incremental impact of large/small values of x_t.

bond spread changes or small bond spread changes in country i). This is a test that allows for an unrestricted form of nonlinearity (conditional on the quantile, of course). This procedure, once translated into a Bayesian framework, can deal with the heteroskedasticity in the data – which is quite pervasive in general. The identification of nonlinearity in a QR framework is rather different than in the OLS case. We stick for simplicity to the linear model regressing $y_{i,t}$ on $y_{j,t}$, and forget for a second any discussion on the biases of the coefficients. When considering QR, we model the quantiles of the conditional distribution of $y_{i,t}$ given the knowledge of $y_{j,t}$. Moreover, the relationship between $y_{i,t}$ and $y_{j,t}$ is estimated as a linear regression with Gaussian innovation term, therefore the relationship for the quantiles are assumed to be linear. Precisely, the quantiles will be:

$$y_{i,t}(\tau) = \beta_{0,\tau} + \beta_{1,\tau} y_{j,t} + F_{\eta t}^{-1}(\tau) \tag{3}$$

where: τ is the quantile of interest, $y_{i,t}(\tau)$ is the τ-quantile of the conditional distribution of $y_{i,t}$, and $F_{\tau}^{-1}(\eta_t)$ is the unconditional quantile of the innovation density. Note that the coefficients in the linear quantile model are quantile-dependent (i.e. they are $\beta_{0,\tau}$ and $\beta_{1,\tau}$).

When the model is truly linear for all realizations of $y_{i,t}$ - i.e. the model is truly $y_{i,t} = \beta_0 + \beta_1 y_{j,t} + \eta_t$ for any quantiles of $y_{i,t}$ - then the coefficients $\beta_{k,\tau} for \quad k = 0, 1$ will become the same across quantiles (i.e. for example the β_1 of the quantile $\tau = 0.5$, $\beta_{1,0.5}$, will be equal to the β_1 of the quantile $\tau = 0.9$, $\beta_{1,0.9}$), and therefore constant and equal to β_1. The only element differing across the conditional quantiles of y_t is given by $F_{\eta t}^{-1}(\tau)$ which varies with τ by construction. In fact when τ is larger, the innovation intensity value η_t is larger by construction because we select the larger values of the Gaussian distribution. In this case, the regression lines estimated for the different quantiles will just be "parallel" lines, see Figure 1.

Evidence of contagion and therefore the presence of a different relationship between $y_{i,t}$ and $y_{j,t}$ (i.e. evidence of nonlinearity) are associated with changes in the coefficient β_1 across quantiles or, equivalently, with the observation of "non-parallel" lines for the different quantiles, see Figure 2[13]. Thus, by testing the stability of the QR coefficients across quantiles, we can verify the linearity assumption, i.e. that the coefficients $\beta_{1,\tau}$ are the same across quantiles. A symptom of contagion is thus now provided by an instability in the $\beta_{1,\tau}$ QR coefficients[14]. This feature means that the quantile approach allows us to test jointly the asymmetric linkage among changes in bond spreads in response to large and small, positive and negative shocks, this is an innovation in the contagious literature.

We perform both tests given that they have advantages and disadvantages. The OLS is simple and intuitive, but it is the weakest one in terms of its ability to detect contagion or deal with heteroskedasticity. The quantile regression is flexible in its assumption on nonlinearity, and regarding the country in which the crisis starts, but its ability to detect contagion relies exclusively on the different biases that might appear across quantiles. One advantage is that if the coefficients are precisely estimated, the test can be quite powerful.[15]

3 The Data

Each of the EMU countries issues, independently from other countries, short and long-term debt, via Treasury bills and bonds respectively. The yields reflect an inflation risk, which

[13]When dealing with QR, a further relevant element is the correct specification of the model; that is, conditional quantiles should not cross. The consequences are particularly severe when quantile-crossing happens for quantiles close to the median, or in the middle of the support of the explanatory variable.

[14]Note that the QR provides a collection of linear quantiles. These are the quantiles of the conditional density of $y_{i,t}$ given $y_{j,t}$. In a linear model, the conditional density of $y_{i,t}$ remains Gaussian with a given variance and a known *mean* relation between $y_{i,t}$ and x_t irrespective of the value of $y_{j,t}$. In contrast, in a QR framework, the conditional density of $y_{i,t}$ given $y_{j,t}$ might change across different values of $y_{j,t}$. Here, we do not observe the *mean* relation between variables, but the *quantiles* of the conditional density. As a consequence, the conditional density might have location, scale, symmetry, tails that change across values of $y_{j,t}$ because the quantiles are moving away from a *linear* model, that is, they are not "parallel".

[15]In the appendix, we also report results for the test developed in Rigobon (2000), and used in Rigobon (2003), called the DCC test that is specifically designed to deal with simultaneous equations and omitted variables when there is heteroskedasticity in the data. The disadvantage of this procedure is that it needs information on the origins of the crisis. In other words, in the case of the European crisis the test would be conditional on knowing that the crisis started in Greece. The nonlinearity detected here refers to the change in the relation between countries, verifying whether the transmission mechanism is stable during market turbulence. The point of view is thus that of the information flow and the test allows us to look at the potential change in the information flow when, for instance, markets are experiencing high volatility. In this framework, a symptom of contagion is provided by the change in the transmission mechanism.

should be controlled by the ECB, and economic conditions and default risks, which are country-specific and differ from one to another. This implies that several decisions should be taken when comparing the cross-European bond market. We consider daily data for 5-year Euro-denominated bond redemption yields for seven Eurozone countries: France, Germany, Greece, Ireland, Italy, Portugal and Spain, plus the UK, which is not in the EMU. 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 UK. We use the 5-year maturity as a good and informative proxy for the default risk. The next decision is how to compute a spread from a risk-free rate. We follow Beber, Brandt, and Kavajecz (2009) and calculate the bond spreads relative to the 5-year swap rates because interest rate swaps are commonly seen as providing the market participants' preferred risk-free rate.[16]

We collect data from Thomson-Reuters for the sample period from January 2003 to April 2013. Figure 3 shows the 5-year redemption yields for the eight countries; and Figures 4 and 5 show the bond spreads, the Euro and British pound swap rates, and the changes in bond spreads mainly used in the analysis in this paper. There are large differences among the countries from November 2008 onward. The bottom panel in Figure 4 indicates that the differences are not due to swap rates. The UK spread is higher than all the EMU countries' spread in the initial years of our sample, but the swap rate is also higher there, resulting in very similar spreads. Then, the yields of three periphery countries (Greece, Ireland, and Portugal) increase substantially from the end of 2008 and explode in 2010. The Irish spread falls in the second part of 2011; Portugal experiences a similar pattern from the beginning of 2012. The Greek spread does not reconverge and only stops in spring 2012, when the European Union, ECB and International Monetary Fund (IMF) bailout was implemented to restructure Greek debt.

Italy and Spain follow a different pattern, with yields very low until 2010, but experiencing

[16]Another possible approach would be 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".

substantial increases relative to Germany and France from the summer of 2011 onward. The Italian spread is larger than the Spanish one at the end of 2011, before both decline in the first quarter of 2012, but again increases after that. Rates are more moderate in the last few months of the sample, with the Spanish spread higher than the Italian one.

Economic conditions and political decisions can be linked to the fluctuations described above. The introduction of the Euro in the late 1990s, and the replacement of local currency in 2002, harmonized Treasury yields in the EMU. The ECB succeeded in getting inflation under control in all countries, resulting in lower yields. The first instability in the spreads is visible from summer 2007 onward, and in particular during 2008 when the Great Financial Crisis started in the US. However, a larger discrepancy emerged after Greece started to have issues with its accounts and it was revealed that Greece had "played" the European Commission rule by maintaining its Debt-to-GDP ratio below 60% artificially for several years. In May 2010, the European Union and the IMF provided a bailout loan to Greece to help the government pay its creditors; but it soon became apparent that this would not be enough and a second loan was necessary. The agreement was difficult to reach. Greece experienced a large amount of political uncertainty with several elections, and a debt restructuring was only agreed in 2012.

The focus of this paper is twofold. First is to investigate whether contagion among European countries started with or after the Greek difficulties that were followed by large increases in the Portuguese, Spanish and Italian spreads. The governments changed in all three countries in 2011; new austerity measures were implemented across EMU; and ECB announced and implemented a new non-standard measure, called the outright monetary transactions (OMT) program, in September 2012, consisting of a bond-buying program for the different members of the union. This program replaced the temporary Securities Markets Program (SMP), which had covered bond purchases since May 2010, with substantially larger volumes since August 2011.

The second focus is the analysis of changes in the shock propagation between the period in which the Euro was introduced and the Treasury yields harmonized, and the period of the debt crisis.

Such considerations suggest that we split our analysis into three different samples:

- 01-Jan-2003 to 29-Dec-2006.
- 01-Nov-2008 to 30-Nov-2011.
- 01-Dec-2011 to 30-Apr-2013.

The first sample is the calm and harmonization period, which we label the *pre-crisis* period. The second refers to the turbulent times before the ECB announced the Long-Term Refinancing Operations (LTRO), which we label as the *crisis* period. The third sample concentrates on the main actions taken to resolve the Euro-crisis. It corresponds to the introduction of the ECB LTRO program in December 2011, the restructuring of Greek debt, the Eurogroup summit of 29 June 2012 at which was decided to use the EFSF/ESM instruments in order to stabilize the markets of all member states honoring all of their European commitments on schedule, and Draghi's announcement on 26 July 2012, at the Global Investment Conference in London, in which he stated: "The ECB is ready to do whatever it takes to preserve the Euro. And believe me, it will be enough!". It also includes the introduction of the ECB's OMT program and the inconclusive Italian elections in February 2013. We label it the *ECB intervention* period.

Data from January 2007 to October 2008 are not considered in the main analysis so as to exclude fluctuations related to the beginning of the Great Financial Crisis in the US.

We calculate daily changes in bond spreads and to support the choice of the three samples considered from the statistical point of view we performed structural break tests on both the individual series and on the stability of the cross-linkage β-coefficients. For the individual series, after 2006, for every date we use as a break, we reject the null that there has been not a structural break. For the cross-linkage beta coefficients (of which there 56) we find that we largely reject the null hypothesis of no break in the period 2007-2008 and in November

2011 supporting our decision to split the analysis into three samples and to exclude the period 2007-2008.[17]

Table 1 reports means, standard deviations minimum and maximum values for changes in the bond spreads of the eight countries divided into the three samples described above. It also gives the median values of the absolute changes in the bond spreads in basis points (Median). The average values of the changes in the bond spreads range widely across countries and samples. All the changes in the bond spreads are very small and close to zero in the first sample (2003-2006); on the other hand, changes in the bond spreads increase substantially for countries such as Greece, Portugal, Ireland, Italy and Spain in the second sample of 2008-Nov2011. The recovery sample of 2011 to 2013 indicates a huge reduction in the bond spreads for the non-core countries. In fact, the changes in the bond spread are, on average, negative for Greece, Ireland, Italy, Portugal and Spain. The standard deviations as well as the differences between the maximum and minimum values, indicate that the changes in bond spreads present significant time-series variation. The last column in Table 1 suggests that the differences might have large economic values.

Since we focus on the co-movement in the bond spreads among the different countries, in addition to common changes attributable to a set of global common factors, we also 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 using a GARCH(1,1) model.

To provide some additional descriptive statistics, Table 2 reports the correlation matrix of the daily changes in the bond spreads for the three samples. Table 2 shows, that while there is clearly significant cross-sectional correlation in the changes of bond spreads, the correlations are far from perfect and differ widely across the three samples. The correlations are relatively high in the pre-crisis sample, among the EMU countries. They are largely lower in the crisis and

[17] The test performed is a standard Chow (1960) test for structural break, known as the "Structural Change break". The individual results of the tests are provided upon request.

ECB intervention samples. The exceptions are Portugal-Ireland, whose correlation increases in the period 2008-Nov2011 and then decreases, and Italy-Spain, whose correlation remains almost the same across the three samples.

4 Methodology and Results

4.1 Nonparametric Inference

As an initial evaluation of the linearity and stability of the relationship across the bond spreads, we consider a rolling evaluation of the linear correlation. We calculate the correlations among changes in bond yield spreads by considering 60 observations, roughly equivalent to one quarter.

The top panel in Figure 6 plots rolling window correlations from January 2003 through April 2013. Overall, we observe high correlation values between the changes in the bond spreads, generally within the range from 0.5 to 0.9, up to the end of 2008, in line with the unconditional correlation measure provided in Table 2. Some exceptions are provided by the German correlations to other bond spread changes during the first quarter of 2005, which turn out to be negative, and could be associated with the removal of government guarantees for savings banks, see Gropp, Grundl and Guettler (2013). For the UK and Ireland we constantly observe smaller values compared to the other countries. From September 2008, the overall picture changes, and after a transient increase during that month, average correlations start to decrease, eventually reaching a value around 0.2 (the actual overall average). Reading them simply, these results provide evidence of a Euro-disintegration rather than contagion among the different countries, in the period from 2009-2013.

Moreover, from a simple visual comparison between the pre-crisis period and the crisis period it is clear that shock transmission in the Eurozone has changed significantly because of the US crisis and the debt crisis, with, however, a significant reduction in the pairwise correlation from 0.7 to 0.2. The bottom panel in Figure 6 shows, however, that this huge reduction seems very heterogeneous.

We link this to these possible elements: the change in the transmission mechanism due to the 2007-2008 event, the debt crisis of 2009-2013, and the inappropriateness of the linear correlations for measuring the dependence across countries, as highlighted by Forbes and Rigobon (2002), indicating that a simple inspection of the linear correlation coefficient might lead to inappropriate conclusions due to the presence of heteroskedasticity. Indeed, we know that, since September 2008, the overall market volatility has increased.

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

In summary, even if the use of short windows for the correlation analysis is aimed at comparing "normal" and "contagion" periods, this analysis highlights the difficulties of investigating comovements and disentangling the effects between large and small shocks (i.e. to provide an answer to our first question in this paper) and between periods (i.e. before and after the sovereign crisis, the second question we aim to investigate in this paper).

4.2 Drawing Inference using Linear Regression Models

To deal with the problem that arises from the heteroskedasticity in the data, and the bias it produces in the correlation measures, a very rough and simple method is to estimate the relationship using projection methods, i.e. performing a linear OLS regression of $y_{i,t}$ on the level and powers of the explanatory $y_{j,t}$ as described in the previous section. In this setting, we verify the existence of nonlinearities, and thus search for symptoms of contagion, by studying the significance of the coefficients of nonlinear linkages, such as the second- and third-order terms, as well as linear linkages.

To investigate the nonlinearity in the relationship between the changes in the bond 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 linear regression with GARCH(1,1) as the baseline model:

$$\begin{aligned} y_{i,t} &= \beta_{ij,0} + \beta_{ij,1} y_{j,t} + \gamma_{ij}' X_{t-1} + \sigma_{ij,t} \varepsilon_{ij,t} && (4) \\ \varepsilon_{ij,t} | I^{t-1} &\sim D(0,1) && (5) \\ \sigma_{ij,t}^2 &= \theta_{ij,0} + \theta_{ij,1} e_{ij,t-1}^2 + \theta_{ij,2} \sigma_{ij,t-1}^2 && (6) \end{aligned}$$

where i and j are the two country identifiers, and 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, $e_{ij,t-1} = \sigma_{ij,t} \varepsilon_{ij,t}$.[18] Moreover, the parameters in the GARCH equation (6) 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 (4) are estimated using quasi-maximum likelihood with robust standard errors. In the rest of the section, we drop the 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 bond spreads of only two countries, $y_{i,t}$ and $y_{j,t}$. The null hypothesis of linearity is tested by using the following

[18]We 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 5-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 were all obtained from the Bloomberg system. The results, again, were unchanged.

extended model:

$$
\begin{aligned}
y_{i,t} &= \beta_0 + \beta_1 y_{j,t} + \gamma' X_{t-1} + \sum_{l=2}^{p} \beta_l \left(y_{j,t}\right)^l + \sigma_t \varepsilon_t && (7) \\
\varepsilon_t | I^{t-1} &\sim D\left(0,1\right) && (8) \\
\sigma_t^2 &= \theta_0 + \theta_1 e_{t-1}^2 + \theta_2 \sigma_{t-1}^2 && (9)
\end{aligned}
$$

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

Tables 3-5 show that the coefficients of the powers in equation (7), if singularly considered, are statistically significant in many cases but with a negative sign. Specifically, β_2 and β_3 (i.e. the coefficients of the square and cubic terms) are statistically significant, respectively, in 43 and 45 cases out of 56 during the 2003-2006 period. Their relevance is weaker from 2008 onward: they are significant in 25 cases out of 56 from November 2008 to November 2011; from December 2011 to April 2013, β_2 is statistically significant in 11 cases only, β_3 in 13. Moreover, jointly testing their significance shows evidence of their relevance in 49 out of 56 cases for 2003-2006, 25 out of 56 in the range from November 2008 to November 2011, and only 13 for the period December 2011 to April 2013. Those results suggest that there is evidence of nonlinearity, and that it is stronger during the low-volatility period ranging from 2003 to 2006. In contrast, during the crisis, the evidence of nonlinearity weaken and is at a minimum during the ECB intervention period.

However, if we compare the impact from the linear term to the coefficients associated with the squared and cubed changes used to explain the bond spread variation, we note that the coefficients are extremely small and sometimes negative, indicating a concave relationship rather than a convex one. This trait is common across countries, and is not associated with a specific dependent country nor on the country where the bond spread movements originated. More specifically, if we calculate the economic relevance of the coefficients by multiplying them by the squared and cubic values of the median of the absolute bond spreads for country j reported in Table 6 for the period from 2008 to November 2011, we see that the economic impact of the nonlinearity is extremely small. A similar result is observed for the other subsamples.[19]

We thus face some evidence of nonlinearity albeit with a limited economic impact. The possible sources of this behavior might lie in the inappropriateness of the linear specification and in the fact that such regressions might be subject to omitted variable or simultaneous equations biases. The biases are nonlinear functions of the conditional volatility and can be mistakenly interpreted as evidence of nonlinearities when not properly corrected for. These issues will be dealt with below. Thus far, however, whatever evidence of nonlinearity we do find implies a very small effect and the presence of a negative coefficient, more in the direction of a weaking of the relationships between countries, rather than contagion. In any case, in order to cope with the potential impact of endogeneity biases, in the robustness section we estimate the model in equation (7) with instrumental variables (excluding the GARCH term). Our results are further confirmed; there is even weaker evidence of nonlinearities once the parameters are estimated with an endogeneity-robust method.[20]

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 linkages between the changes in the bond spreads 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. We thus address the problem from a different technical viewpoint and consider QR between changes in the bond spreads of any two countries.

However, the above discussion is largely based on a simple comparison among the estimated coefficients for single subsamples. To complete the analysis and further support our choice of single-period analysis, we perform a structural break analysis. Our aim is to verify that the

[19] The tables for the other subsamples are included in the appendix.

[20] For additional details and comments see the robustness section.

relations across sovereign bonds have really suffered a change in their structural relations across periods, rather than within periods. To that purpose we perform a standard Chow-type test for structural break on the coefficient β_1 in the linear relation (7). The test performed comes from a model without GARCH terms in the residuals, but we consider standard errors robust to the presence of heteroskedasticity. Furthermore, to obtain a clearer picture, we run the test on a rolling window of four years, testing for a break occurring after the end of the second year. We roll over the test sample with a monthly step (roughly 22 days). The test is performed on all asset pairs, obtaining 56 sequences of test outcomes as a result. Figure 7 reports the time series of the median p-value and of the first and third quartiles (quantiles are computed across the 56 tests). We can clearly see that the hypothesis of a structural break starts being widely accepted in the second half of 2007, and peaks at the end of 2008 - and at beginning of 2009. Clearly, some heterogeneity across countries is present, mostly because some countries (e.g. the UK) faces a structural break earlier, and others, like Italy and Spain, later.

However, the graph shows a relevant pattern supporting our initial claim, that a break occurred in the second half of 2008. As a result, the previous analysis results are not influenced by changes in structural relations, and differences in the coefficients estimated on separate subsamples can differ.

4.3 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 allow us to measure shifts in the propagation intensity when large shocks occur. As described in the section above, the advantage is that quantile regressions are a particularly efficient way to estimate a linear relationship that varies across quantiles and therefore to detect the presence of interdependence asymmetries in the data.

Starting from the linear model in equation (4), our purpose is to verify whether the $\beta-$coefficient is changing across quantiles of the dependent variable $y_{i,t}$.[21] As the parameters differ across quantiles, the overall model is highly nonlinear, i.e. the β_τ would differ across quantiles. The quantile regression parameters are estimated by solving the following minimization problem:

$$min_{\Theta_\tau} \sum_{t=1}^{T} \rho_\tau \left(y_{i,t} - \beta_{ij,0} - \beta_{ij,1} y_{j,t} - \gamma'_{ij} X_{t-1} \right) \tag{10}$$

where $\rho_\tau(a)$ is the *check* function for quantile τ of the dependent variable y_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 subscripts i and j are dropped for the sake of brevity.

The minimization of equation (10) leads to the estimation of the τ quantile for $y_{i,t}$. This specific quantile depends linearly on $y_{j,t}$ and X_{t-1}, and is thus conditioned to the evolution of the covariates and of the y_j. The conditional quantile is denoted as

$$\widehat{y_{i,t}}(\tau) = \widehat{\beta}_{0,\tau} + \widehat{\beta}_{1,\tau} y_{j,t} + \widehat{\gamma}'_\tau X_{t-1} \tag{11}$$

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.[22] For details on QR see Koenker (2005).

The most relevant coefficient in our analysis is $\hat{\beta}_{1,\tau}$, which represents the coefficient of the propagation of shocks from the change in the bond spreads of country j to the change in the bond spreads of country i, conditional on other information in X, and at a certain quantile τ of the dependent variable.

To analyse the link between the changes in the bond spreads, we estimate the quantile regressions in equation (10) across each pair of bond spread variables, also conditioning on the

[21] We stress that the coefficient β_1 in equation (4) represents the link between the dependent variable $y_{i,t}$ and the explanatory $y_{j,t}$ and thus represents the impact on country i of shocks that originated in country j

[22] To simplify the notation, and following the standard practice for representing quantile regression outputs, the parameter $\widehat{\beta}_{0,\tau}$ includes also the τ quantile of the innovation density.

lagged exogenous variables used in equation (4).[23] Given the estimates, we perform two evaluations: first, we graphically analyze the variation in 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.

Figures 8-9 report the values of the $\beta_{1,\tau}$ coefficient across different quantile levels for selected countries and subsamples. Note that each panel is obtained from a different quantile regression (we are thus not considering system estimation, or the estimation of quantile regressions with several bond spreads as explanatory variables). Furthermore, the panels report the 95% confidence intervals (red lines) obtained with the Markov Chain Marginal Bootstrap method of Kocherginsky, He, and Mu (2005). In drawing the graphs we evaluated the quantile regression for the following quantiles: $\tau = 0.01, 0.02, 0.03, 0.04, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 0.95, 0.96, 0.97, 0.98, 0.99$.

From a global evaluation of all the figures (including those presented in the appendix), two common features emerge. At first, the coefficients are almost flat across quantiles, suggesting that the dependence between the movements of any two bond spreads does not change as a function of the size and sign of the movements. In particular, the values of $\widehat{\beta}_{1,\tau}$ around the median change in the bond spread (for example $\tau = 0.50$) are very similar to those in the extreme quantiles ($\tau = 0.95$ or $\tau = 0.99$).

This indicates that the hypothesis of contagion is barely 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 bond spreads of the different countries, i.e. the linkages among the different countries are the same whether we are looking at normal or turbulent times.[24]

Secondly, as expected, the dispersion of each quantile regression coefficient is much larger

[23] The introduction of the covariates allows us to control for the impact of common information. Lagged bond changes are not included since we believe that the past information is either already included in the actual bond spread or conveyed by the covariates.

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

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 zero.

Third, surprisingly, there is evidence during the pre-crisis period of 2003-2006 that, in presence of large changes (positive or negative), the relationship will be lower, i.e. the values of $\widehat{\beta}_{1,\tau}$ for $\tau = 0.01, 0.02, 0.03, 0.04, 0.05$ and $\tau = 0.95, 0.96, 0.97, 0.98, 0.99$ are lower values than for the median quantiles and this is true not only for the relationship between core countries and peripheral countries but also for core versus core or peripheral versus peripheral (we report results for the impact of Greece to France, France to Germany, Ireland and Italy, Spain to Italy and Italy to Spain, but we obtained similar results for the relationships between various combinations of core and peripheral countries for the various combinations).

In the other two subsamples we considered, 2008-Nov2011 and Dec2011-Apr2013, the reduction of the $\widehat{\beta}_{1,\tau}$ in the extreme quantiles compared to the median one is less relevant and in general we observe a huge reduction in all of the $\widehat{\beta}_{1,\tau}$ in those two samples compared to those observed for 2003-2006.

In this study, the most interesting equivalence occurs across the upper quantiles and can easily be tested.

Tables 7-9 report the tests for equivalence across quantiles for the following three null hypotheses: $H_{0,1} : \widehat{\beta}_{0.90} = \widehat{\beta}_{0.95} = \widehat{\beta}_{0.99}$, $H_{0,2} : \widehat{\beta}_{0.99} = \widehat{\beta}_{0.95} = \widehat{\beta}_{0.5}$, and $H_{0,3} : \widehat{\beta}_{0.95} = \widehat{\beta}_{0.90} = \widehat{\beta}_{0.5}$. The tables refer to the periods from January 2003 to December 2006, from November 2008 to November 2011, and from December 2011 to April 2013. Additional tables are reported in the appendix.

Notice that the test focuses on the bond spread coefficients only, thus excluding the impact of the control covariates. The Wald test statistic has a Chi-square density with two degrees of freedom (two restrictions are tested in all cases). Notably, in almost all the cases, the tests suggest the validity of the null hypothesis. We observe rejections of the null from 2003 to

2006, in particular when comparing to the median (19 rejections for $H_{0,2}$ and 17 for $H_{0,3}$ at 1% level).[25], while the other periods the rejections are very few (with a maximum of 4 for $H_{0,3}$ in 2008-Nov2011 at 1% level)

The large number of rejections during the pre-crisis period are well represented by the pattern we described earlier in Figures 8-9: in the presence of large shocks in one country, its relationship with the other countries will become weaker!

The few rejections we find for the second crisis period are related to the impact of France to Germany, Italy to Spain, and France and Germany to Greece but in none of these cases there is a significant increase in the $\beta-$coefficient, see Figures 8-9 and Figures reported in the Appendix; instead in all the four cases there is a significant reduction not an increase in the $\beta-$coefficient.

The reduction in the coefficient of the impact of Italy to Spain indicates that when Spain is facing large changes in the bond yield spread the linkage with Italy is not very strong and this could be due to the fact that Spain started to have difficulties before Italy did and therefore the linkages between the two countries started to decrease when Spain faced the main shocks; the same applies to Greece-Germany and Greece-France.

The more interesting result is that of France versus Germany. Larger shocks in France are associated with lower linkages with Germany. Interestingly, we do not find the same effect from Germany to France. This means that large and small shocks in Germany are transmitted with the same intensity to France, but the opposite is not true. Moreover, as the figures show, the confidence intervals are very large on the extreme quantiles indicating the large uncertainty on the relationship. 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 that accounts for heteroskedasticity in the quantile regression.

The tests thus suggest that the interdependence across the changes in the bond spreads

[25] We recall that the total number of equations is 56.

does not vary in its slope across the upper quantiles. Equivalently, we have a strong evidences of similar $\widehat{\beta}_{1,\tau}$ values across quantiles, in particular during the crisis period.

Therefore, to answer our first question, in line with our definition of contagion our results suggest that there is no presence of contagion in the sample periods considered, and that shock transmission does not differ on days with large spread changes compared to those with small changes. This result applies to all three periods considered, that is, during the turmoil of the debt crisis as well. We do not find relevant difference between our comparison for core versus non-core countries and non-core countries versus non-core countries.

Having performed a structural break test and shown that the relationships in the bond spreads among European countries are stable in each period, we can now also attempt to address the second question of this paper: how shock transmission in the Eurozone has changed over the three periods. Comparing the coefficients we have estimated for the different countries, it seems that the results suggest the presence of a strong reduction in the interrelationship between the Euro countries.

To provide an idea of the change in the relationship among the eight countries, we consider a directed relationship network that plots the intensity of the relationships in the three samples, see Figures 10-12. The thickness of each arrow represents the level of the $\beta-$coefficients. Given that we do not find significant differences among the quantiles (the only exception is France versus Germany), we calibrate the intensity using the $\beta-$coefficients estimated for the median quantile. The algorithm used for the network graphs automatically posts at the center those countries that are strongly connected with the others. Black and thick lines indicate coefficients above 0.75, the Red lines indicates connections between 0.75 and 0.5 and Blue lines connections below 0.5. The graphical representation of the network of relationships among the seven EMU countries and the UK is astonishing and represents the change from a smoothly integration among the EMU countries in the first sample and the loss of integration in the second and third periods.

In particular, the network representation for the sample period of 2003-2006 indicates that there is no hub, but the network structure shows a strong relationship among the seven Euro countries, and a less intense relationship with the UK. It is striking how homogeneous is the intensity of the relationship among the seven Euro countries, indicating that the market for sovereign debt considered these bonds to be substitutes, and that the adjustment of the bond yield spread in one country generated an instantaneous adjustment in the bond spread of another.

The structure is completely different in the sample period 2008-Nov2011, during which the intensity of the interrelationship is no longer homogeneous among the seven Euro countries. Figure 12 depicts a hub-and-spoke network structure, with Italy is the hub of the network relationships. There is evidence of significant relationships among the peripheral countries but of a lower intensity than in the previous sample, indicating a reduction in the intensity of the shock transmission during the debt crisis. This is even more relevant for Germany and the UK, where the intensity of the relationship is much lower than in the previous sample considered (Orange lines indicate connections between 0.1 and 0.25). There is also evidence of asymmetry in the intensity of the transmission: changes in the bond yield spread of France are transmitted with an almost one-to-one intensity (0.96) to Spain, while changes in the spread of Spain are transmitted to France with an intensity equal to 0.22. That is, an increase in the bond yields of Spain of 10bp corresponds to an increase of the bond yield of France of 2.2bp. For Germany, this asymmetry is even stronger. Shocks in Germany are transmitted (with different intensity) to all the other countries; but the only countries that significantly affect Germany are France (0.76) and the UK (0.13).

This indicates that in the period 2008-Nov2011 the market for sovereign debt started to distinguish between these bonds that are no longer substitutes, so that an adjustments of the bond yield spread in one country generate a significantly lower-intensity adjustment in the bond spread in another country, indicating a significant loss of integration among the bond yield spreads.

This reduction is even more significant for the third sample, with, again, in general, a strong reduction in their interrelationships, and the only evidence of strong (compared to others) relationships among France, Italy and Spain.[26] The evidence of disintegration is well depicted by the network graph, with Germany and the UK showing evidence of a flight-to-quality effect, i.e. the transmission coefficients are negative and significant with respect to Italy, Portugal and Spain (Green lines indicates coefficients below -0.25).

To summarize, in this subsection, we have found that the relationships across the quantiles are 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 samples considered. A comparison of the different sample periods considered indicates that sovereign risk propagation intensity is lower rather than higher for the most recent period compare to the pre-crisis period of 2003-2006. In other words, rather than generating contagion, the recent sovereign debt crisis has generated "Euro-disintegration", i.e. sovereign debt changes in the countries that belong to the Euro-area are less related to one other, and shock transmission, even if still present, is of a lower intensity than during the period 2003-2006.

The network analysis shows relevant differences between the coefficients of the shock transmissions among the EMU countries and between them and the UK but we cannot claim that these coefficients are statistically different. In the previous subsection we tested for the presence of structural breaks in the linear regression framework. Here, we perform a similar analysis focusing on quantile regressions. As in the linear regression case, we test for structural breaks on a single coefficient, that captures the relation between any two changes in bond spreads. We obtain estimates on four year rolling window with one month step, testing for a change in the coefficients occurring at the end of the second year. However, to simplify the computation

[26]In this representation, we have excluded Greece in this sample period because data on its bond spread are only available up to March 2012.

of the test statistic, we consider the following specification of the conditional quantile:

$$\widehat{y_{i,t}}\,(\tau) = \widehat{\beta}_{0,\tau} + \widehat{\beta}_{1,\tau} y_{j,t} + \widehat{\delta}_{1,\tau} y_{j,t} d_t + \widehat{\gamma'}_{\tau} X_{t-1} \tag{12}$$

where d_t is a step dummy assuming unit value after the break date, and $\widehat{\beta}$ denotes the estimated coefficients of the parameter β. In this framework, a change in the β coefficient is equivalent to a statistically significant δ coefficient. In fact, before the break date, the relation between the two changes in the bond spreads is monitored by the β value, while after the break date, the relation comes from $\beta + \delta$. We thus verify the statistical significance of the δ and also its stability across quantiles. That is, for a given break date we check that δ_τ is constant across different values of τ. Summary results of the test are reported in Figure 13. In the first panel we report, for different quantiles, the average p-value for the test of significance on the coefficient δ_τ. The results are consistent with those reported in the linear regression case and support the existence of a break in 2008. The second panel is just a confirmation of that result, showing that the break-related coefficient δ_τ is, in most cases, stable across quantiles, and also add further support to the findings of linearity.

It is quite surprising that the Euro disintegration started in October 2008 and not after the Greece crisis of 2009. This result indicates that the evidences of disintegration across Eurozone economies is due to the change in the market perception of the synchronization of those economies. Such a modification was originated by the US crises and lead to a divergence across the Eurozone economies, and to the fiscal crises of 2010.[27]

One aspect that we have not considered, however, is the possibility that the quantile regressions could be affected by the presence of heteroskedasticity. As mentioned above, we explore

[27] A simple analysis of the Repo rates observed across different sovereign bonds in the sample 2003-2013 confirms our intuition. We observe that the various rates were very similar up to September 2008. From October 2008, a recurrent date in our structural break exercise, there is a clear change in the picture, with a divergence across rates that has not yet recovered up to mid 2013. Moreover, cross country exposures among financial institutions has been reduced from 2009 to 2011 as shown by Brutti and Saure'(2013) using the results provided by BIS reporting.

this topic in the following section.

4.4 Bayesian Quantiles with Heteroskedasticity

The absence of variability across the quantiles suggests a linear interdependence across large changes in the bond spreads. This difference might be due to the absence of the GARCH component in the quantile regressions used in the previous subsection. Indeed, the contagious event described in Section 2 could introduce heteroskedasticity over time, with higher volatility in crisis periods than normal times, see equation (1). However, it might also introduce heteroskedasticity across quantiles, especially at low and high quantile levels, where the volatility might be more sensitive to the contagion term.

As mentioned before, QR 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 (over time and across quantiles). 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. Again, this will occur at low and high quantile levels especially, 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 (10).

The changes in the bond spreads are assumed to follow a linear model with heteroskedasticity as described in equation (4), 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 (10) and minimizes the following logical quantile criterion function:

$$min_{\Theta_\tau,\alpha_\tau} \sum_{t=1}^{T} \left(\frac{\rho_\tau \left(y_{i,t} - \beta_{ij,0} - \beta_{ij,1} y_{j,t} - \gamma'_{ij} X_{t-1} \right)}{\sigma_{ij,t}(\tau)} + log(\sigma_{ij,t}(\tau)) \right) \tag{13}$$

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 omitted 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 (2009) 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 identifying the reference quantile. We choose a Bayesian approach to estimate the parameters because we believe this method has several advantages including: (i) accounting for parameter uncertainty through the simultaneous inference of all model parameters; (ii) exact inferences 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 it is the standard approach, we assume a normal prior for $\Theta_\tau \sim N(\underline{\Theta}_{0,\tau}, \underline{\Sigma})$. $\underline{\Theta}_{0,\tau}$ is set equal to the frequentist estimates of model (10); and $\underline{\Sigma}$ is chosen 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 (13).

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 parameter estimates accounting for heteroskedasticity are, in most of the cases, very similar to the results of the quantile regression presented in the previous section, where heteroskedasticity was not taken into account. Figures 14-15 report the values of the $\beta_{1,\tau}$ coefficient across different quantile levels for selected countries and subsamples as in Figures 8-9; the results for all countries and samples are reported in the appendix.[28] The uncertainty is in most of the cases lower and the confidence intervals are smaller than those estimated in the previous section, particularly for smaller and larger quantiles, see for example the case Germany versus France.[29] The median values are very similar to those in the previous analysis and linearity cannot be rejected in most case. The few exceptions are the four cases identified previously as significant changes but with a reduction of the beta coefficients, confirming the same finding in the previous section regarding the impact of France to Germany, Italy to Spain, France and Germany to Greece.

The main differences are for the impact of Spain to Italy and France to Italy and Ireland. Allowing for heteroskedasticity in fact produces more precise quantile estimates, above all in the tails, signaling contagion evidence in this relationship that standard QR cannot find. The results indicate that the presence of contagion could be related only to the impact of Spain to Italy (and not vice versa). Therefore, the large shocks that Spain experienced in 2011 transmitted with an amplified magnitude to Italy relative to previous years, but the large shocks that Italy experienced in the same year did not imply a similar mechanism for Spain, but actually the opposite. Nevertheless, this is consistent with the theoretical model outlined in Section 2, where the contagion might be observed in just one country, the one with shocks

[28]Our results are robust to different prior values, including priors centred around frequentist estimates with very small variance.

[29]Figures 8-9 and 14-15 have the same scale, and the plots of quantiles in the latter one are often overlapping, indicating that the magnitude of the uncertainty is smaller in that case.

from the contagious factor transmitted at higher intensity (parameters satisfy $\delta > 1$ and $\delta > \alpha$ in equation (1)). Similar results are found for the relation between France-Ireland and France-Italy. [30] All these findings indicate that there is no evidence of contagion from peripheral countries to core countries and among peripheral countries the only evidence of contagion is from Spain to Italy. On the other side the data indicates that potential evidence of contagion arises from the core country France and it may generate significant contagion effects to Ireland and Italy, but not to the other countries. As described in Section 2, this indicate that there are other factors (could be panic or other) that generate a stronger effect on the relationship among the yield spread of the different countries as shown in figure 2.

To sum up, the relationships are confirmed to be remarkably stable and linear across quantiles for almost all the cross-linkages considered.[31]

Finally, figures for the last sample, Dec2011-2013 confirms evidence of no-contagion, but rather linkages are weaker and the disintegration of the Euro has not fully stopped despite the ECB intervention.

As we did in the previous subsection, we investigate the presence of breaks in the β parameter of equation (13). Similarly to what we did for equation (12), we add a step dummy assuming unit value after the step date at the end of the second year, and estimate the parameter $\widehat{\delta}_{1,\tau}$ on a four-year rolling window with a one-month increment at each new estimation. We obtain posterior densities of $\widehat{\delta}_{1,\tau}$ over the different rolling windows, for the different τ quantiles, and the

[30] Furthermore, results in appendix indicate that the linkage from Germany to Portugal and from UK to Portugal also increases, but only at 99% quantile.

[31] Despite the certainty that a structural break occurred in 2008, we perform exactly the same exercise over the entire sample, 2003–2011. We do not find a linear relationship: for smaller and larger quantiles, in most of the cases, we reject the notion that the coefficients are the same. As we would expect when allowing for heteroscedasticity, the differences among quantiles are larger for the Bayesian estimates. The pattern, especially for the Bayesian coefficients, follows 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 those in the pre-crisis period. This is particularly evident for the coefficients associated with Greece, Ireland, Italy, Portugal, and Spain, whereas France's relationships with Germany and the UK are more stable over time, such as we also find in the analysis of the subperiods. This result is encouraging because it clearly indicates that the (Bayesian) methodology has enough power to reject certain samples.

56 cross-country comparisons we study, and we infer whether zero is in the credibility interval for different quantiles.

For most of the countries, we find that zero is not in the credible interval of the posterior for $\widehat{\delta}_{1,\tau}$ when the step-up is assumed to be in the last quarter of 2008, and particularly for values of τ closer to 1. The coefficient is often estimated to be negative, confirming previous evidence that the sovereign risk propagation intensity is lower rather than higher after 2008. Anticipating or postponing the step dummy moves the posterior estimates toward zero.

A further element that we have not discussed so far, is the possible impact of endogeneity issues in the quantile regression framework. However, it is likely that the simultaneity bias will affect QR coefficients in the same manner across quantiles. As a consequence, since we are not interested in analyzing the point values of the coefficients, but rather in testing their equivalence, the presence of a bias will not affect the power of the test greatly. Nevertheless, in order to cope with this issue, in the next section dedicated to robustness, and in particular in the appendix, we summarize the results obtained with a QR instrumental variable estimator and a test for parameter stability with omitted variables and simultaneous equations.

5 Robustness Analysis

In order to verify the results reported above, we run a number of checks. In particular, we consider additional subsamples, precisely 2008-2012 and 2008-2013, and different estimation methods for both the generalized linear regression model of (7) and for the QR. The results in the appendix reported in the previous sections are confirmed.

We also run the same analyses for the changes in countries' CDS for the last two subsamples. Reliable CDS data are in fact not available before 2007 for all countries. However, the analysis confirms the results we obtained with the bond yield spreads and the estimated coefficients are very similar. Exeptions are Greece and Portugal that highlights an increase of the linkage with the other countries considered above the 95th percentile. Since we do not find the same evidence for bond data, this result could be related to liquidity issues that may have affected the CDS market when Greece and Portugal are facing large shocks.

We use a different approach to evaluate the possible presence of nonlinearities in the relationship across bond spreads: the exceedence correlation measures proposed by Longin and Solnik (2001). Even with this different methodology we find a reduction in the exceedence correlation coefficients from the 2003-2006 sample and to 2008-2011 and 2011-2013 samples. During the debt crisis the tails show evidence of a reduction of the exceedence correlation rather than an increase. However, this methodology has the drawback of being bias by heteroschedasticity and this may explain the reduction of the exceedence correlations in the tails.

Finally, we apply two tests for parameter stability under omitted variables in the appendix. More specifically, we use the approach proposed by Rigobon (2003) who proposes a solution to the identification in simultaneous equation models based on the heteroskedasticity observed in the data. Moreover, we perform a quantile regression where parameters have been estimated with instrumental variables. Both exercises indicate that the answers we provide to our two main questions - the presence of contagion and changes in the shock transmission between the sample periods - are robust.

6 Discussion

Recent European events have spurred a new discussion of contagion. In previous crises, the US in 1987, Mexico in 1994, Thailand in 1997, Russia in 1998, the US again in 2001, etc., it was relatively clear who was the "culprit" generating the crises. This is not the case in Europe. 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 European situation. The purpose of this paper is to offer an assessment of contagion risk based on quantile regressions that account for the possibility of heteroskedasticity when extreme events occur.

The paper offers two main contributions: methodological and empirical. From the methodological point of view, the paper has developed a procedure to evaluate financial contagion based on quantile regressions when contagion is defined as a change in the propagation mechanisms of shocks across countries or industries. The quantile regression allows us to evaluate the asymmetries in the response to shocks, between large and small, and positive and negative. In other words, a crisis, which is generally associated with large and positive shocks in the bond yield spread, can be compared to normal times - that exhibit small shocks, closer to zero.

The second contribution is empirical. We evaluate contagion within the Eurozone from 2003 to 2013. We split the sample into three parts: pre-crisis, crisis, and ECB intervention. We find that the transmission mechanism is constant between the crisis period 2008-Nov2011 and the ECB intervention of Dec2011-Apr2013. The only exceptions among the 56 cross-linkages beta is the impact of Spain to Italy and France to Italy and Ireland, where we observe evidence of contagion in the period 2008-Nov2011, but in the sample Dec2011-Apr2013 this evidence of contagion disappears possible following the ECB intervention. In the analysis we performed about changes through time of the intensity of linkages among countries we find, nevertheless, that the coefficients actually drop rather than increase after the US crisis suggesting that the linkage within the Eurozone countries falls during this time. These two results are surprising when compared to the ongoing discussion. They are consistent, however, with a simple explanation that the US crisis changed market perceptions on the degree of synchronization between Eurozone economies, and the fiscal crises of 2010 were a consequence of this divergence. This result is confirmed by the divergence observed in Repo rates among the Euro countries from October 2008. On top of this cross country exposures among financial institutions has been reduced from 2009 to 2011 as shown by Brutti and Saure'(2013) using data provided by BIS reporting. Future research should explore this conjecture further.

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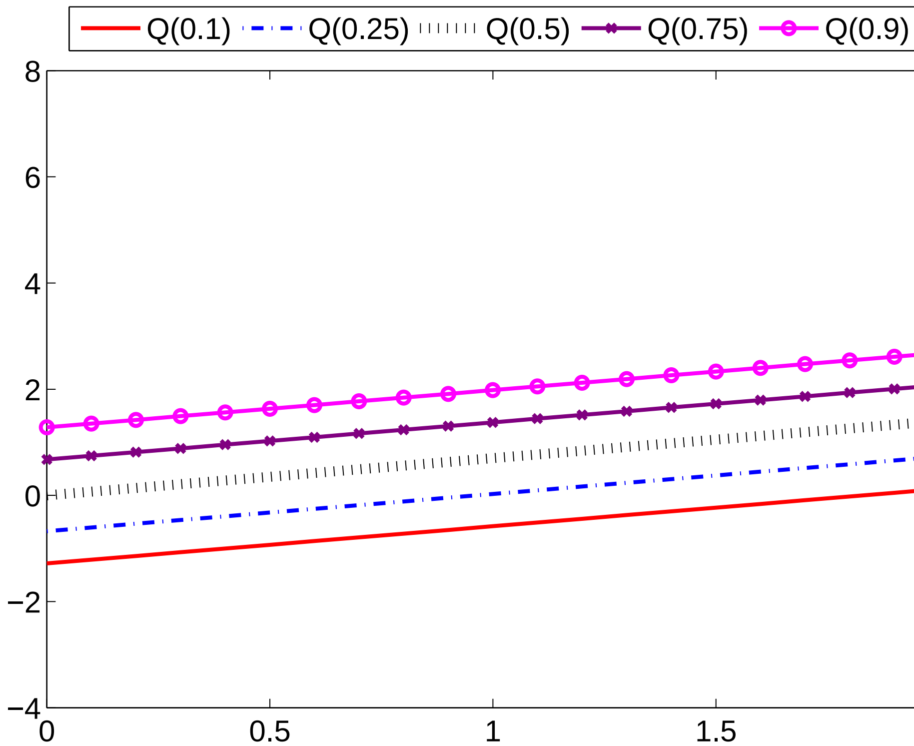
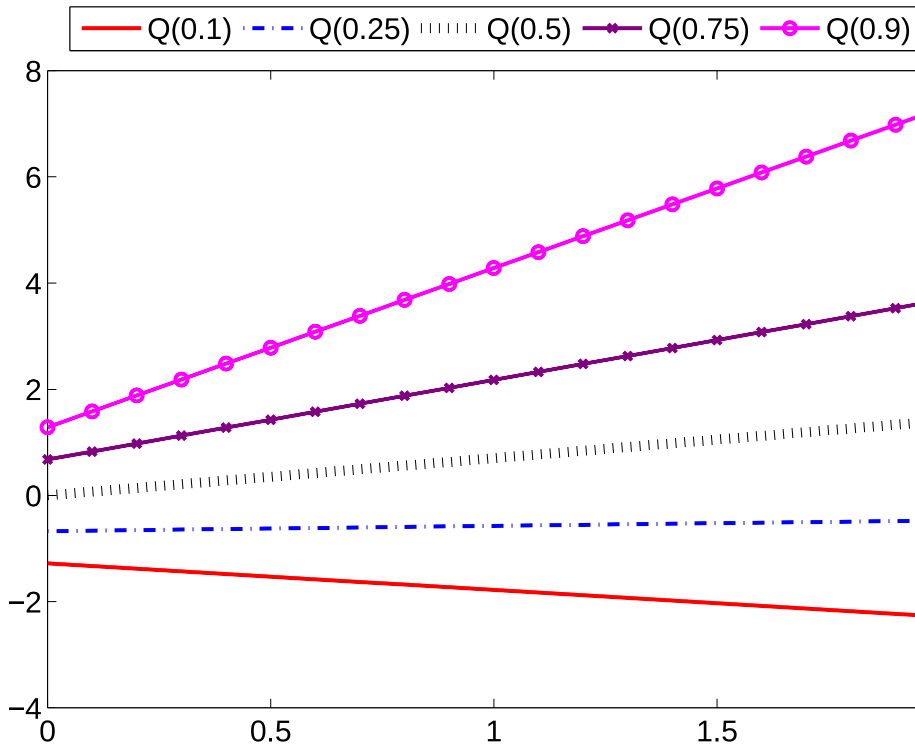
Figure 1: **Quantile regression and parallel quantiles**



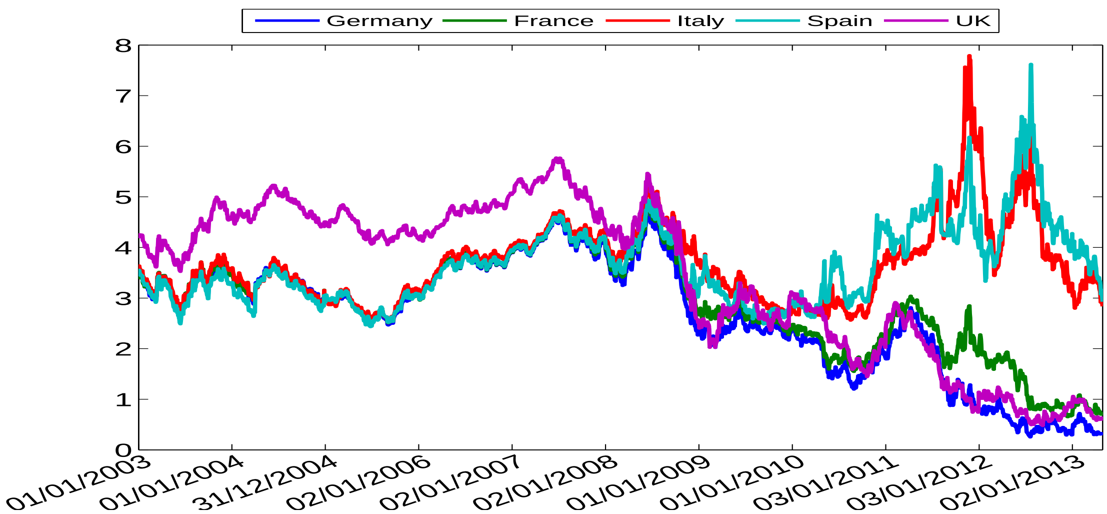
This figure reports quantile regression lines $y_{i,t}(\tau) = \beta_{0,\tau} + \beta_1 y_{j,t} + F_{\eta_t}^{-1}(\tau)$ when the true underlying model is linear, that is $\beta_{1,\tau} = \beta_1$, or the coefficient does not change among quantiles. In this representation the coefficient is always equal to 0.5, and therefore the slope coefficient of the regression line is always the same across values τ (we used values ranging from 0.1 to 0.9). The regression line is represented with the different values of $y_{j,t}$ reported in the horizontal axis and the quantile realizations $y_{i,t}(\tau)$ reported in the vertical axis. The difference among quantiles is characterized by the intercept $F_{\tau}^{-1}(\eta_t)$ which is the unconditional quantile of the innovation density (that does depend on the quantile τ). The coefficient $\beta_{0,\tau}$ has been set equal to 0.

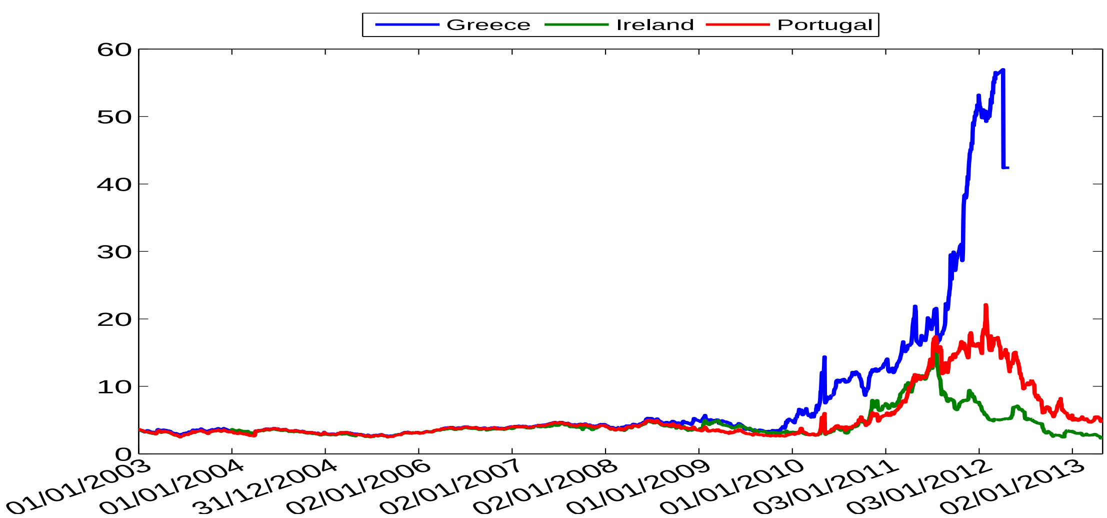
Figure 2: **Quantile regression and non-parallel quantiles**



This figure reports quantile regression lines $y_{i,t}(\tau) = \beta_{0,\tau} + \beta_1 y_{j,t} + F_{\eta_t}^{-1}(\tau)$ when the true underlying model is non-linear, that is $\beta_{1,\tau}$ changes among quantiles. In this representation we have that $\beta_{1,0.1} = -0.5$, $\beta_{1,0.25} = 0.0$, $\beta_{01,.5} = 0.5$ $\beta_{1,0.75} = 1$ and $\beta_{1,0.9} = 2$ (the quantile considered, τ, ranges from 0.1 to 0.9, the same values used in Figure 1). The regression line is represented with the different values of $y_{j,t}$ reported in the horizontal axis and the quantile realizations $y_{i,t}(\tau)$ reported in the vertical axis. The difference among quantiles is characterized by the intercept $F_{\tau}^{-1}(\eta_t)$ which is the unconditional quantile of the innovation density (that does depend on the quantile τ). The coefficient $\beta_{0,\tau}$ has been set equal to 0.

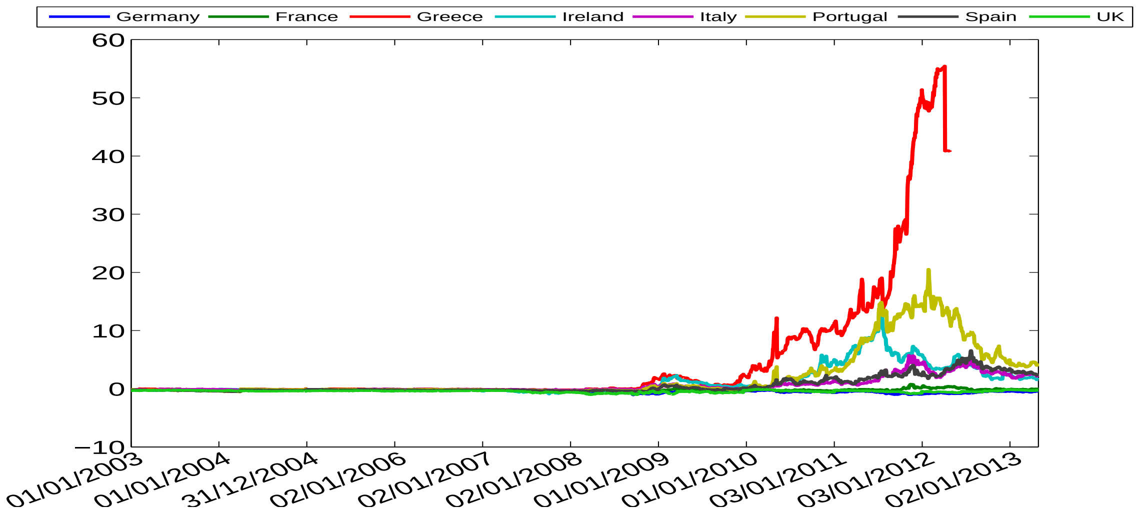
Figure 3: **5 years Bond Redemption Yields**

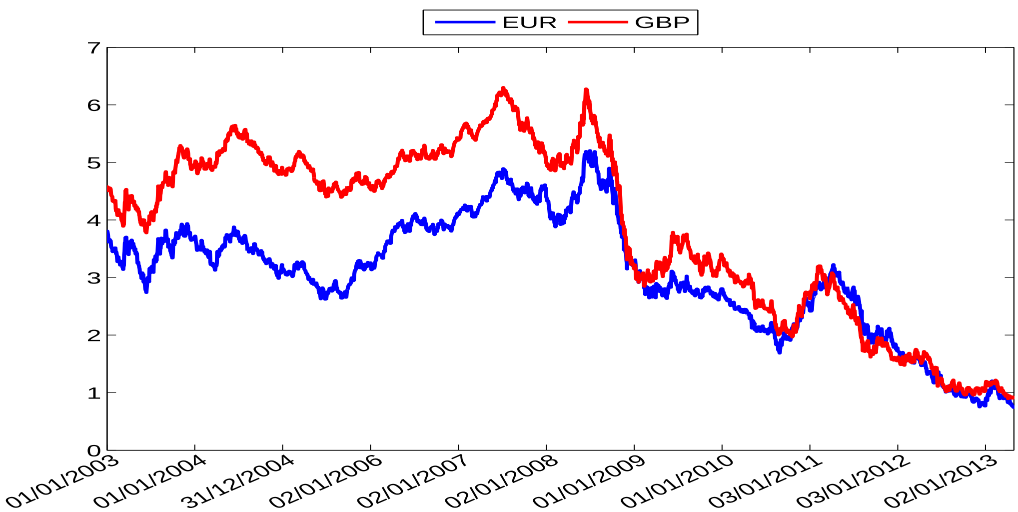




This figure shows daily 5 years Bond redemption yields obtained from Thomson-Reuters spanning from January 1, 2003 to March 10, 2012 for Greece and to April 30 2013 for the other countries. The first panel reports Germany (Blue line), France (Green line), Italy (Red line), Spain (Cyan line) and United Kingdom (Magenta line). The second panel reports Greece (Blue line), Ireland (Green line) and Portugal (Red line).

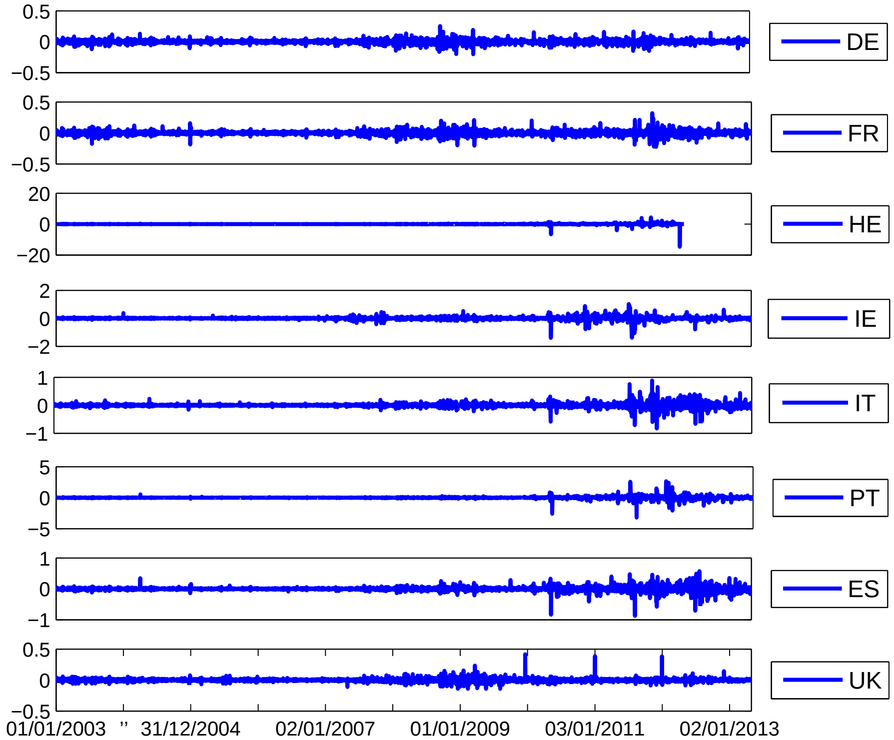
Figure 4: **5 years Bond Yield Spreads**





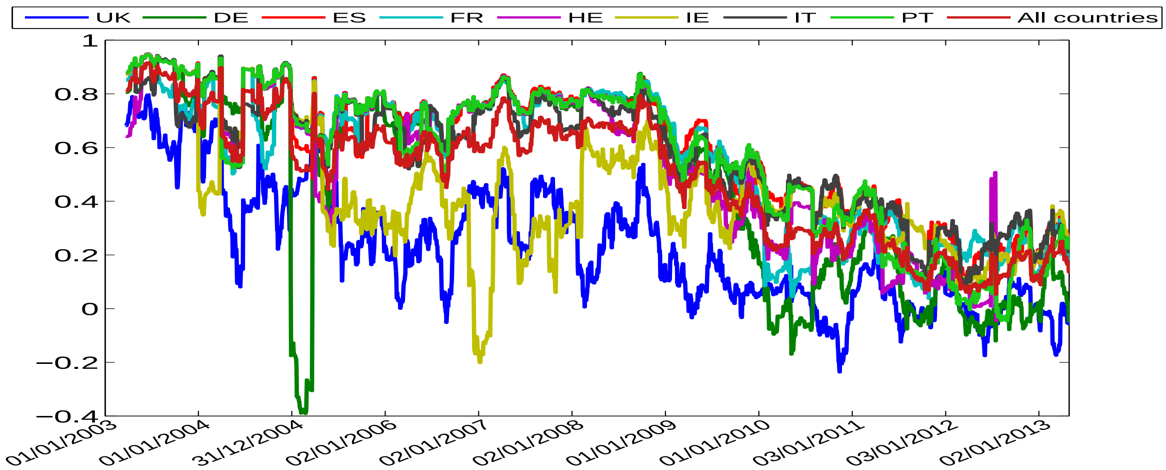
The first panel of this figure shows the daily 5 years bond yield spreads calculated as the difference between the 5 years Bond redemption yields and the 5 years Euro swap rate for the Eurozone countries and the British pound swap rate for UK. The sample period considered ranges from January 1, 2003 to to March 10, 2012 for Greece and to April 30 2013 for the other countries. The second panel shows Euro swap rate and the British pound swap rate from January 1, 2003 to April 30 2013.

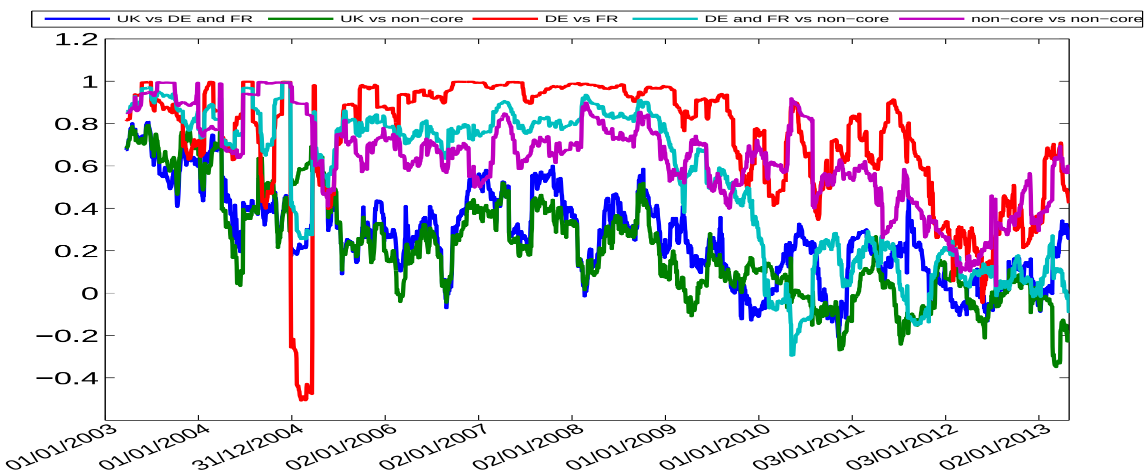
Figure 5: **Changes in 5 years Bond Yield Spreads**



This figure plots the changes in the 5-year bond yield spreads (in %) of France (FR), Germany (DE), Greece (GR), Ireland (IE), Italy (IT), Portugal (PT), Spain (ES) and United Kingdom (UK). Data are obtained from Thomson-Reuters and span the period from January 1, 2003 to March 10, 2012 for Greece and to April 30, 2013 for the other countries.

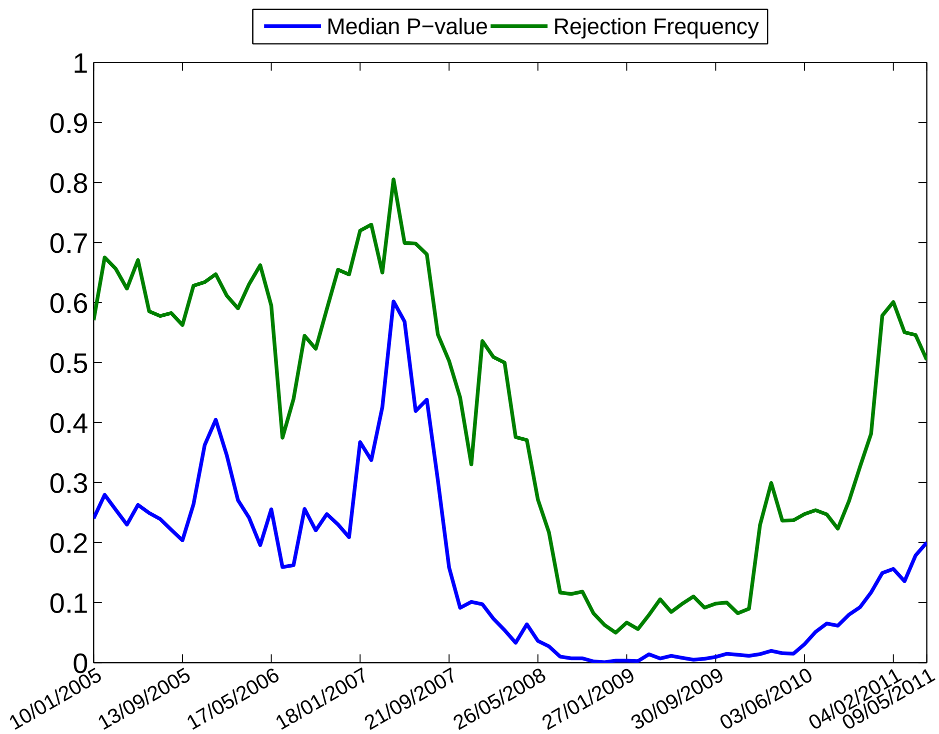
Figure 6: **Average Rolling Correlations on Yield-Spread Changes**





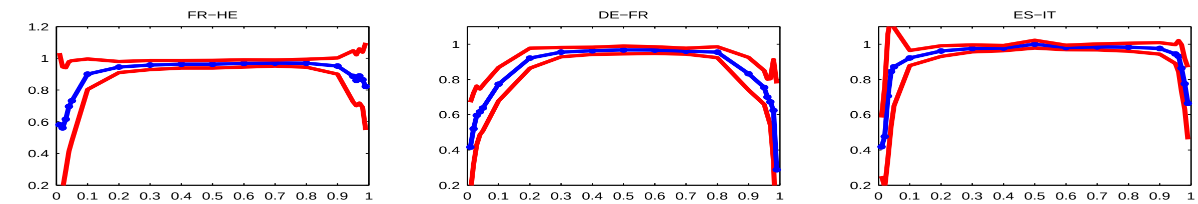
The first panel of this figure plots the average of the pairwise rolling correlation of 5 years yield spread changes of the 7 Eurozone countries considered: France (FR), Germany (DE), Greece (GR), Ireland (IE), Italy (IT), Portugal (PT) and Spain (ES) and the United Kingdom (UK). The Red line reports the average of all the pairwise rolling correlation among the eight countries considered. The rolling window considered is of 60 observation. Data are obtained from Thomson-Reuters and span the period from January 1, 2003 to March 10, 2012 for Greece and to April 30, 2013 for the other countries. The second panel reports some example of pairwise correlations. The rolling correlation of UK with the core countries France and Germany (Blue line), UK with non-core countries (Green line), Germany with France (Red line), core (Germany and France) with non-core countries (Cyan line) non-core with non-core (Magenta line).

Figure 7: **Structural Instability in the Linear Regression**

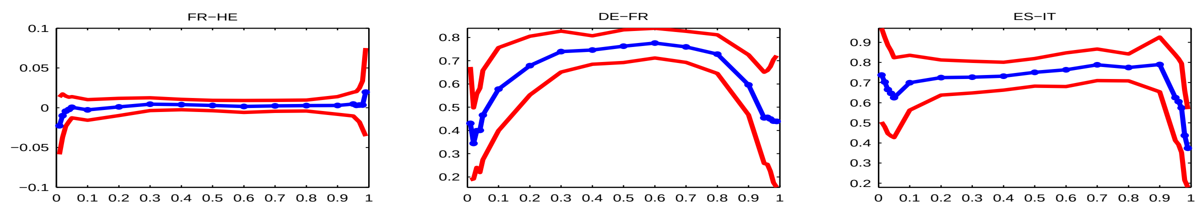


This figure shows the results of the Chow-type test for a structural break in the coefficient β_1 in the linear relation (7). The test is performed on a rolling window of four years, testing for a break occurring after the end of the second year. The lines report median p-values (Blue line) and the 75% quantile (Green line) over the 56 cross-country regressions.

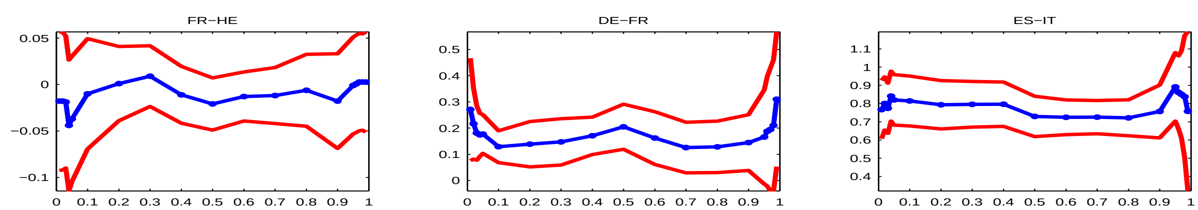
Figure 8: **Samples of Quantile Regression Coefficients for Different Bond Spreads.**



2003-2006



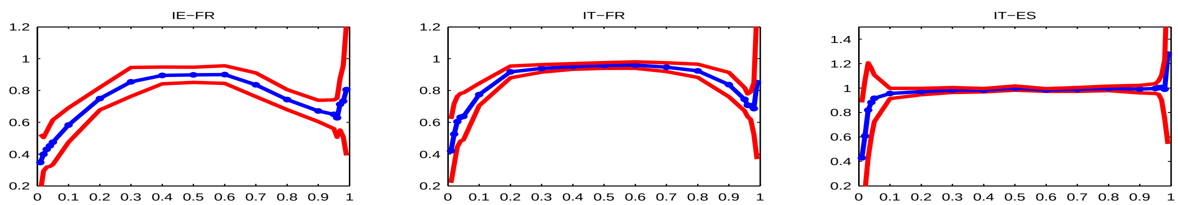
2008-2011



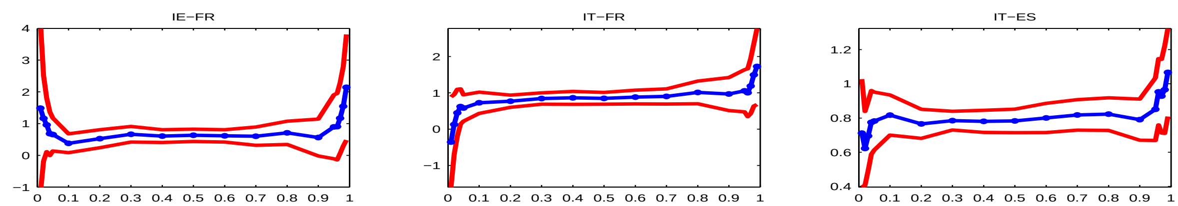
2011-2013

This figure shows the estimated coefficients $\widehat{\beta}_{1,\tau}$ of the Quantile regression $\widehat{y_{i,t}}(\tau) = \widehat{\beta}_{0,\tau} + \widehat{\beta}_{1,\tau} y_{j,t} + \widehat{\gamma}'_{\tau} X_{t-1}$ for three pairs of countries: in the first block country i is France (FR) and country j is Greece (HE), in the second block country i is Germany (DE) and country j is France (HE), in the third block country i is Spain (ES) and country j is Italy (IT). We consider three different periods, January 1, 2003 to December 29, 2006, November 1, 2008 to November 30, 2011, and December 1, 2011 to March 10 2012 for FR-HE and to April 30, 2013 for DE-FR and ES-IT. The red lines represent the 95% confidence intervals obtained with the Markov Chain Marginal Bootstrap method of Kocherginsky, He, and Mu (2005).

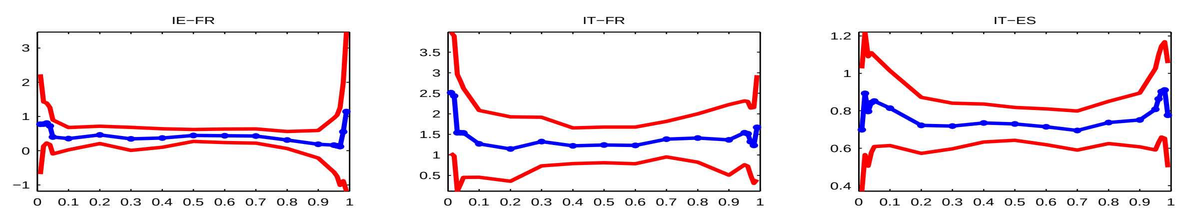
Figure 9: **Samples of Quantile Regression Coefficients for Different Bond Spreads.**



2003-2006



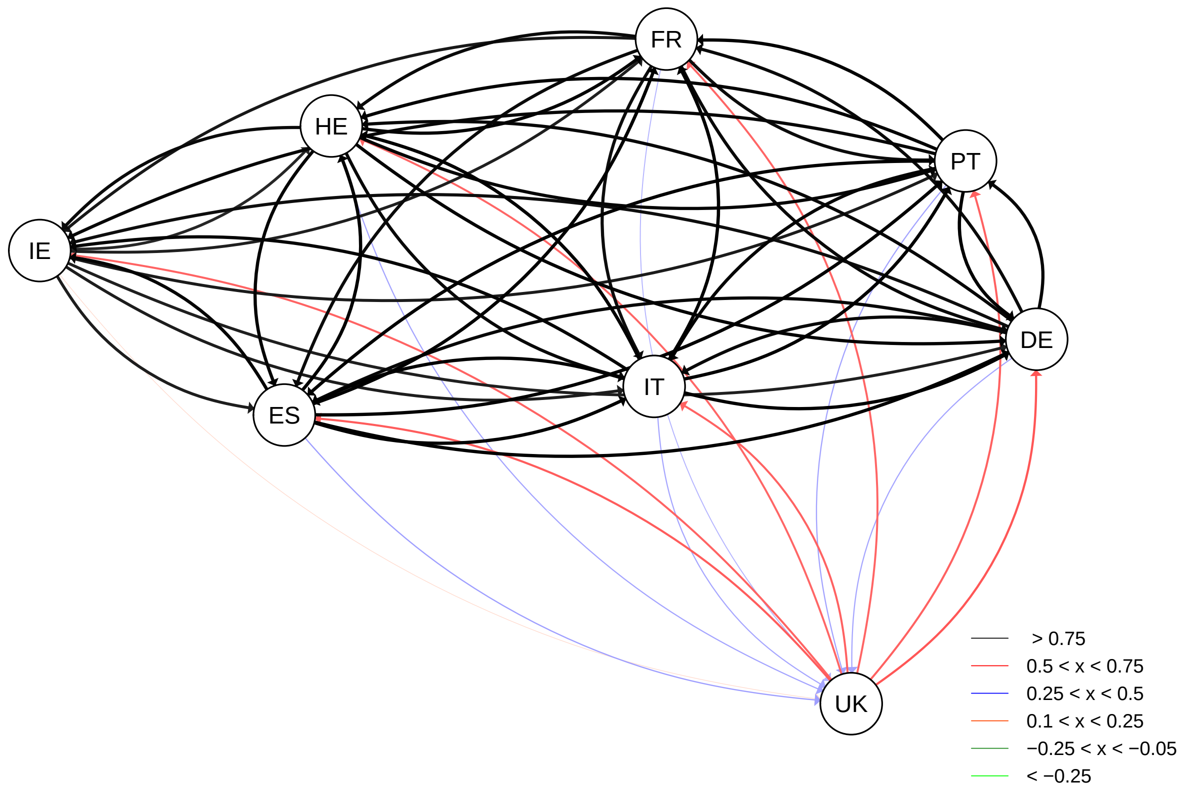
2008-2011



2011-2013

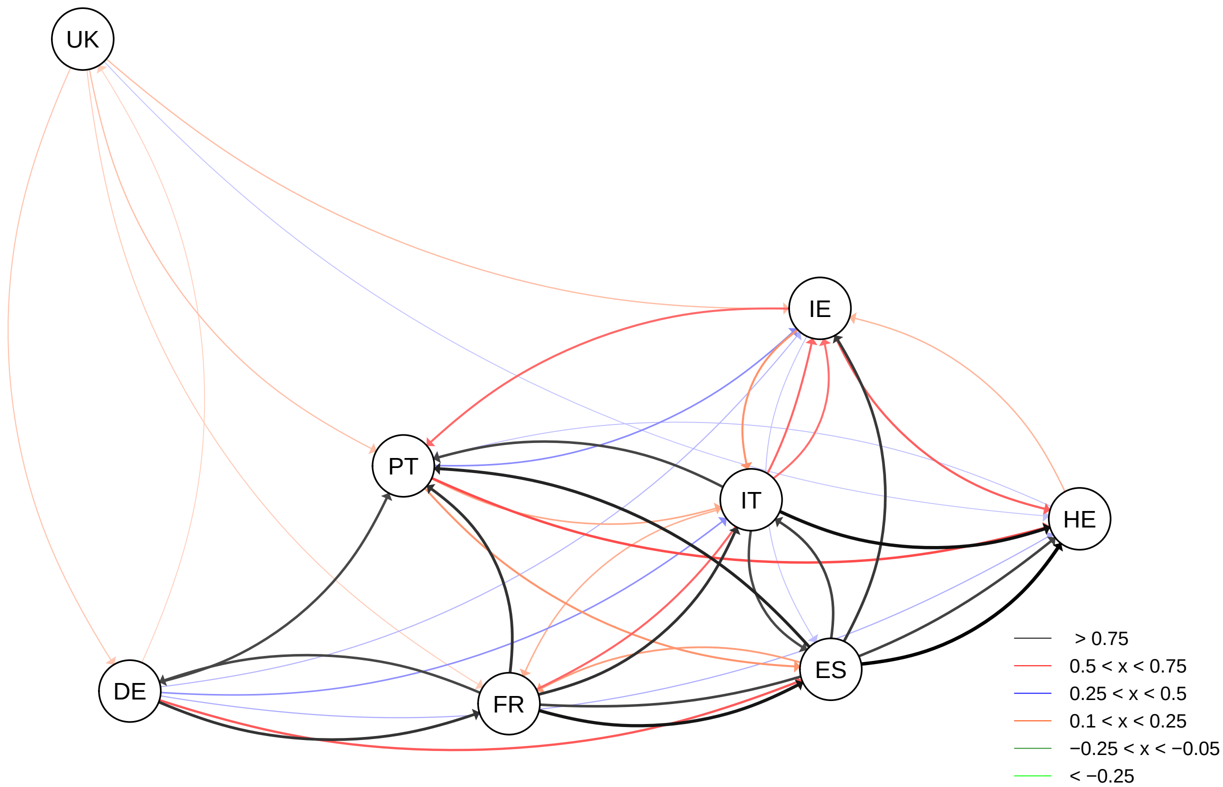
This figure shows the estimated coefficients $\widehat{\beta}_{1,\tau}$ of the Quantile regression $\widehat{y_{i,t}}\,(\tau) = \widehat{\beta}_{0,\tau} + \widehat{\beta}_{1,\tau} y_{j,t} + \widehat{\gamma'}_{\tau} X_{t-1}$ for three pairs of countries: in the first block country i is Ireland (IE) and countries j is France (FR), in the second block country i is Italy (IT) and country j is France (FR), in the third block country i is Italy (IT) and country j is Spain (ES). We consider three different periods, January 1, 2003 to December 29, 2006, November 1, 2008 to November 30, 2011, and December 1, 2011 to April 30, 2013. The red lines represent the 95% confidence intervals obtained with the Markov Chain Marginal Bootstrap method of Kocherginsky, He, and Mu (2005).

Figure 10: **Network Graphs 2003-2006**



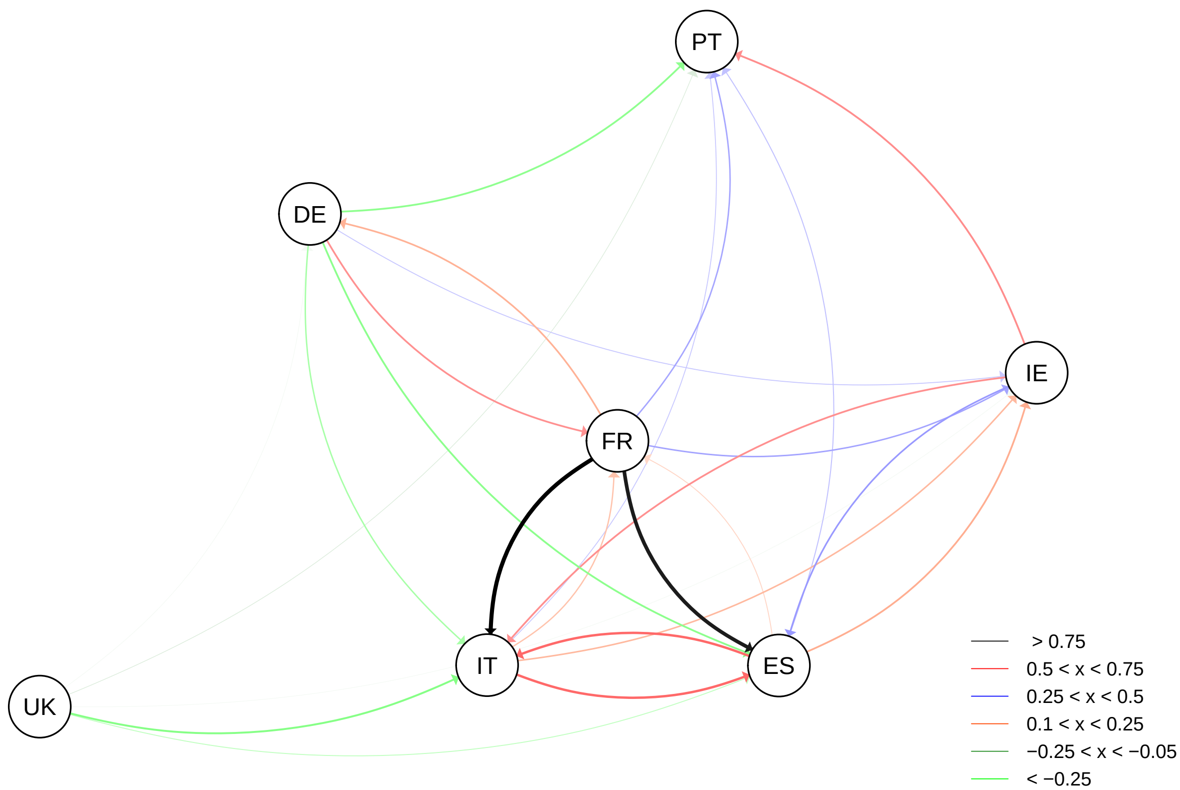
This figure shows the directed relationship network that derives from the estimated Quantile Regression coefficients $\beta_{1,\tau}$ for the sample period 2003-2006. The arrows start from country j and reach country i. The color and the thickness of each arrow represent the level of the associated coefficients as indicated in the legend, where the $\widehat{\beta}_{1,\tau}$ is indicated with x and in particular the Black line indicate an estimated $\widehat{\beta}_{1,\tau}$ coefficient above 0.75, the Red line a coefficient between 0.75 and 0.5, the Blue line a coefficient between 0.5 and 0.25, the Orange line coefficient between 0.25 and 0.1, the Grey line a negative coefficients between -0.25 and -0.05, that is a flight to quality for country j versus country i and the Green line a negative coefficient below -0.25 that is a strong flight to quality. The eight countries considered are respectively: DE=Germany, FR=France, HE=Greece, IE=Ireland, IT=Italy, PT=Portugal, ES=Spain, UK=United Kingdom.

Figure 11: **Network Graphs 2008-2011**



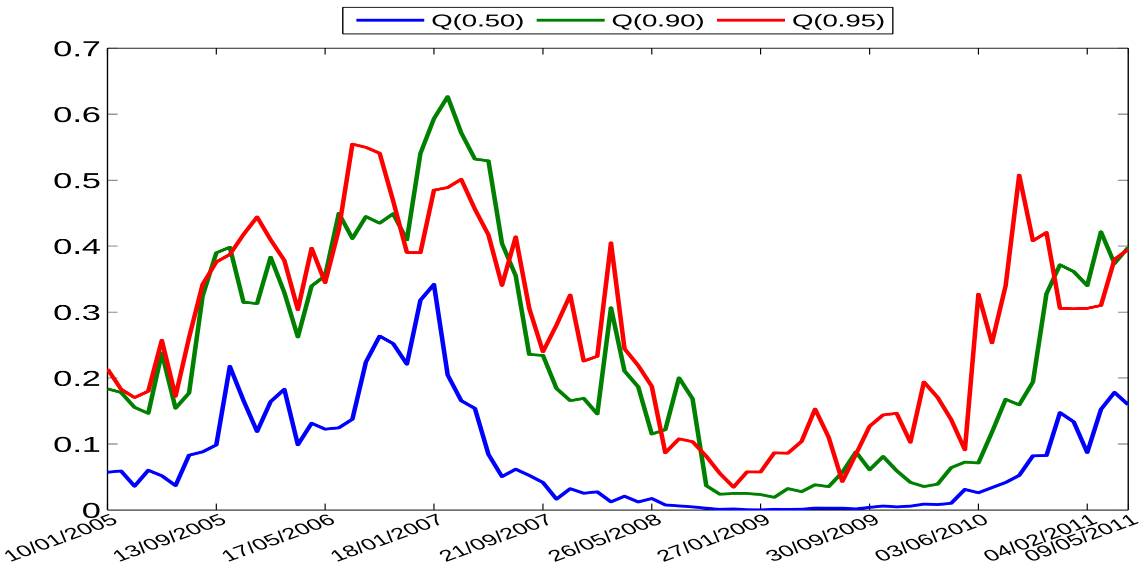
This figure shows the directed relationship network that derives from the estimated Quantile Regression coefficients $\widehat{\beta}_{1,\tau}$ for the sample period 2008-Nov2011. The arrows start from country j and reach country i. The color and the thickness of each arrow represent the level of the associated coefficients as indicated in the legend, where the $\widehat{\beta}_{1,\tau}$ is indicated with x and in particular the Black line indicate an estimated $\widehat{\beta}_{1,\tau}$ coefficient above 0.75, the Red line a coefficient between 0.75 and 0.5, the Blue line a coefficient between 0.5 and 0.25, the Orange line coefficient between 0.25 and 0.1, the Grey line a negative coefficients between -0.25 and -0.05, that is a flight to quality for country j versus country i and the Green line a negative coefficient below -0.25 that is a strong flight to quality. The eight countries considered are respectively: DE=Germany, FR=France, HE=Greece, IE=Ireland, IT=Italy, PT=Portugal, ES=Spain, UK=United Kingdom.

Figure 12: **Network Graphs 2011-2013**

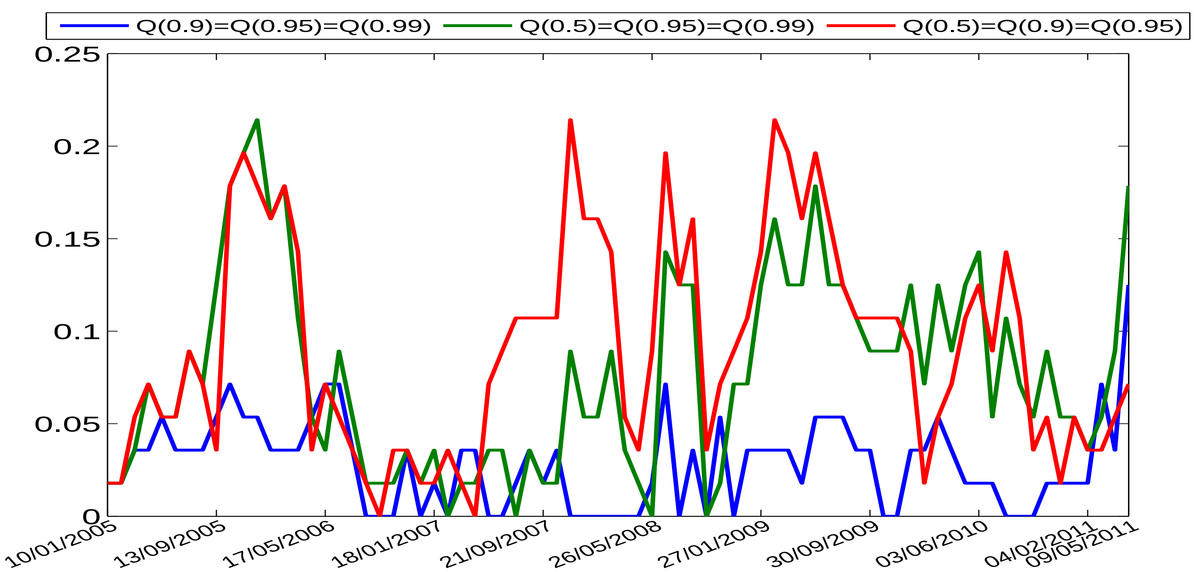


This figure shows the directed relationship network that derives from the estimated Quantile Regression coefficients $\widehat{\beta}_{1,\tau}$ for the sample period Dec 2011-Apr2013. The arrows start from country j and reach country i. The color and the thickness of each arrow represent the level of the associated coefficients as indicated in the legend, where the $\widehat{\beta}_{1,\tau}$ is indicated with x and in particular the Black line indicate an estimated $\widehat{\beta}_{1,\tau}$ coefficient above 0.75, the Red line a coefficient between 0.75 and 0.5, the Blue line a coefficient between 0.5 and 0.25, the Orange line coefficient between 0.25 and 0.1, the Grey line a negative coefficients between -0.25 and -0.05, that is a flight to quality for country j versus country i and the Green line a negative coefficient below -0.25 that is a strong flight to quality. The seven countries considered are respectively: DE=Germany, FR=France, IE=Ireland, IT=Italy, PT=Portugal, ES=Spain, UK=United Kingdom. Greece has been excluded because our sample stops at March 10 2013 for Greece.

Figure 13: **Structural Instability in Quantile Regression**



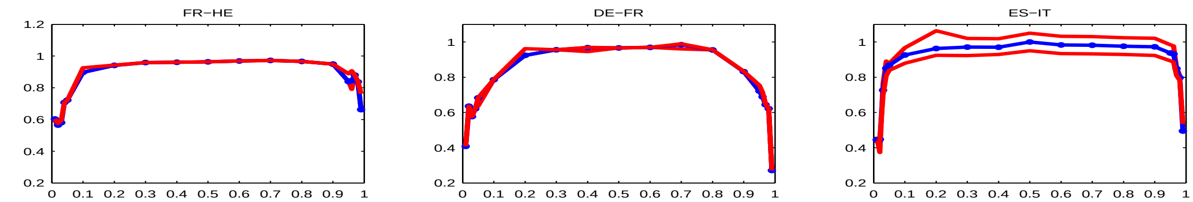
Median p-value across quantiles for the structural break test



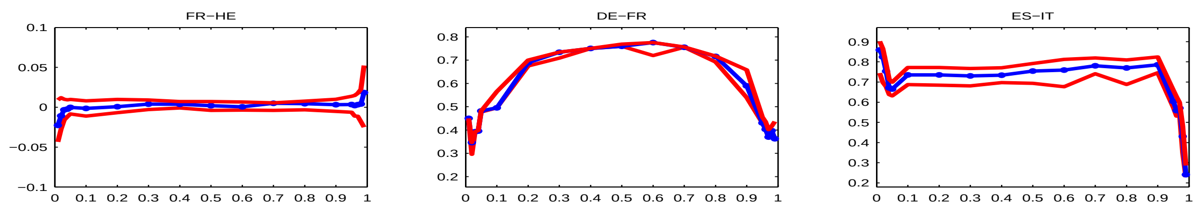
Fraction of rejection of the null of stability across quantiles

This figure shows the results for a structural break test in the coefficient $\widehat{\beta}_{1,\tau}$ in the quantile regression (12). The test is performed on a rolling window of four years, estimating the following quantile regression $\widehat{y_{i,t}}(\tau) = \widehat{\beta}_{0,\tau} + \widehat{\beta}_{1,\tau} y_{j,t} + \widehat{\delta}_{1,\tau} y_{j,t} d_t + \widehat{\gamma'}_{\tau} X_{t-1}$ testing for a break occurring after the end of the second year, i.e. testing whether the quantile regression coefficient of the dummy variable d_t, $\widehat{\delta}_{1,\tau}$, is statistically different than zero. The top panel reports the median p-values of the $\widehat{\delta}_{1,\tau}$ coefficient over the 56 cross-country regressions for the 50%, 90% and 95% quantiles. The bottom panel reports the fractions of rejection of the null of stability across quantiles, for three different hypotheses: Q(90)=Q(95)=Q(99), Q(50)=Q(90)=Q(95), Q(50)=Q(95)=Q(99), over the 56 cross-country regressions.

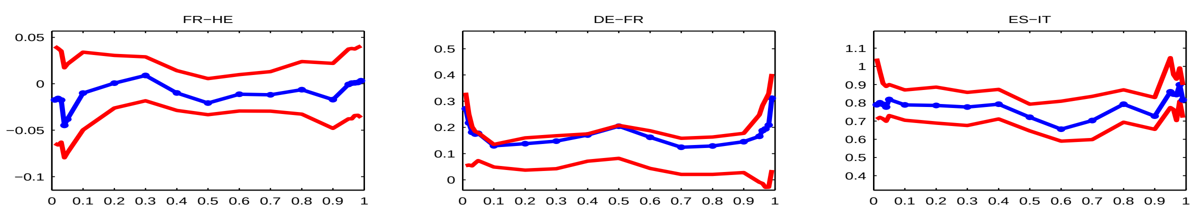
Figure 14: **Samples of Quantile Regression Coefficients with Heteroskedasticity for Different Bond Spreads.**



2003-2006



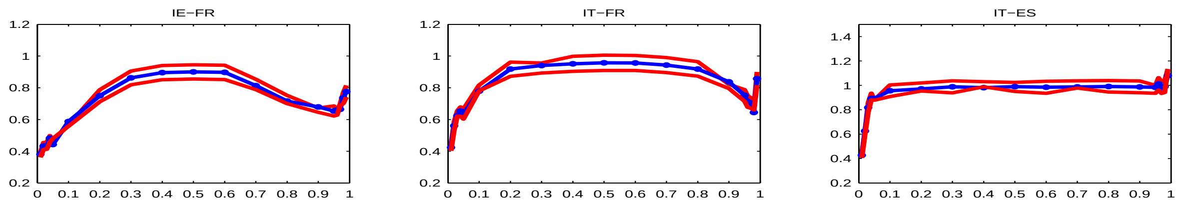
2008-2011



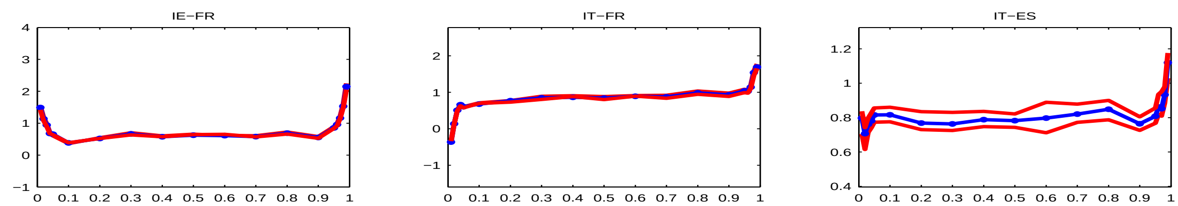
2011-2013

This figure shows the estimated coefficients $\widehat{\beta}_{1,\tau}$ of the Bayesian Quantile regression with heteroschedasticity for three pairs of countries: in the first block country i is France (FR) and country j is Greece (HE), in the second block country i is Germany (DE) and country j is France (HE), in the third block country i is Spain (ES) and country j is Italy (IT).. We consider three different periods, January 1, 2003 to December 29, 2006, November 1, 2008 to November 30, 2011, and December 1, 2011 to March 10 2012 for FR-HE and to April 30, 2013 for DE-FR and ES-IT. The red lines represent the 95% high posterior regions.

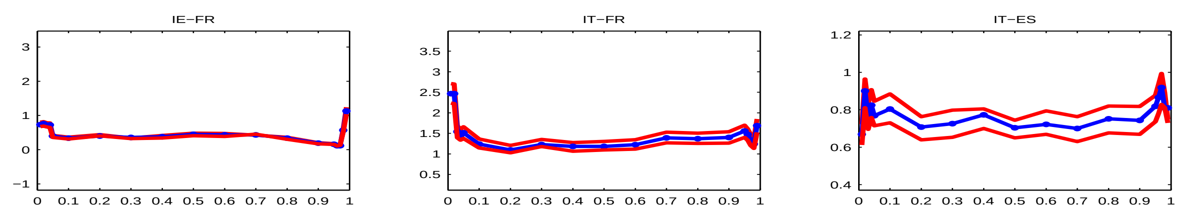
Figure 15: **Samples of Quantile Regression Coefficients with Heteroskedasticity for Different Bond Spreads.**



2003-2006



2008-2011



2011-2013

This figure shows the estimated coefficients $\widehat{\beta}_{1,\tau}$ of the Bayesian Quantile regression with heteroschedasticity for three pairs of countries: in the first block country i is Ireland (IE) and countries j is France (FR), in the second block country i is Italy (IT) and country j is France (FR), in the third block country i is Italy (IT) and country j is Spain (ES). We consider three different periods, January 1, 2003 to December 29, 2006, November 1, 2008 to November 30, 2011, and December 1, 2011 to April 30, 2013. The red lines represent the 95% higher posterior regions.

	Mean	St. Dev.	Min	Max	Median
			2003-2006		
France	0.01	2.58	-18.55	15.82	120.00
Germany	0.01	2.27	-12.10	13.00	115.00
Greece	0.02	2.70	-20.05	29.10	115.00
Ireland	-0.01	2.94	-17.70	37.10	140.00
Italy	0.01	2.49	-15.65	22.70	110.00
Portugal	0.00	2.80	-17.45	51.90	115.00
Spain	0.01	2.49	-14.15	34.50	115.00
U.K.	0.00	1.70	-7.90	7.55	90.00
Eur.	0.00	0.01	-0.09	0.09	20.00
L.R.	0.00	0.01	-0.03	0.02	30.00
R.A.	-0.02	1.60	-11.78	7.19	0.67
			2008-2011		
France	0.09	4.66	-22.50	31.90	220.00
Germany	-0.01	3.94	-20.20	19.05	193.00
Greece	5.27	48.45	-657.95	428.20	850.00
Ireland	0.87	18.24	-140.15	102.20	551.00
Italy	0.65	10.64	-70.85	88.60	360.00
Portugal	1.96	25.57	-321.65	258.00	530.00
Spain	0.52	9.59	-87.25	47.70	398.00
U.K.	0.01	3.90	-14.24	41.40	160.00
Eur.	0.00	0.01	-0.12	0.06	30.00
L.R.	0.00	0.02	-0.18	0.14	70.00
R.A.	0.01	3.12	-23.80	14.44	1.30
			2011-2013		
France	-0.08	4.59	-18.20	16.90	240.00
Germany	0.13	2.63	-11.00	14.60	160.00
Greece	-0.38	82.71	-1464.20	223.40	260.00
Ireland	-1.48	10.40	-78.60	60.90	420.00
Italy	-0.75	14.84	-83.30	65.10	700.00
Portugal	-3.20	38.80	-207.40	265.20	1300.00
Spain	-0.23	14.82	-70.50	57.15	685.00
U.K.	0.13	3.01	-8.75	38.30	105.00
Eur.	0.00	0.01	-0.09	0.01	20.00
L.R.	0.00	0.01	-0.04	0.03	20.00
R.A.	-0.01	2.15	-10.33	6.05	1.00

Table 1: This table presents summary statistics for the changes in daily 5 years bond spreads and the changes in the covariates (Euribor, Eur.; Liquidity Risk, L.R.; Risk Appetite, R.A.) for the three sample period: January 1,2003 to December 29,2006; November 1, 2008 to November 30, 2011; December 1, 2011 to April 30, 2013 (to March 10, 2012 for Greece), respectively. The statistics presented are percentage mean values (Mean), standard deviation values (St. Dev.), minimum and maximum values (Min and Max), and median values of the absolute spreads in basis points (Median) (Eur., L.R. and R.A. are in %).

	France	Germany	Greece	Ireland	Italy	Portugal	Spain	UK	Eur.	L.R.
Sample: January 2003 - December 2006										
Germany	0.717									
Greece	0.771	0.725								
Ireland	0.591	0.562	0.545							
Italy	0.796	0.714	0.751	0.595						
Portugal	0.717	0.726	0.849	0.523	0.723					
Spain	0.795	0.774	0.851	0.561	0.763	0.93				
UK	0.478	0.458	0.461	0.344	0.501	0.398	0.464			
Eur.	0.012	0.004	0.026	0.069	0.02	0.016	0.015	0.039		
L.R.	0.013	0.002	-0.013	0.007	0.014	0.009	0.012	0.044	0.044	
R.A.	0.025	0.041	0.034	0.051	0.03	0.033	0.044	0.011	-0.054	0.054
Sample: November 2008 - November 2011										
Germany	0.654									
Greece	0.027	-0.106								
Ireland	0.174	0.052	0.424							
Italy	0.343	0.073	0.297	0.447						
Portugal	0.021	-0.006	0.427	0.629	0.37					
Spain	0.36	0.106	0.348	0.482	0.765	0.407				
UK	0.112	0.172	-0.005	0.033	-0.028	-0.002	0.016			
Eur.	0.034	0.047	0.003	0.008	-0.004	0.037	-0.004	-0.067		
L.R.	-0.075	-0.173	0.115	-0.038	0.039	0.002	0.039	-0.052	0.123	
R.A.	-0.004	-0.142	0.175	0.185	0.236	0.194	0.203	-0.055	-0.006	0.044
Sample: December 2011 - April 2013										
Germany	0.298									
Greece	-0.001	-0.019								
Ireland	0.167	0.015	-0.009							
Italy	0.455	-0.087	0.029	0.354						
Portugal	0.082	-0.098	0.065	0.15	0.125					
Spain	0.362	-0.118	0.024	0.339	0.764	0.085				
UK	0.029	0.005	0.112	0.024	-0.07	-0.021	-0.051			
Eur.	0.113	0.062	-0.054	0.053	-0.05	-0.031	-0.124	-0.042		
L.R.	-0.002	0.078	-0.041	0.018	-0.047	0.006	-0.093	-0.149	0.604	
R.A.	0.185	-0.151	-0.008	0.23	0.35	0.08	0.337	0.02	-0.023	-0.03

Table 2: This table presents unconditional correlations on the three subsamples of interest between the changes in the bond spreads and the changes in the covariates (Euribor, Eur.; Liquidity Risk, L.R.; Risk Appetite, R.A.).

y_i	y_j	P-value	β_1	β_2	β_3	y_i	y_j	P-value	β_1	β_2	β_3
France	Germany	<1e-3	1.088	0.007	-0.008	Italy	France	<1e-3	0.764		-0.001
France	Greece	<1e-3	0.938	-0.026	<1e-3	Italy	Germany	<1e-3	1.029	0.017	-0.008
France	Ireland	<1e-3	0.643	0.004	-0.001	Italy	Greece	<1e-3	0.779	-0.003	-0.001
France	Italy	0.999	0.786			Italy	Ireland	<1e-3	0.606		<1e-3
France	Portugal	<1e-3	0.926	-0.016		Italy	Portugal	<1e-3	0.826	0.003	<1e-3
France	Spain	<1e-3	1.051	-0.004	-0.001	Italy	Spain	<1e-3	0.799		-0.001
France	UK	0.371	0.6		0.002	Italy	UK	0.019	0.715	-0.008	0.004
Germany	France	<1e-3	1.001	-0.021	-0.005	Portugal	France	0.005	0.772		-0.001
Germany	Greece	<1e-3	0.894	-0.034	<1e-3	Portugal	Germany	<1e-3	0.956	0.029	-0.003
Germany	Ireland	<1e-3	0.612		<1e-3	Portugal	Greece	<1e-3	0.821	-0.011	<1e-3
Germany	Italy	<1e-3	0.924	-0.044		Portugal	Ireland	<1e-3	0.646	0.005	-0.001
Germany	Portugal	<1e-3	0.902	-0.045	0.001	Portugal	Italy	<1e-3	0.91	-0.005	-0.001
Germany	Spain	0.999	0.876			Portugal	Spain	<1e-3	0.959	0.009	<1e-3
Germany	UK	<1e-3	0.773	-0.023	-0.011	Portugal	UK	0.189	0.619	0.022	
Greece	France	0.003	0.87		-0.001	Spain	France	<1e-3	0.907	-0.008	-0.001
Greece	Germany	<1e-3	0.952	0.025	-0.001	Spain	Germany	<1e-3	0.939	0.009	-0.002
Greece	Ireland	<1e-3	0.661	0.005	-0.001	Spain	Greece	<1e-3	0.846	-0.033	0.001
Greece	Italy	<1e-3	0.937	-0.014	-0.001	Spain	Ireland	<1e-3	0.715	0.004	-0.001
Greece	Portugal	<1e-3	0.914	-0.006		Spain	Italy	<1e-3	0.907	-0.013	-0.001
Greece	Spain	0.999	0.952			Spain	Portugal	<1e-3	0.884	-0.02	<1e-3
Greece	UK	0.284	0.726	0.016		Spain	UK	0.197	0.553		0.004
Ireland	France	<1e-3	0.814	-0.013	-0.002	UK	France	0.002	0.336	-0.007	-0.001
Ireland	Germany	<1e-3	1.05	-0.02	-0.005	UK	Germany	<1e-3	0.398	-0.013	-0.002
Ireland	Greece	<1e-3	0.925	-0.01	-0.001	UK	Greece	<1e-3	0.394	-0.005	<1e-3
Ireland	Italy	<1e-3	0.925	-0.014	-0.001	UK	Ireland	<1e-3	0.212	0.003	<1e-3
Ireland	Portugal	<1e-3	0.904	-0.014		UK	Italy	<1e-3	0.42	-0.005	-0.001
Ireland	Spain	<1e-3	0.89	-0.011	<1e-3	UK	Portugal	<1e-3	0.381		
Ireland	UK	0.032	0.776	-0.018	-0.007	UK	Spain	<1e-3	0.424		

Table 3: This table reports the results of the test for linearity and tests for the significance of the coefficients from equation (5) in the sample from January 1, 2003 to December 29, 2006. The p-value column reports the likelihood ratio test result for a null hypothesis that the parameters of the squared and cubed explanatory bond spread are significant. Parameters for linear, squared and cubed explanatory are reported in the following columns. Missing coefficients were not found to be statistically significant (single coefficient test).

y_i	y_j	P-value	β_1	β_2	β_3	y_i	y_j	P-value	β_1	β_2	β_3
France	Germany	0.001	0.793	-0.01		Italy	France	0.999	0.705		
France	Greece	0.59				Italy	Germany	0.013	0.552	-0.016	
France	Ireland	0.001	0.053		<1e-3	Italy	Greece	0.004	0.075	<1e-3	
France	Italy	<1e-3	0.227	0.001	<1e-3	Italy	Ireland	0.774	0.269		
France	Portugal	0.011	0.02			Italy	Portugal	0.001	0.234	<1e-3	<1e-3
France	Spain	<1e-3	0.225		<1e-3	Italy	Spain	0.016	0.737	-0.004	<1e-3
France	UK	0.31	0.095			Italy	UK	0.058	0.134	0.017	
Germany	France	<1e-3	0.814	-0.013	-0.001	Portugal	France	0.019	0.936		
Germany	Greece	0.902	-0.011			Portugal	Germany	0.079	0.637		
Germany	Ireland	0.252				Portugal	Greece	<1e-3	0.266	<1e-3	
Germany	Italy	0.011	0.061		<1e-3	Portugal	Ireland	<1e-3	0.468		<1e-3
Germany	Portugal	0.014	0.014		<1e-3	Portugal	Italy	<1e-3	0.723	-0.008	<1e-3
Germany	Spain	<1e-3	0.092		<1e-3	Portugal	Spain	<1e-3	0.76	-0.012	<1e-3
Germany	UK	0.014	0.199			Portugal	UK	0.999			
Greece	France	<1e-3	0.657	-0.05	0.001	Spain	France	0.001	0.919	-0.009	<1e-3
Greece	Germany	0.192	0.509	-0.016		Spain	Germany	<1e-3	0.677		
Greece	Ireland	0.999	0.502			Spain	Greece	0.266	0.083		<1e-3
Greece	Italy	<1e-3	0.909	-0.022	<1e-3	Spain	Ireland	<1e-3	0.264	-0.003	<1e-3
Greece	Portugal	<1e-3	0.807	-0.003	<1e-3	Spain	Italy	<1e-3	0.761	-0.004	<1e-3
Greece	Spain	<1e-3	0.854	-0.019	<1e-3	Spain	Portugal	<1e-3	0.309	<1e-3	<1e-3
Greece	UK	0.239				Spain	UK	0.765			
Ireland	France	0.061	0.832	-0.014		UK	France	0.011	0.102		<1e-3
Ireland	Germany	0.202	0.416			UK	Germany	<1e-3		-0.008	0.001
Ireland	Greece	<1e-3	0.182	<1e-3	0.000	UK	Greece	0.283			
Ireland	Italy	0.008	0.849	-0.005	<1e-3	UK	Ireland	0.064			
Ireland	Portugal	0.247	0.539			UK	Italy	0.999			
Ireland	Spain	<1e-3	0.796	-0.006		UK	Portugal	0.308			
Ireland	UK	0.438				UK	Spain	0.011	0.042		

Table 4: This table reports the results of the test for linearity and tests for the significance of the coefficients from equation (5) in the period from November 1, 2008 to November 30, 2011. The p-value column reports the likelihood ratio test result for a null hypothesis that the parameters of the squared and cubed explanatory bond spread are significant. Parameters for linear, squared and cubed explanatory are reported in the following columns. Missing coefficients were not found to be statistically significant (single coefficient test).

y_i	y_j	P-value	β_1	β_2	β_3	y_i	y_j	P-value	β_1	β_2	β_3
France	Germany	0.022	0.647			Italy	France	0.065	1.172		0.004
France	Greece	0.166				Italy	Germany	0.001			
France	Ireland	0.008	0.116			Italy	Greece	0.875			
France	Italy	0.57	0.105			Italy	Ireland	<1e-3	0.768	-0.008	<1e-3
France	Portugal	0.097	0.034			Italy	Portugal	0.103	0.128		
France	Spain	0.463	0.073			Italy	Spain	0.181	0.729		
France	UK	0.346				Italy	UK	0.493	-0.674		
Germany	France	0.594	0.177			Portugal	France	0.002	1.426	0.146	
Germany	Greece	0.957				Portugal	Germany	0.352			
Germany	Ireland	0.215				Portugal	Greece	0.458			
Germany	Italy	0.043	-0.034			Portugal	Ireland	0.999	1.052		
Germany	Portugal	0.836				Portugal	Italy	0.015	0.844	-0.008	<1e-3
Germany	Spain	0.354	-0.027			Portugal	Spain	0.009	0.717		
Germany	UK	0.16		0.018	-0.001	Portugal	UK	0.02			
Greece	France	0.028			0.006	Spain	France	0.645	1.069		
Greece	Germany	0.963				Spain	Germany	0.036			
Greece	Ireland	<1e-3				Spain	Greece	0.117			
Greece	Italy	<1e-3		0.017	<1e-3	Spain	Ireland	<1e-3	0.715	-0.008	
Greece	Portugal	0.999				Spain	Italy	0.08	0.857	-0.003	<1e-3
Greece	Spain	0.294				Spain	Portugal	0.014	0.099		<1e-3
Greece	UK	0.999	3.894			Spain	UK	0.764			
Ireland	France	0.379	0.462			UK	France	0.029	-0.117	-0.006	0.001
Ireland	Germany	0.345				UK	Germany	0.312			
Ireland	Greece	0.945				UK	Greece	<1e-3			<1e-3
Ireland	Italy	0.213	0.233			UK	Ireland	<1e-3		0.001	<1e-3
Ireland	Portugal	0.019	0.088			UK	Italy	<1e-3			
Ireland	Spain	<1e-3	0.154	-0.003	<1e-3	UK	Portugal	0.999			
Ireland	UK	0.003		0.134	-0.003	UK	Spain	0.999	-0.035		

Table 5: This table reports the results of the test for linearity and tests for the significance of the coefficients from equation (5) in the sample from December 1, 2011 to April 30, 2013 (to March 10, 2012 for Greece). The p-value column reports the likelihood ratio test result for a null hypothesis that the parameters of the squared and cubed explanatory bond spread are significant. Parameters for linear, squared and cubed explanatory are reported in the following columns. Missing coefficients were not found to be statistically significant (single coefficient test).

y_i	y_j	$\beta_2 y_j^2$	$\beta_3 y_j^3$	y_i	y_j	$\beta_2 y_j^2$	$\beta_3 y_j^3$
France	Germany	-0.014		Italy	France		
France	Greece			Italy	Germany	-0.021	
France	Ireland		0.000	Italy	Greece	0.000	
France	Italy	0.002	0.000	Italy	Ireland		
France	Portugal			Italy	Portugal	0.000	0.000
France	Spain		0.000	Italy	Spain	-0.005	0.000
France	UK			Italy	UK	0.014	
Germany	France	-0.018	0.000	Portugal	France		
Germany	Greece			Portugal	Germany		
Germany	Ireland			Portugal	Greece	0.000	
Germany	Italy		0.000	Portugal	Ireland		0.000
Germany	Portugal		0.000	Portugal	Italy	-0.01	0.000
Germany	Spain		0.000	Portugal	Spain	-0.016	0.000
Germany	UK			Portugal	UK		
Greece	France	-0.072	0.000	Spain	France	-0.012	0.000
Greece	Germany	-0.021		Spain	Germany		
Greece	Ireland			Spain	Greece		0.000
Greece	Italy	-0.027	0.000	Spain	Ireland	-0.005	0.000
Greece	Portugal	-0.003	0.000	Spain	Italy	-0.005	0.000
Greece	Spain	-0.026	0.000	Spain	Portugal	0.000	0.000
Greece	UK			Spain	UK		
Ireland	France	-0.02		UK	France		0.000
Ireland	Germany			UK	Germany	-0.011	0.000
Ireland	Greece	0.000	0.000	UK	Greece		
Ireland	Italy	-0.006	0.000	UK	Ireland		
Ireland	Portugal			UK	Italy		
Ireland	Spain	-0.008		UK	Portugal		
Ireland	UK			UK	Spain		

Table 6: This table reports the economic impact of the coefficients for the quadratic and cubic explanatory variables in (5) for the period November 1, 2008 to November 30, 2011. Values are reported in basis points. Missing coefficients were found to be non significant.

y_i	y_j	$H1$	$H2$	$H3$	y_i	y_j	$H1$	$H2$	$H3$
France	Germany	0.185	0.264	0.442	Italy	France	0.005	0	0
France	UK	0.448	0.66	0.476	Italy	Germany	0.43	0.243	0.187
France	Spain	0.011	0.02	0.016	Italy	UK	0.584	0.458	0.693
France	Italy	0.136	0.12	0.586	Italy	Spain	0.729	0.663	0.803
France	Ireland	0.187	0	0	Italy	Ireland	0.702	0	0
France	Portugal	0.05	0.072	0.151	Italy	Portugal	0.784	0.575	0.503
France	Greece	0.478	0.473	0.631	Italy	Greece	0.21	0.109	0.087
Germany	France	0.016	0	0	Ireland	France	0.644	0	0
Germany	UK	0.713	0.751	0.925	Ireland	Germany	0.14	0.005	0.001
Germany	Spain	0.01	0.011	0.706	Ireland	UK	0.559	0.516	0.6
Germany	Italy	0.009	0.009	0.242	Ireland	Spain	0.571	0.049	0.007
Germany	Ireland	0.047	0	0	Ireland	Italy	0.374	0.001	0
Germany	Portugal	0.028	0.027	0.204	Ireland	Portugal	0.223	0.008	0.003
Germany	Greece	0.004	0.005	0.104	Ireland	Greece	0.043	0	0
UK	France	0.505	0.957	0.382	Portugal	France	0	0	0
UK	Germany	0.253	0.122	0.457	Portugal	Germany	0.28	0.322	0.324
UK	Spain	0.182	0.155	0.541	Portugal	UK	0.344	0.727	0.346
UK	Italy	0.802	0.97	0.536	Portugal	Spain	0.478	0.622	0.247
UK	Ireland	0.149	0.154	0.739	Portugal	Italy	0.155	0.201	0.566
UK	Portugal	0.736	0.731	0.956	Portugal	Ireland	0.188	0	0
UK	Greece	0.64	0.754	0.612	Portugal	Greece	0.785	0.57	0.715
Spain	France	0.001	0	0	Greece	France	0	0	0
Spain	Germany	0.781	0.653	0.503	Greece	Germany	0.516	0.434	0.747
Spain	UK	0.921	0.845	0.868	Greece	UK	0.753	0.916	0.764
Spain	Italy	0.006	0.003	0.094	Greece	Spain	0.652	0.637	0.998
Spain	Ireland	0.112	0	0	Greece	Italy	0.987	0.916	0.67
Spain	Portugal	0.23	0.052	0.051	Greece	Ireland	0.283	0	0
Spain	Greece	0.75	0.747	0.85	Greece	Portugal	0.926	0.94	0.889

Table 7: This table presents the p-values of the tests for stability across quantiles in the relation between the bond spreads of country i and country j. The models were estimated using the sample data from January 1, 2003 to December 29, 2006. The null hypotheses are associated with the equality across the upper quantiles ($H1$) $H_0 : \widehat{\beta}_{1,0.90} = \widehat{\beta}_{1,0.95} = \widehat{\beta}_{1,0.99}$, and the equality of the upper quantiles with the median ($H2$) $H_0 : \widehat{\beta}_{1,0.99} = \widehat{\beta}_{1,0.95} = \widehat{\beta}_{1,0.50}$, and ($H3$) $H_0 : \widehat{\beta}_{1,0.95} = \widehat{\beta}_{1,0.90} = \widehat{\beta}_{1,0.50}$.

y_i	y_j	$H1$	$H2$	$H3$	y_i	y_j	$H1$	$H2$	$H3$
France	Germany	0.581	0.901	0.573	Italy	France	0.288	0.247	0.748
France	UK	0.193	0.472	0.267	Italy	Germany	0.264	0.158	0.288
France	Spain	0.946	0.732	0.567	Italy	UK	0.118	0.133	0.25
France	Italy	0.659	0.941	0.499	Italy	Spain	0.058	0.08	0.605
France	Ireland	0.66	0.564	0.76	Italy	Ireland	0.472	0.507	0.848
France	Portugal	0.306	0.233	0.681	Italy	Portugal	0.441	0.079	0.1
France	Greece	0.806	0.833	0.946	Italy	Greece	0.58	0.58	0.893
Germany	France	0.066	0.002	0.003	Ireland	France	0.147	0.202	0.697
Germany	UK	0.247	0.597	0.289	Ireland	Germany	0.497	0.489	0.838
Germany	Spain	0.424	0.941	0.38	Ireland	UK	0.564	0.784	0.45
Germany	Italy	0.607	0.564	0.175	Ireland	Spain	0.702	0.348	0.394
Germany	Ireland	0.638	0.529	0.55	Ireland	Italy	0.74	0.152	0.152
Germany	Portugal	0.951	0.608	0.415	Ireland	Portugal	0.836	0.582	0.685
Germany	Greece	0.886	0.912	0.97	Ireland	Greece	0.366	0.345	0.831
UK	France	0.509	0.767	0.494	Portugal	France	0.222	0.092	0.071
UK	Germany	0.44	0.576	0.31	Portugal	Germany	0.231	0.028	0.054
UK	Spain	0.654	0.714	0.785	Portugal	UK	0.325	0.34	0.934
UK	Italy	0.905	0.98	0.89	Portugal	Spain	0.973	0.974	0.977
UK	Ireland	0.59	0.63	0.808	Portugal	Italy	0.499	0.644	0.727
UK	Portugal	0.424	0.562	0.601	Portugal	Ireland	0.753	0.755	0.965
UK	Greece	0.685	0.703	0.95	Portugal	Greece	0.682	0.589	0.717
Spain	France	0.765	0.683	0.711	Greece	France	0.327	0.037	0.004
Spain	Germany	0.658	0.27	0.153	Greece	Germany	0.064	0.001	0.002
Spain	UK	0.148	0.274	0.346	Greece	UK	0.639	0.93	0.3
Spain	Italy	0	0.001	0.009	Greece	Spain	0.977	0.988	0.98
Spain	Ireland	0.473	0.639	0.168	Greece	Italy	0.958	0.955	0.991
Spain	Portugal	0.837	0.151	0.127	Greece	Ireland	0.418	0.542	0.665
Spain	Greece	0.65	0.599	0.537	Greece	Portugal	0.735	0.825	0.651

Table 8: This table presents the p-values of the tests for stability across quantiles in the relation between the bond spreads of country i and country j. The models have been estimated using the sample data from November 1, 2008 to November 30, 2011. The null hypotheses are associated with the equality across upper quantiles $(H1)$ $H_0 : \widehat{\beta}_{1,0.90} = \widehat{\beta}_{1,0.95} = \widehat{\beta}_{1,0.99}$, and the equality of upper quantiles with the median $(H2)$ $H_0 : \widehat{\beta}_{1,0.99} = \widehat{\beta}_{1,0.95} = \widehat{\beta}_{1,0.50}$, and $(H3)$ $H_0 : \widehat{\beta}_{1,0.95} = \widehat{\beta}_{1,0.90} = \widehat{\beta}_{1,0.50}$.

y_i	y_j	$H1$	$H2$	$H3$	y_i	y_j	$H1$	$H2$	$H3$
France	Germany	0.57	0.336	0.421	Italy	France	0.843	0.699	0.744
France	UK	0.924	0.542	0.567	Italy	Germany	0.789	0.797	0.872
France	Spain	0.875	0.94	0.862	Italy	UK	0.809	0.556	0.595
France	Italy	0.486	0.375	0.588	Italy	Spain	0.756	0.759	0.732
France	Ireland	0.346	0.279	0.841	Italy	Ireland	0.885	0.785	0.895
France	Portugal	0.974	0.418	0.179	Italy	Portugal	0.94	0.941	0.996
France	Greece	0.7	0.698	0.669	Italy	Greece	0.309	0.219	0.2
Germany	France	0.41	0.53	0.495	Ireland	France	0.69	0.555	0.424
Germany	UK	0.834	0.874	0.827	Ireland	Germany	0.903	0.775	0.749
Germany	Spain	0.167	0.131	0.78	Ireland	UK	0.235	0.247	0.953
Germany	Italy	0.295	0.345	0.765	Ireland	Spain	0.572	0.362	0.395
Germany	Ireland	0.884	0.909	0.955	Ireland	Italy	0.851	0.841	0.964
Germany	Portugal	0.173	0.134	0.605	Ireland	Portugal	0.297	0.368	0.757
Germany	Greece	0.129	0.127	0.909	Ireland	Greece	0.254	0.164	0.191
UK	France	0.844	0.343	0.267	Portugal	France	0.828	0.829	0.982
UK	Germany	0.546	0.572	0.864	Portugal	Germany	0.351	0.358	0.929
UK	Spain	0.488	0.459	0.831	Portugal	UK	0.515	0.469	0.699
UK	Italy	0.225	0.075	0.076	Portugal	Spain	0.798	0.729	0.816
UK	Ireland	0.147	0.243	0.434	Portugal	Italy	0.702	0.701	0.769
UK	Portugal	0.328	0.206	0.52	Portugal	Ireland	0.719	0.561	0.63
UK	Greece	0.134	0.117	0.628	Portugal	Greece	0.085	0.011	0.284
Spain	France	0.997	0.988	0.983	Greece	France	0.787	0.665	0.662
Spain	Germany	0.114	0.167	0.672	Greece	Germany	0.48	0.32	0.598
Spain	UK	0.717	0.527	0.698	Greece	UK	0.809	0.874	0.842
Spain	Italy	0.171	0.231	0.157	Greece	Spain	0.931	0.915	0.925
Spain	Ireland	0.908	0.89	0.968	Greece	Italy	0.95	0.948	0.94
Spain	Portugal	0.927	0.712	0.676	Greece	Ireland	0.91	0.691	0.491
Spain	Greece	0.629	0.804	0.625	Greece	Portugal	0.85	0.786	0.797

Table 9: This table presents the p-values of the tests for stability across quantiles in the relation between the bond spreads of country i and country j. The models have been estimated using the sample data from December 1, 2011 to April 30, 2013 (to March 10, 2012 for Greece). The null hypotheses are associated with the equality across upper quantiles ($H1$) $H_0 : \widehat{\beta}_{1,0.90} = \widehat{\beta}_{1,0.95} = \widehat{\beta}_{1,0.99}$, and the equality of upper quantiles with the median ($H2$) $H_0 : \widehat{\beta}_{1,0.99} = \widehat{\beta}_{1,0.95} = \widehat{\beta}_{1,0.50}$, and ($H3$) $H_0 : \widehat{\beta}_{1,0.95} = \widehat{\beta}_{1,0.90} = \widehat{\beta}_{1,0.50}$.