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Measuring Sovereign Contagion in Europe[☆]

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Abstract

This paper analyzes sovereign risk shift-contagion, i.e. positive and significant changes in the propagation mechanisms, using bond yield spreads for the major eurozone countries. By emphasizing the use of two econometric approaches based on quantile regressions (standard quantile regression and Bayesian quantile regression with heteroskedasticity) we find that the propagation of shocks in euro's bond yield spreads shows almost no presence of shift-contagion in the sample periods considered (2003-2006, Nov. 2008-Nov. 2011, Dec. 2011-Apr. 2013). 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 Nov. 2008-Nov. 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

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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.
Keywords: Sovereign Risk, Contagion, Disintegration

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1. Introduction

The sovereign debt crisis in Europe that began in late 2009 has reignited the literature on market integration, shift in the transmission channels and 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 Euro area? Through which channel should the shock be transmitted? Clearly, these are important questions for economists, policy-makers, and practitioners.

The aim of this paper is to shed light on these issues and mostly on the issue regarding the presence of shift in the transmission channels and contagion. However, addressing these questions requires the surmounting of some extraordinary empirical challenges.[1]

Our objective is to present convincing evidence of the amount of stability of the parameters and therefore investigate the presence of shift-contagion that takes place during the euro sovereign crisis. In other words, we are interested in understanding the amount of potential shift-contagion that exists within the European sovereign debt market, where contagion is defined as the size of the positive difference in the propagation after a large negative realization has taken place, compared to the propagation after an average realization.

We examine sovereign bonds yield spreads 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

[1] For a survey indicating the shortcomings of most empirical methods see Rigobon (2001).

to April 2013 and investigate the following questions:

a) Is there any presence of shift-contagion in the sample period 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? If yes, why?

We propose quantile regressions for measuring shift-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 shift-contagion in the European sovereign bond market 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 shift-contagion hypothesis.

We apply a standard quantile regression and, also, a Bayesian heteroskedastic version where the conditional variance of the residuals follows a Generalized Auto Regressive Conditional Heteroskedasticity (GARCH)(1,1) specification. The key advantage of using such flexible approaches is that, as explained in details in Section 2, the identification of shift-contagion could be due to (i) effective changes in the transmission channels of shocks among European countries, the effect that we want to investigate, or to (ii) omitted variables or latent factors, and (iii) endogeneity issues. However, as we will explain, if we find stability in the parameters on both the standard and Bayesian quantile regressions (i.e. no shift-contagion), this result is robust to omitted variables and endogeneity issues because omitted variables and endogeneity issues are strictly related to heteroskedasticity effects. Moreover, we evaluate the parameter stability by also controlling for the existence of a structural break. In fact, shift-contagion is a special case of a structural break, with coefficients linking variables increasing (or decreasing) after the break date. If structural instability is ignored, we could mix data from different regimes, and thus quantiles are not those of a specific density but are recovered from a mixture of different densities. Therefore, ignoring structural instability could take to wrong conclusions as we show below; on the contrary, testing for it (i) robustifies our analysis, (ii) allows identifying the timing of extreme events, and (iii) distinguishes shift-contagion from other changes in the transmission mechanism, for example, the existence of different economic regimes.

We have two main results. First, when we split the full sample to focus on the beginning and expansion of the fiscal crisis across the Nov. 2008-Nov. 2011 sample, and the European Central Bank and European Union intervention across the Dec. 2011-Apr. 2013 sample, we find that for almost every pair of countries in our data the transmission mechanism is constant across the two samples (the few exceptions are from France to Ireland, from France to Italy and from Spain to Italy in the *crisis* period of Nov. 2008-Nov. 2011 using the quantile regression with heteroskedasticity). This is the case for both bond yields and CDS.[2] 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.[3]

[2]The CDS data are used for a robustness check. 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.

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

Second, if we ignore structural instability and merge the full sample 2003-2013, our analysis shows evidence of shift-contagion. However, the result is not robust to instability. If we infer the dates of the instability in the transmission parameters, we show that the shift in the propagation mechanisms happened in fall 2008. Moreover, we find that the coefficients actually fall as opposed to increase. This implies that what changed the coefficients was the Lehman crisis, and that market participants, if anything, understood that euro countries bond yields were going to be less synchronized than before, and not more. A researcher ignoring such instability will have wrong conclusions on the presence of shift-contagion. The evidence also confirms that the sample split above, motivated by economic and political events, is supported by statistical data analysis.

At a first glance, both results are surprising. A simple explanation, however, can rationalize them. The market perception anticipated the fiscal problems in the European periphery countries as a consequence of the US financial meltdown. This is why the shift in the parameters takes place in the first event and not in the following European events. And the market participants also realized 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.

Throughout the paper we refer to shift-contagion as defined in Forbes and Rigobon (2002), thus pointing at the (in)stability in the transmission channel of shocks. According to Forbes and Rigobon (2002) contagion occurs when there is a change in the propagation mechanisms after a macroeconomic event; such as a credit default, a currency depreciation, a financial crises, etc. However, the empirical literature has different definitions of contagion and there is not yet an agreement on the most appropriate definition of contagion. Our paper does not aim at solving such a problem. On the contrary, we take an empirical viewpoint, as stated at the beginning of this introduction, and maintain a focus on shift-contagion. For a reader interested in the multiple iterative reviews on contagion that already exist in the literature, among others, we cite Pericoli and Sbracia (2003), Dungey et al. (2005), and Pesaran and Pick (2007) and

Forbes(2012).

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. 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) Ang and Longstaff (2013) and Augustin (2013). 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 (for a survey on CDS literature see Augustin et al (2014)). Moreover, using a broad panel of bank and sovereign CDS data, Acharya, Drechsler and Schnabl (2014) concentrate on the financial sector bailouts and show that bank and sovereign credit risk are intimately linked. Fratzscher and Rieth (2015) find similar evidence in a longer sample. Kallestrup, Lando and Murgoci (2016) also show that cross-border financial linkages affect CDS spreads beyond that which can be explained by exposure to common factors.

Few papers concentrate instead on the determinants of sovereign spreads in the EMU and the issue of contagion among sovereign securities within the EMU. In particular, Caceres and Segoviano (2010) investigate the effect on the sovereign spread of the default probability of 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. Bai, Julliard and Yuan (2012) study the spillover from aggregate credit risk premium to individual country credit risk premia and from aggregate liquidity to individual country liquidity risk. Cappiello, Gerard, Kadareja and Manganelli (2014) use the quantile regression similar to our analysis to investigate contagion in the equity markets during the financial crisis of the 1990 and 2000.

Several works investigate correlation dynamics of sovereign risk using CDS data. For example De Santis and Stein (2015) use Smooth Conditional Correlation GARCH model and show that their model suggests a shift to a crisis regime for Italy, Spain and Germany already in August 2007 in line with our structural break analysis. Ait-Sahalia, Laeven and Pelizzon (2014) adopt a multivariate setting with credit default intensities driven by mutually exciting jump processes and shows the presence of relevant jumps in the default intensities and the clustering of high default probabilities both in time (over days) and in space (across countries). 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. Beirne and Fratzscher (2013) investigate a similar issue looking to 31 countries. Ludwig (2014) find evidences of both wake-up call and pure contagion building on the model of Pesaran and Pick (2007). Our paper complements and extends this literature by investigating the degree of co-movement among sovereign bond spreads (and sovereign CDSs) after controlling for common factors that explain credit spreads, as highlighted by the previous literature.

From a methodological contribution, the literature already contains contributions focusing on the identification of shift-contagion. Among others, Alter and Beyer (2014), Claeys and Vasicek (2014) and Kalbaska and Gatkowski (2012) apply a linear Vector Autoregressive (VAR) model. Bekeart et al. (2014) and Manasse and Zavalloini (2013) use a linear factor model. Longstaff et al. (2011) and Arghyrou and Kontonikas (2012) use principal component analysis and linear regressions. In these studies, evidence in favor of phenomena as contagion and interdependence could be driven by the linear regression assumption implicit in their models. On the contrary, Boyson et al. (2010) and Zhang et al. (2011) apply nonlinear methods, including quantile regression in Boyson et al. (2010). Finally, Ahnert and Bertsch (2017) introduce a theoretical model for wake-up call contagion. Our paper clarifies which are the elements that must be taken into account in order to avoid erroneously identifying the effects of omitted variables and/or endogeneity as (shift-)contagion.

Therefore, a preliminary discussion on the methodological aspects, as provided in Section 2, is essential, and has the clear objective of avoiding biases in the subsequent analyses.

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. Quantile regression and shift-contagion

As stressed above, the empirical literature has different definitions of contagion. However, by concentrating on the shift in the transmission mechanisms, the strength of the "contagion" is related to the stability of the parameters. Although this definition seems straightforward, its empirical implementation is difficult.

Assume we were to measure the propagation mechanisms across two countries by just concentrating in a linear regression framework:

$$y_{i,t} = \beta y_{j,t} + \eta_t, \tag{1}$$

where the variables $y_{i,t}$ and $y_{j,t}$ represent stock markets, interest rates, or any asset prices across two different countries, and η_t is an innovation term.[4] The question of shift-contagion, a significant increase of the β coefficient (that capture the intensity of propagation) boils down to determining the stability of this linear relationship. Stability is associated with a fixed β

[4]The model might be easily augmented with the introduction of lagged common control variables, as we will do in the empirical analyses of Section 4. We do not introduce, at this stage, the control variables, to provide a discussion of the methodology by using a simpler notation.

coefficient independently of the size of the shock (small/large) or over time (absence of structural breaks). Instead, we have shift-contagion when we observe a significant increase of the β coefficient, i.e. shift-contagion, when, by conditioning on an economic event (before/after), or on the size of the shocks (small/large), or on the market phase (tranquil/crisis), the coefficients of the transmission mechanism on the stress scenario (after the event, for large shocks, on a crisis period) are larger (i.e. increased) compared to those observed for the baseline scenario (that is before the event, on small shocks or on tranquil periods). We stress that, focusing on the occurrence of an extreme event, shift-contagion is a special case of a structural break.

We suggest to test for shift-contagion by estimating the model coefficients by means of quantile regression (QR) given the flexibility of the approach and the insightful parameter interpretation we might derive.

The quantile regressions 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 changes or small changes in country i). This is a test that allows for an unrestricted form of non-linearity (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 and not necessarily only associated with shift-contagion. The identification of a positive shift in a QR framework is rather different than other methods, such as in the OLS case. First, when considering QR, we model the quantiles of the conditional distribution of $y_{i,t}$ given the knowledge of $y_{j,t}$. Second, if the relationship between $y_{i,t}$ and $y_{j,t}$ is estimated as a linear regression with time invariant innovation term, the relationship for the quantiles are also linear. Precisely, the quantiles will be:

$$y_{i,t}\left(\tau\right) = \beta_{0,\tau} + \beta_{1,\tau} y_{j,t} + F_{\eta_t}^{-1}\left(\tau\right), \tag{2}$$

where, to be general, we added an intercept ($\beta_{0,\tau}$), τ is the quantile of interest, $y_{i,t}\left(\tau\right)$ is the τ-quantile of the conditional distribution of $y_{i,t}$, and $F_{\tau}^{-1}\left(\eta_t\right)$ is the unconditional quantile of the innovation density. Notice 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 $\beta_{k,\tau}\, for\, k = 0, 1$ will be equal across quantiles (i.e. for example β_1 of the quantile $\tau = 0.5$, $\beta_{1,0.5}$, will be equal to 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 innovation distribution. In this case, the regression lines estimated for the different quantiles will just be "parallel" lines, see Figure 1.

Evidences of shift-contagion and therefore of the presence of a different, positively shifted relationship between $y_{i,t}$ and $y_{j,t}$, 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.[5] Thus, by testing the stability of the QR coefficients across quantiles, we can verify the stability assumption, i.e. whether the coefficients $\beta_{1,\tau}$ are the same across quantiles. A symptom of contagion is thus provided by an instability in the $\beta_{1,\tau}$ QR coefficients.[6] This feature means that the quantile approach allows us to test jointly asymmetric linkages across changes in bond spreads in response to large and small, positive and negative shocks, this is an innovation in the contagion literature.

A question still remains open: why do we suggest the use of QR? Shift-contagion is always measured conditional on a particular event. Most of the time it is thus conditioned on time,

[5]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.

[6]Notice 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".

for example, before and after certain market event. In general, these events have implications on the sign and size of the shocks. The quantile regression allows for a flexible conditioning. It conditions the regression to large, small, positive, and negative shocks and it is implicitly testing conditional on a large and varied set.

Furthermore, several contributions focus on the linear representation in equation (1), ideally estimated by means of least squared methods (and variations of this approach). However, such an estimation approach is likely to suffer from parameter instability for reasons extraneous to a change in the underlying coefficient. First, the model might suffer from endogeneity. Clearly, if a country has an impact on another one, it is reasonable to assume that the exact same mechanism is at work in the opposite direction. Second, it suffers from omitted variable bias. There might be other factors affecting both asset prices that are unobservable and only appear after a macroeconomic event, or that are simply omitted from the analysis. Third, the relationship by itself could be unstable, that is truly non-linear, and therefore the transmission of larger shocks might be different from smaller ones.[7] In all these cases, instability in the OLS estimates could be wrongly interpreted in favour of shift-contagion. Quantile regression is robust to such an error.

By slicing the space in a large number of cases (i.e. using many quantiles), conditioning on large/small and positive/negative shocks, the empirical evidence of parameter stability can only be associated with the absence of shift contagion. Such a result holds irrespective of the existence of omitted variable or endogeneity. In the Appendix A we provide a longer discussion on that point by focusing on a simplified model and further supporting the previous claim. Here we just point out a few additional elements. We first note that endogeneity biases can be properly accounted for by also controlling for heteroskedasticity, which is likely to be present in financial data, in particular during turmoils. In fact, in the presence of endogeneity biases and

[7]See Pavlova and Rigobon (2007, 2008) and Martin (2013) for some simple international finance general equilibrium models in which the relationship among asset prices is non-linear.

in the absence of shift contagion, parameter instability might be observed due to the presence of heteroskedasticity. To rule out such a case, we must consider Bayesian Quantile Regression with heteroskedastity. If, under the latter, parameters are unstable, we do have evidence of shift-contagion as we are implicitely controlling for omitted variables and endogeneity. This first use of quantile regression allows us to answer our first question, i.e. how shock transmission is 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 possible presence of shift-contagion? Notice that we test for changes in the beta-parameters (and thus the null hypothesis is the absence of shift-contagion), and this can lead to shift-contagion if the beta coefficients are higher during turmoil times compared to a stable market phase. The latter case can be identified by contrasting simple quantile regression outcomes and Bayesian quantile regression with heteroskedasticity results. If both convey the same information, then heteroskedasticity is not playing a role. Therefore, from the empirical viewpoint, what we need is just the estimation of both Quantile Regression and Bayesian Quantile Regression with heteroskedasticity. If both suggest parameter stability, then we do not have shift contagion. On the contrary, if both suggest instability, we do have shift contagion. If just standard quantile regression shows instability, then this is due to heteroskedasticity and, again, we do not have shift contagion.

However, one might question that structural changes in the markets can distort results. In fact, shift-contagion can be also seen as a special case of a structural change in a linear model parameter; the requirement to label as shift-contagion a break is that transmission across countries increases after an economic event (causing the break). In order to control for this possibility, and thus to identify this form of shift-contagion, three approaches are available: splitting the samples in different periods following economic and political events and compare results; testing instability via a moving window estimation approach; or via the introduction of a time dummy in the quantile regression framework. In the first case, shift-contagion can be inferred within sub-samples. Within each sub-sample that could be assumed unaffected by the break, shift-contagion, if present, might be associated with different propagation mechanisms conditional on shock sign and size. However, the comparison across sub-samples might be difficult as the occurrence of a break could change the structural relations. Thus, it is not possible to determine the presence of shift-contagion by a simple comparison of sub-samples outcomes. The second case might provide some insight. In fact, the stability of rolling window estimates of the linkage coefficients across countries can be studied to investigate eventual changes over time. The method is easy, but the drawback is that the sample size must be decided a priori. Differently, in the third approach, the significance of the dummy can be statistically tested to highlight the occurrence of a break in the given date and comparison across quantiles can allow to respond whether the event has an impact on all quantiles and therefore investigating shift-contagion controlling for all the biases before mentioned, that is the presence of factor/omitted variables, or of endogeneity.

We extend formulation in (2) and consider the following specification of the conditional quantile:

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

where d_t is a step dummy assuming unit value after the break date to be tested. 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 variables $y_{i,t}$ (its $\tau-$quantile) and $y_{j,t}$ is monitored by the β value, while after the break date, the relation comes from $\beta + \delta$. By allowing the break date to span the full sample, eventual evidence of instability can be associated with specific dates.

In our analysis, we first estimate the quantile regression model in three distinct periods and we mainly test shift-contagion conditional on such time periods. The sample division is initially supported by economic motivation. Then, we test statistical changes in the transmission coefficient across samples and highlight structural breaks supporting the original divisions. We also apply quantile regression to the full sample from 2003 till 2013 and discuss how such an exercise will bring to wrong conclusions.

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 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 benchmark bond index[8] 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.[9] We collect data from Thomson-Reuters for the sample period from January 2003 to April 2013, see Appendix B for additional figures.

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

[8]We consider the benchmark bond indexes produced by Thomson-Reuters. For the indexes one might recover both the total returns as well as the redemption yields.

[9]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, using the Bund as benchmark may lead to the existence of a significant "convenience yield".

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, the full sample 01-Jan-2003 to 30-Apr-2013 in this analysis.

Such considerations suggest that, beside considering full sample analysis, we also split our data 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 focus on the full sample allows highlighting the possible presence of shift-contagion occurrences. However, those might be associated to different drivers, and some insight could be given by the subsample analyses. 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 honouring 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 subsample analysis so as to exclude fluctuations related to the beginning of the Great Financial Crisis in the US. Furthermore, to shed further light on the events possibly originating shift-contagion, we also repeat the analysis using the full sample and inferring shift-contagion by the use of a shift dummy for the transmission coefficients in the quantile regressions. The dummy is supposed to capture the up- or down-turn shift and repetition of the estimation in consecutive rolling windows with monthly step increases provides evidence on the dates of breaks.

Further, as a preliminary check, 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 in a linear model. 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 are 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.[10]

Since we focus on the co-movement in the bond spreads among the different countries, we cannot exclude the possible effect attributable to global factors. We thus consider a set of additional covariates that proxy for those global factors. Namely, we 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.

Table 1 reports means, standard deviations, minimum and maximum values for changes

[10]The test performed is a standard Chow (1960) test for structural break, known as the "Structural Change break".

in the bond spreads of the eight countries for both the full sample and the three sub-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 sub-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 Nov. 2008-Nov. 2011. 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 a significant time-series variation that emerges in the sub-samples. This, obviously, cannot be detected by the full sample analyses, that are largely affected by the 2008-2011 period. The last column in Table 1 suggests that the differences might have large economic values, with significant differences across periods.

To provide some additional descriptive statistics, Table 2 reports the correlation matrix of the daily changes in the bond spreads for the four 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. This is coupled with the similar values observed across EMU countries in Table 1. The correlations are largely lower in the crisis and ECB intervention samples. The exceptions are Portugal-Ireland, whose correlation increases in the period Nov. 2008-Nov. 2011 and then decreases, and Italy-Spain, whose correlation remains almost the same across the three samples. By looking at the full-sample figures, one cannot see a clear picture.

4. Methodology and Results

4.1. Quantile Regressions

Quantile regressions (QR) 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 2, 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

$$y_{i,t} = \beta_{ij,0} + \beta_{ij,1} y_{j,t} + \gamma'_{ij} X_{t-1} + \varepsilon_{ij,t} \tag{4}$$

our purpose is to verify whether the $\beta-$coefficient is changing across quantiles of the dependent variable $y_{i,t}$.[11] Moreover, the matrix X_{t-1} contains the set of lagged covariates that proxy the global common factors. As the parameters differ across quantiles, the overall model is highly non-linear, i.e. the β_τ would differ across quantiles. The quantile regression parameters are estimated by solving the following minimization problem:

$$min_{\Theta_\tau} \sum_{t=1}^{T} \rho_\tau \left(y_{i,t} - \beta_{ij,0} - \beta_{ij,1} y_{j,t} - \gamma'_{ij} X_{t-1} \right), \tag{5}$$

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

[11] We stress that the coefficient $\beta_{ij,1}$ in equation (4) represents the link between the dependent variable $y_{i,t}$ and the explanatory $y_{j,t}$ and thus represents a measure of the correlation or association between the shocks in country j and the conditional quantiles of country i. Adrian and Brunnermeier (2016) apply a similar methodology to their model by resorting to quantile regression with attention posed on the quantile of the financial system. However, the way the estimation results are used is different. In fact, Adrian and Brunnermeier (2016) focus on the change in the risk level (proxy by the Value-at-risk) of the market when the financial company originating the instability moves from the median to a quantile. Differently, we focus on the existence and strength of the link.

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 (5) 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 conditional on the evolution of the covariates and of the y_j. The conditional quantile is denoted as

$$\widehat{y_{i,t}}\,(\tau) = \widehat{\beta}_{0,\tau} + \widehat{\beta}_{1,\tau} y_{j,t} + \widehat{\gamma'}_\tau X_{t-1}, \tag{6}$$

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.[12] 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 in the system, namely 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.[13]

However, to better analyse the link between the changes in the bond spreads, we estimate the quantile regressions in equation (5) across each pair of bond spread variables, also conditioning on the lagged exogenous variables used in equation (4).[14] Given the estimates, we perform two evaluations: first, we graphically analyse 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. For the graphical analyses, we evaluated the quantile

[12] 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.

[13] We stress that the coefficient $\hat{\beta}_{1,\tau}$ is a measure of correlation between the change in bond spreads of country j and the quantile of country i, and does not provide evidences of causation. When we refer to the propagation mechanism we interpret the coefficients in terms of their significance, size and sign, without referring to the originating countries of possible shocks, that is, without referring to causation. Similarly, when we discuss coefficients as intensity of transmission of shocks between countries, we do not refer to them with a causation interpretation but just as measures of the link between $y_{i,t}$ and the quantiles of $y_{i,t}$.

[14] 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.

regression for the following quantiles: τ = 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. Moreover, we computed parameters standard errors form the Markov Chain Marginal Bootstrap method of Kocherginsky, He and Mu (2005). Moving to the coefficient stability across quantiles, we must first remember that, in this study, the most interesting equivalence occurs across the upper quantiles, those associated with turbulent periods and an increase in bond spreads. In the following, we will consider tests for three different 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 $H_{0,3} : \widehat{\beta}_{0.95} = \widehat{\beta}_{0.90} = \widehat{\beta}_{0.5}$. These three tests will highlight the possible change of transmission coefficients on the extreme upper tail as compared to the 90% quantile, and when moving from the median to the upper tail. Notice that the tests focus on the bond spread coefficients only, thus excluding the impact of the control covariates. The test statistic, a Wald-type test, has a Chi-square density with two degrees of freedom (two restrictions are tested in all cases).[15]

Figures 3-4 report the values of the $\beta_{1,\tau}$ coefficient across different quantile levels for selected countries, full sample in the top row and sub-samples in the bottom three rows. Notice 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).[16]

We first test on the full sample data (January 2003 - April 2013) if our quantile regression methodology is capable to capture shift-contagion. Table 3 reports the previously described tests of parameter stability across quantiles.

We find statistical evidences of instability in 18 regressions over the 56 pairs we consider. But, in 16 cases the right tail coefficient, which is associated with the turbulent times, is

[15]Despite the test involves parameters belonging to different quantile regression estimates, a system estimation approach is not necessary. In fact, the joint asymptotic distribution of the parameters for different quantile values is asymptotically normal with covariance matrix being a function of elements coming from separate quantile regressions. See Koenker and Basset (1982a,b) and Koenker (2005) for details on the tests and on their power.

[16]Additional graphs are available in the Supplementary online material.

lower than the median value associated with the tranquil periods. For example, for France and Germany there is a change in the intensity of the transmission from Spain and Italy and among each others with a reduction of the tail-coefficient. Several peripheral countries show evidence of lowering coefficient from core countries, in particular Germany, and again reduction of coefficients. Moreover, UK has no evidence of shift-contagion from any other country. The UK coefficients for all quantiles are often very low and close to zero, except for France and Germany, country with similar debt conditions. Finally, coefficients across peripheral countries, and those monitoring the impact of peripheral countries on core countries are stable across quantiles. The first are quite elevate, while the latter are sensibly lower. Therefore, we interpret these results as indication that our methodology can measure shift-contagion if changes in the transmission mechanism exist. The data suggest a number of changes and, in most of the cases, a lowering of the transmission coefficients. However, despite we detect instability, this first analysis cannot shed light on the source of the instability, nor on the event that could have caused it. Nevertheless, the descriptive analyses of our data, as reported in the previous section, suggest that the sovereign market movements starting from 2007 and up to 2008, and thus associated with the subprime crisis,[17] could be related to the instability.

To verify such an hypothesis, following the discussion in Section 2, see equation (3), we test for the presence of structural breaks on a single coefficient that captures the relation between any two changes in bond spreads.

We obtain estimates on a four year rolling window with one month step, testing for a change in the coefficients occurring at the end of the second year.

We thus recover a set of estimated conditional quantiles with the following structure:

$$\widehat{y}_{i,t}\left(\tau\right) = \widehat{\beta}_{0,\tau} + \widehat{\beta}_{1,\tau} y_{j,t} + \widehat{\delta}_{1,\tau} y_{j,t} d_t + \widehat{\gamma}'_{\tau} X_{t-1}, \tag{7}$$

[17] And, somewhat surprisingly, not the EMU sovereign crisis.

where hats denote estimated coefficients and quantities, and X_t is the set of conditioning covariates. According to the general discussion in Section 2, testing the occurrence of a break equals testing the significance of the estimated coefficients $\widehat{\delta}_{1,\tau}$. We thus verify the statistical significance of the break dummy coefficients both on a single-coefficient basis, as well as across quantiles (in the latter case we also verify the stability of the $\widehat{\delta}_{1,\tau}$ coefficients across quantiles, that is, we verify if the dummy coefficient varies across different values of τ).

Summary results of the test are reported in Figure 5. In the first panel we report, for different quantiles, the average p-value for the test of significance on the coefficient δ_τ.[18] 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 no shift-contagion.

The testing approach we develop in the previous paragraph can extend the analysis by inferring the possible date(s) of the shift(s), even when reasonable prior information on it is not available.

Indeed, in our application 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: the market participants anticipated the fiscal problems in the European periphery countries as a consequence of the US financial meltdown and also realized 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.[19]

[18] In the Appendix C.5 we perform an analysis based on linear regression and non-linear regression and perform the same test on parameter stability through time. The results support the existence of a break in 2008.

[19] 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. Repo rates might be interpreted as a possible omitted variable to proxy market perception. However, such strategy could create endogeneity issues since it is not clear if bond spread and Repo rates are exogenous. Our methodology can account for such misspecification. Finally, we also notice that cross country exposures among financial institutions reduced from 2009 to 2011 as

Unfortunately, our approach cannot be used to test instability in the final two years of the sample associated to a new ECB policy, because the sample period is too short. However, the new ECB policy motivated us to split the full sample in the pre-crisis, crisis and ECB intervention periods discussed in section 3. We start from the graphs reporting quantile coefficients.

From a global evaluation of the bottom panels in Figures 3-4 (and for all regressions in the Supplementary online material), 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.[20]

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

shown by Brutti and Saure'(2015) using the results provided by BIS reporting.

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

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 sub-samples we considered, Nov. 2008-Nov. 2011 and Dec. 2011-Apr. 2013, 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.

Tables 4-6 report the tests for equivalence across quantiles for the periods from January 2003 to December 2006, from November 2008 to November 2011, and from December 2011 to April 2013.[21]

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[22]), while in the other periods the rejections are very few (with a maximum of 4 for $H_{0,3}$ in Nov2008-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 3-4: 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 3-4 (Figures for all the other cases are available in the Supplementary online material); 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

[21]Additional tables are reported in the Supplementary online material.
[22]We recall that the total number of equations is 56.

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 that emerge from Tables 4-6 is that of France versus Germany. Larger shocks in France (i.e. when France is the explanatory variable) are associated with lower linkages with Germany (as it can be identified from the point values of the estimated coefficients). 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, i.e. large shocks in France are transmitted with lower intensity to Germany. Such an evidence comes from the different outcomes of the tests, with rejections of the null hypothesis when Germany is the dependent variable, while we do not have a rejection with France as a dependent variable. One aspect that we have not considered, however, is the possibility that the quantile regressions could be affected by the presence of heteroskedasticity. As we discussed in Section 2, heteroskedasticity issues must be taken into account. We thus explore this topic in the following section that accounts for heteroskedasticity in the quantile regression. The analyses there reported will be used as confirmatory of the present section findings.

The tests thus suggest that the interdependence across the changes in the bond spreads does not vary in its slope across the upper quantiles. Equivalently, we have strong evidence 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 versus countries.

We further stress that our quantile regression methodology is powerful enough to detect parameter instability, as we have shown with the full sample analyses. Nevertheless, when moving to sub-samples, rejections of the null of parameter stability from 2008 onward almost disappear. On the contrary, we still have some evidences on instability in the 2003-2006 period, but again associated with a lowering on the link across 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 6-8. 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 Nov.2008-Nov.2011, during which the intensity of the interrelationship is no longer homogeneous among the seven euro countries. Figure 8 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 Nov. 2008-Nov. 2011 the market for sovereign debt started to distinguish between these bonds that are no longer substitutes, so that an adjustment of the bond yield spread in one country generates 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.[23] 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 indicate 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 compared 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 over different samples but we cannot claim that these coefficients are statistically different.

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

4.2. Bayesian Quantiles with Heteroskedasticity

The absence of variability across the quantiles suggests a stable interdependence across large changes in the bond spreads. This difference might be due to the absence of the time-varying volatility component in the quantile regressions used in the previous subsection. Indeed, the shift-contagious events described in Section 2 introduce heteroskedasticity across quantiles,

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

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 the distribution of the shocks has different volatility properties over time and such effects are not explicitly modelled in the quantile regression, bias, or at the least inefficiencies (see discussion in the omitted variable example in Section 2), may occur and incorrect conclusions may result (see, for example, the description of contagion due to endogeneity in Section 2 when countries simultaneously enter into, say, a high volatility regime). 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 (5).

The changes in the bond spreads are assumed to follow a linear model with heteroskedasticity as described in equation (C.3), where the time-varying conditional variance $\sigma^2_{ij,t}$ is modelled 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 (5) and minimizes the following logical quantile criterion function:

$$min_{\Theta_\tau,\alpha_\tau} \sum_{t=1}^{T} \left(\frac{\rho_\tau \left(y_{i,t} - \beta_{ij,0} - \beta_{ij,1} y_{j,t} - \gamma'_{ij} X_{t-1} \right)}{\sigma_{ij,t}(\tau)} + log(\sigma_{ij,t}(\tau)) \right), \tag{8}$$

where $\sigma_{ij,t}(\tau)$ is the square root of residual variance computed using quantile τ estimates of the parameters $\Theta_\tau = \{\beta_{0,\tau}, \beta_{1,\tau}, \gamma'_\tau\}$ and $\alpha_\tau = \{\theta_{ij,0,\tau}, \theta_{ij,1,\tau}, \theta_{ij,2,\tau}\}$:

$$\sigma^2_{ij,t}(\tau) = \theta_{ij,0,\tau} + \theta_{ij,1,\tau} e^2_{ij,t-1} + \theta_{ij,2,\tau} \sigma^2_{ij,t-1}(\tau) \tag{9}$$

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 (5); 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 (8).

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 D 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 9-10 report the values of the $\beta_{1,\tau}$ coefficient across different quantile levels for selected countries, the full sample in the top row and the three subsamples in the following rows as in Figures 3-4.[24] 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.[25]

When focusing on the full sample analysis, we do not find stability in the parameters: for smaller and larger quantiles, in most of the cases, we reject the notion that the coefficients are the same. The differences among quantiles are often larger for the Bayesian estimates than in the previous case. The pattern follows a bell-shaped profile: 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. This result is encouraging because it clearly indicates that the (Bayesian) methodology has enough power to reject certain samples.

As we did in the previous subsection, we investigate the presence of breaks in the β parameter of equation (8). Similarly to what we did for equation (3), 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

[24] The results for all countries and samples are in the Supplementary online material. Moreover, our results are robust to different prior values, including priors centred around frequentist estimates with very small variance.

[25] Figures 3-4 and 9-10 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.

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, confirming our sub-sample choice.

Moving to the sub-sample results, the main differences with the standard QR analysis are for the impact of Spain to Italy and France to Italy and Ireland, above all in the last two sub-samples 2008-2011 and 2011-2013. Allowing for heteroskedasticity in fact produces more precise quantile estimates, above all in the tails, signalling shift-contagion evidence in this relationship that standard QR cannot find. The results indicate that the presence of shift-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. Similar results are found for the relation between France-Ireland and France-Italy.[26] All these findings indicate that there is no evidence of changes in transmission mechanism from peripheral countries to core countries and among peripheral countries the only evidence of shift-contagion is from Spain to Italy. On the other side the data indicates that potential evidence of contagion arises after 2008 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 the quantile regression with heteroskedasticity is robust to endogeneity, therefore the last results possible indicate that there are other factors

[26]Furthermore, our analysis shows that the linkage from Germany to Portugal and from UK to Portugal also increases, but only at 99% quantile. Results are provided in the Supplementary online material.

(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.

Finally, figures for the last sample, Dec. 2011-Apr. 2013 confirm evidence of no shift-contagion, but rather linkages are weaker and the disintegration of the euro has not fully stopped despite the ECB intervention.

5. Robustness Analysis

In order to verify the results reported above, we run a number of checks. This section gives a summary of the main findings, detailed results are provided in Appendix C.

We consider additional sub-samples, precisely Nov. 2008-Jul. 2012 and Nov. 2008-Apr. 2013, and different estimation methods. The detailed results are reported in the Supplementary online material and confirm those already presented in the previous sections, that is there is no evidence of shift-contagion if we extend the sample to most recent dates.

Moreover, we run the same analyses for the changes in countries' CDS for the last two sub-samples. 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. Exceptions 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.

Furthermore, we use three additional approaches to evaluate the possible presence of shift-contagion in the relationship across bond spreads: non-parametric inference based on (i) correlation and (ii) the exceedance correlation measures proposed by Longin and Solnik (2001); and (iii) linear and non-linear regression models. With these different methodologies we find largely changes in the parameters. However, in most of the cases for the approaches (ii) and (iii) these changes in the relationship among countries indicate a reduction in the transmission from the 2003-2006 sample and to 2008-2011 and 2011-2013 samples.

Finally, since we find few cases of shift-contagion we apply two other tests for parameter stability that, under certain circumstances, are robust to the presence of endogeneity and omitted variables in the Appendix C. 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 Nov. 2008-Nov. 2011 and the ECB intervention of Dec. 2011-Apr. 2013. 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 Nov. 2008-Nov. 2011, but in the sample Dec. 2011-Apr. 2013 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'(2015) using data provided by BIS reporting. Future research should explore this conjecture further.

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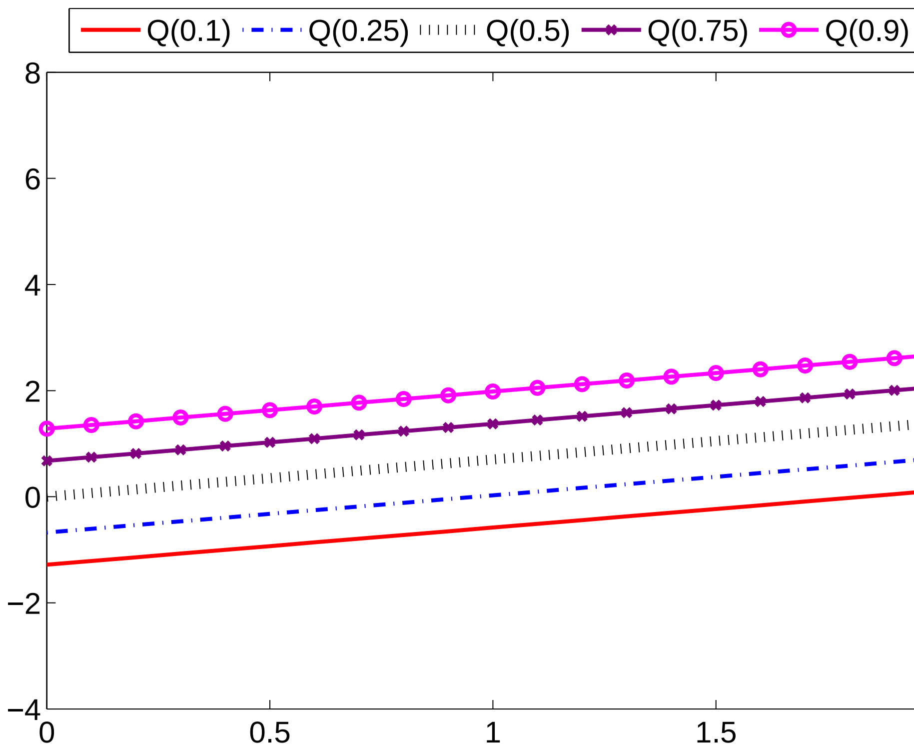
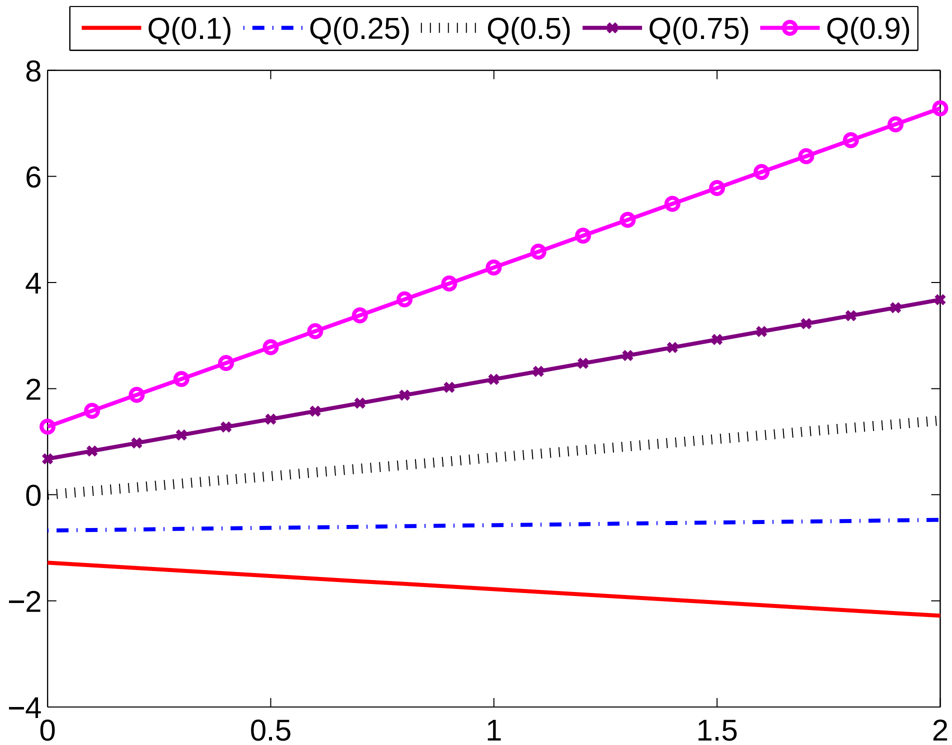
Figure 1: **Quantile regression and parallel quantiles**



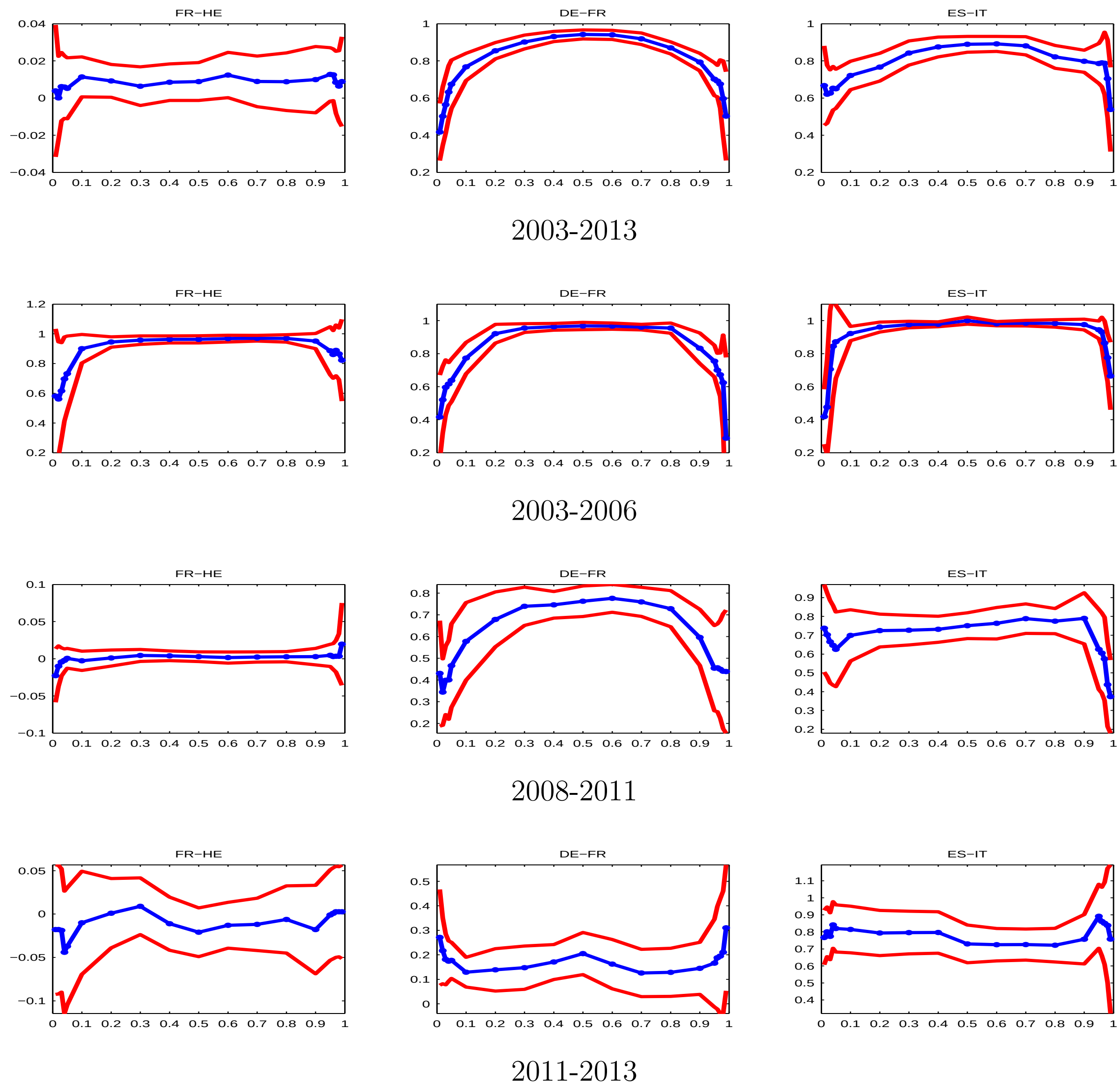
This figure reports quantile regression lines $y_{i,t}(\tau) = \beta_{0,\tau} + \beta_1 y_{j,t} + F_{\eta_t}^{-1}(\tau)$ when the true underlying model is linear, that is $\beta_{1,\tau} = \beta_1$, or the coefficient does not change among quantiles. In this representation the coefficient is always equal 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**



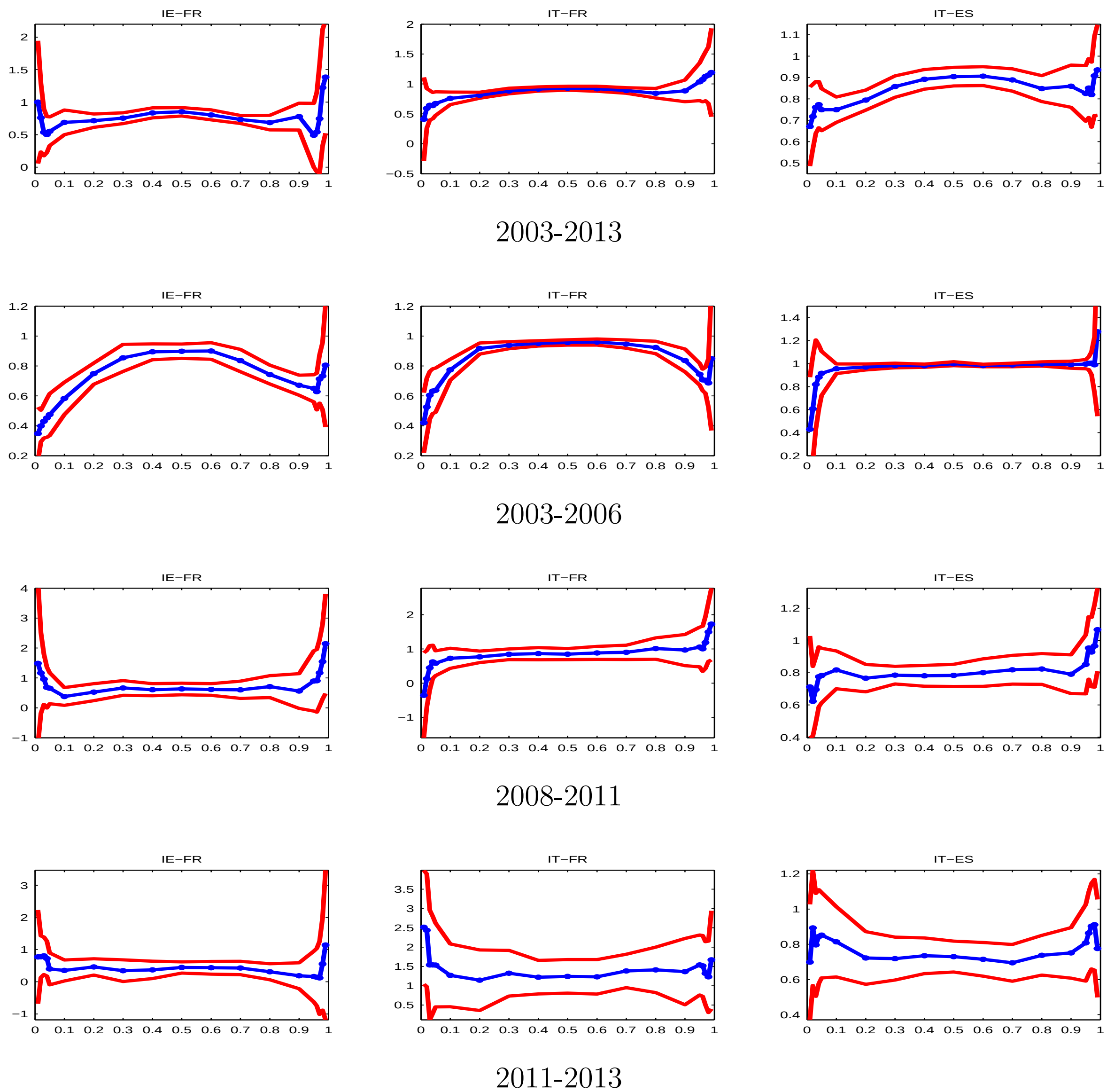
This figure reports quantile regression lines $y_{i,t}(\tau) = \beta_{0,\tau} + \beta_1 y_{j,t} + F^{-1}_{\eta_t}(\tau)$ when the true underlying model is non-linear, that is $\beta_{1,\tau}$ changes among quantiles. In this representation we have that $\beta_{1,0.1} = -0.5$, $\beta_{1,0.25} = 0.0$, $\beta_{01,.5} = 0.5$ $\beta_{1,0.75} = 1$ 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 $F^{-1}_{\tau}(\eta_t)$ 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: **Samples of Quantile Regression Coefficients for Different Bond Spreads.**



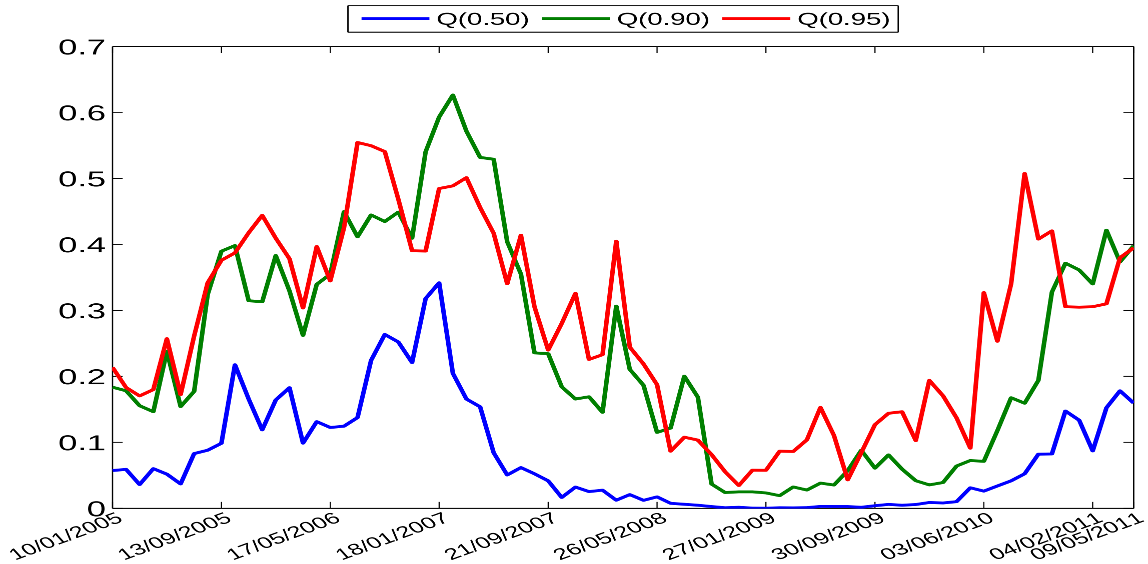
This figure shows the estimated coefficients $\widehat{\beta}_{1,\tau}$ of the Quantile regression $\widehat{y_{i,t}}(\tau) = \widehat{\beta}_{0,\tau} + \widehat{\beta}_{1,\tau} y_{j,t} + \widehat{\gamma'}_{\tau} X_{t-1}$ for three pairs of countries: in the first block country i is France (FR) and country j is Greece (HE), in the second block country i is Germany (DE) and country j is France (FR), 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 4: **Samples of Quantile Regression Coefficients for Different Bond Spreads.**

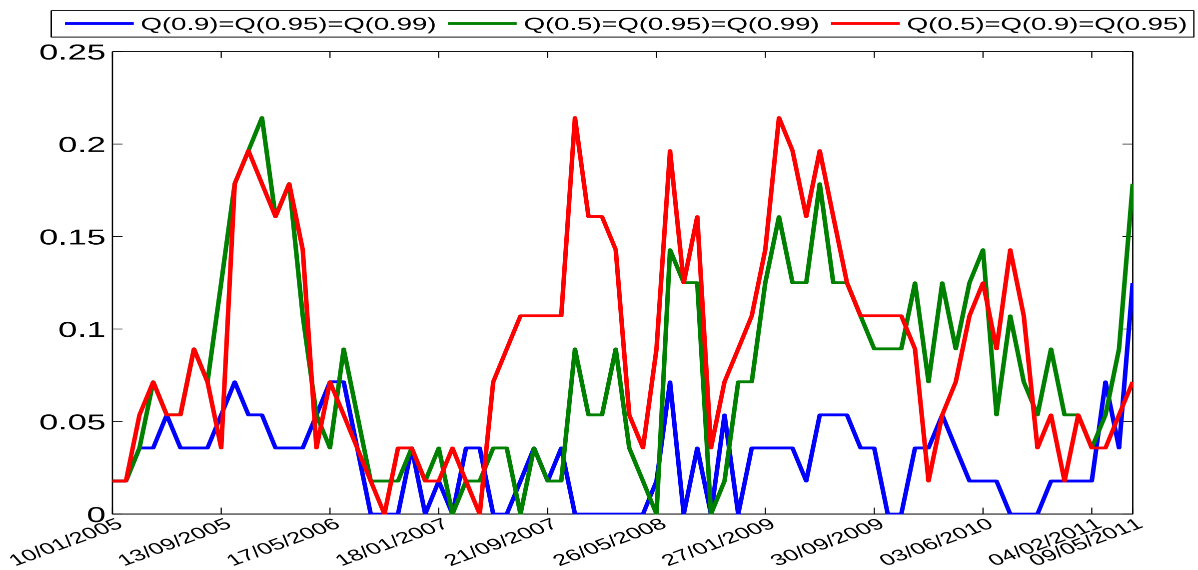


This figure shows the estimated coefficients $\widehat{\beta}_{1,\tau}$ of the Quantile regression $\widehat{y_{i,t}}\,(\tau) = \widehat{\beta}_{0,\tau} + \widehat{\beta}_{1,\tau} y_{j,t} + \widehat{\gamma'}_{\tau} X_{t-1}$ for three pairs of countries: in the first block country i is Ireland (IE) and 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 5: **Structural Instability in Quantile Regression**



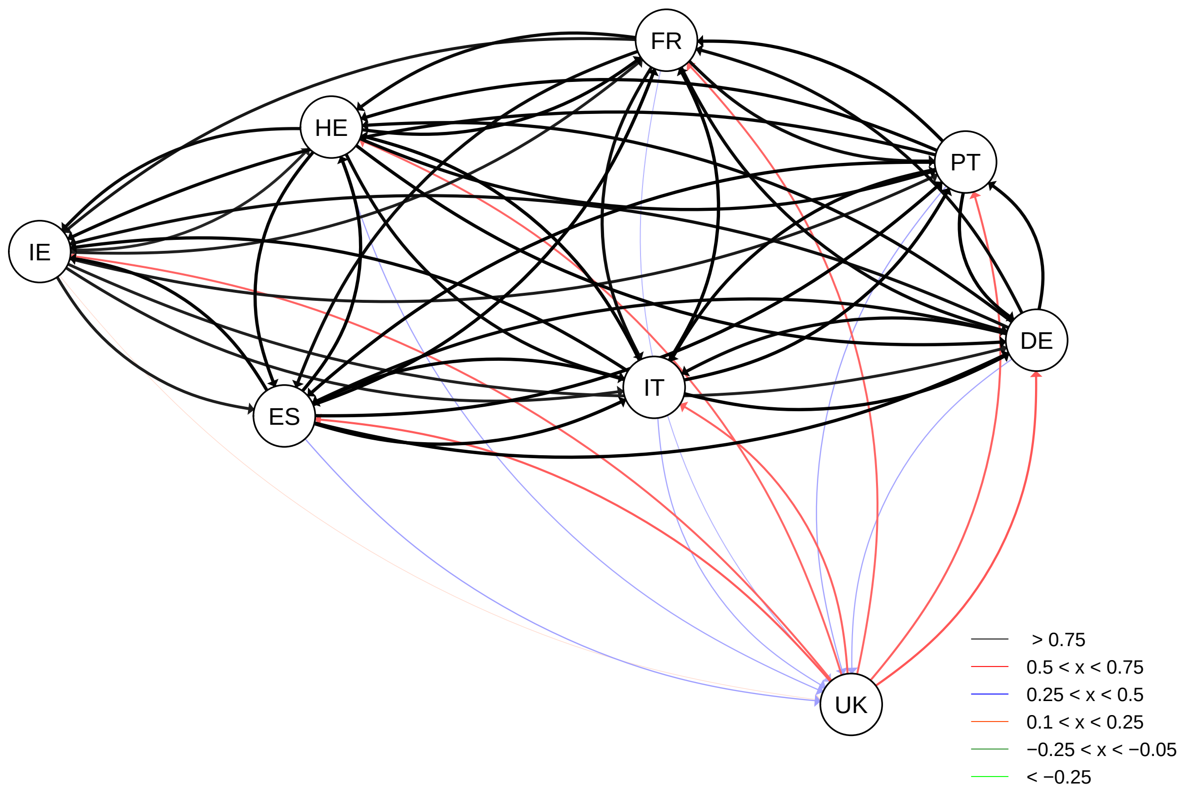
Median p-value across quantiles for the structural break test



Fraction of rejection of the null of stability across quantiles

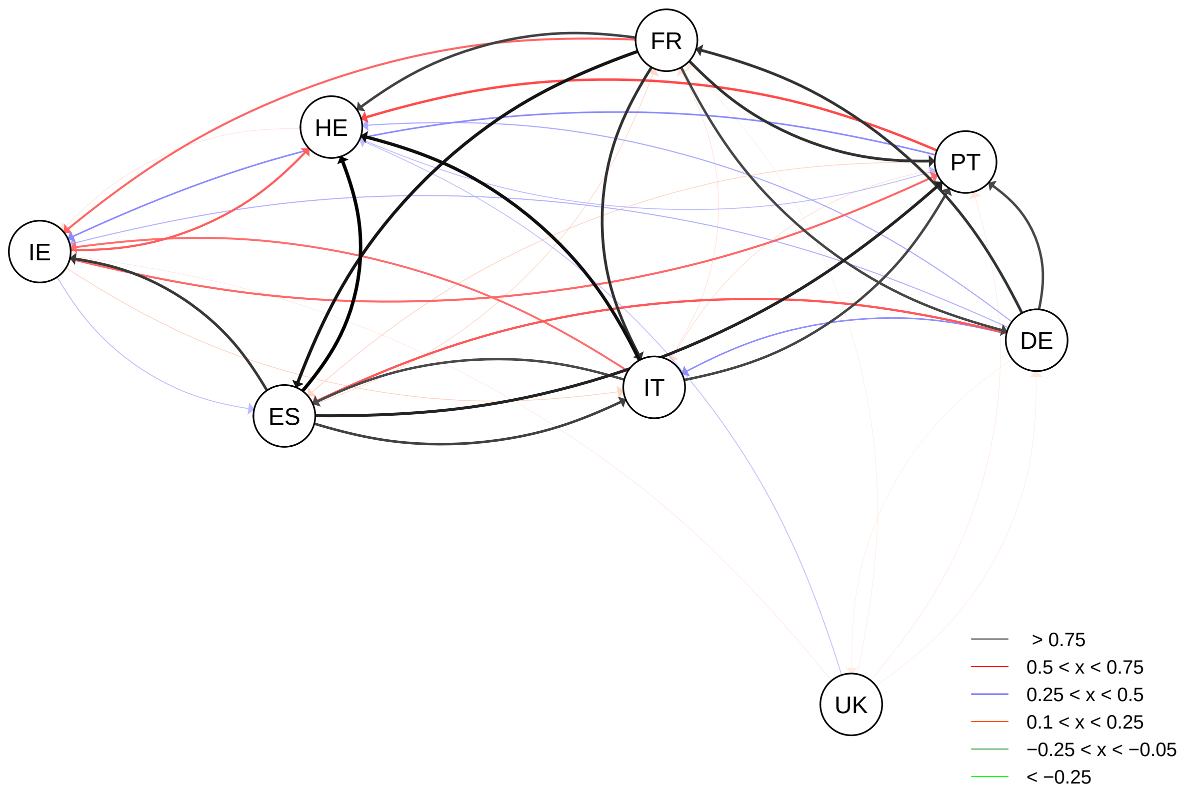
This figure shows the results for a structural break test in the coefficient $\widehat{\beta}_{1,\tau}$ in the quantile regression (3). The test is performed on a rolling window of four years, estimating the following quantile regression $\widehat{y_{i,t}}(\tau) = \widehat{\beta}_{0,\tau} + \widehat{\beta}_{1,\tau} y_{j,t} + \widehat{\delta}_{1,\tau} y_{j,t} d_t + \widehat{\gamma'}_{\tau} X_{t-1}$ 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 6: **Network Graphs 2003-2006**



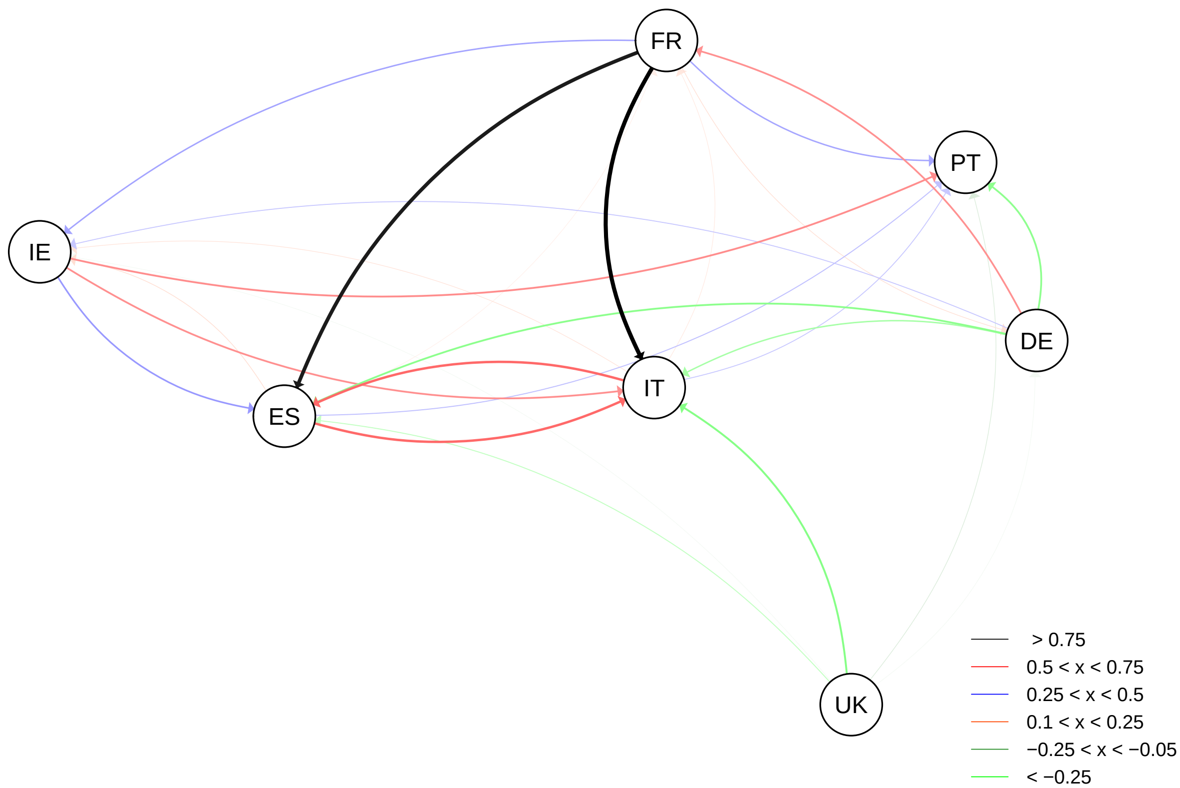
This figure shows the directed relationship network that derives from the estimated Quantile Regression coefficients $\beta_{1,\tau}$ for the sample period 2003-2006. The arrows start from country j and reach country i. The color and the thickness of each arrow represent the level of the associated coefficients 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 7: **Network Graphs 2008-2011**



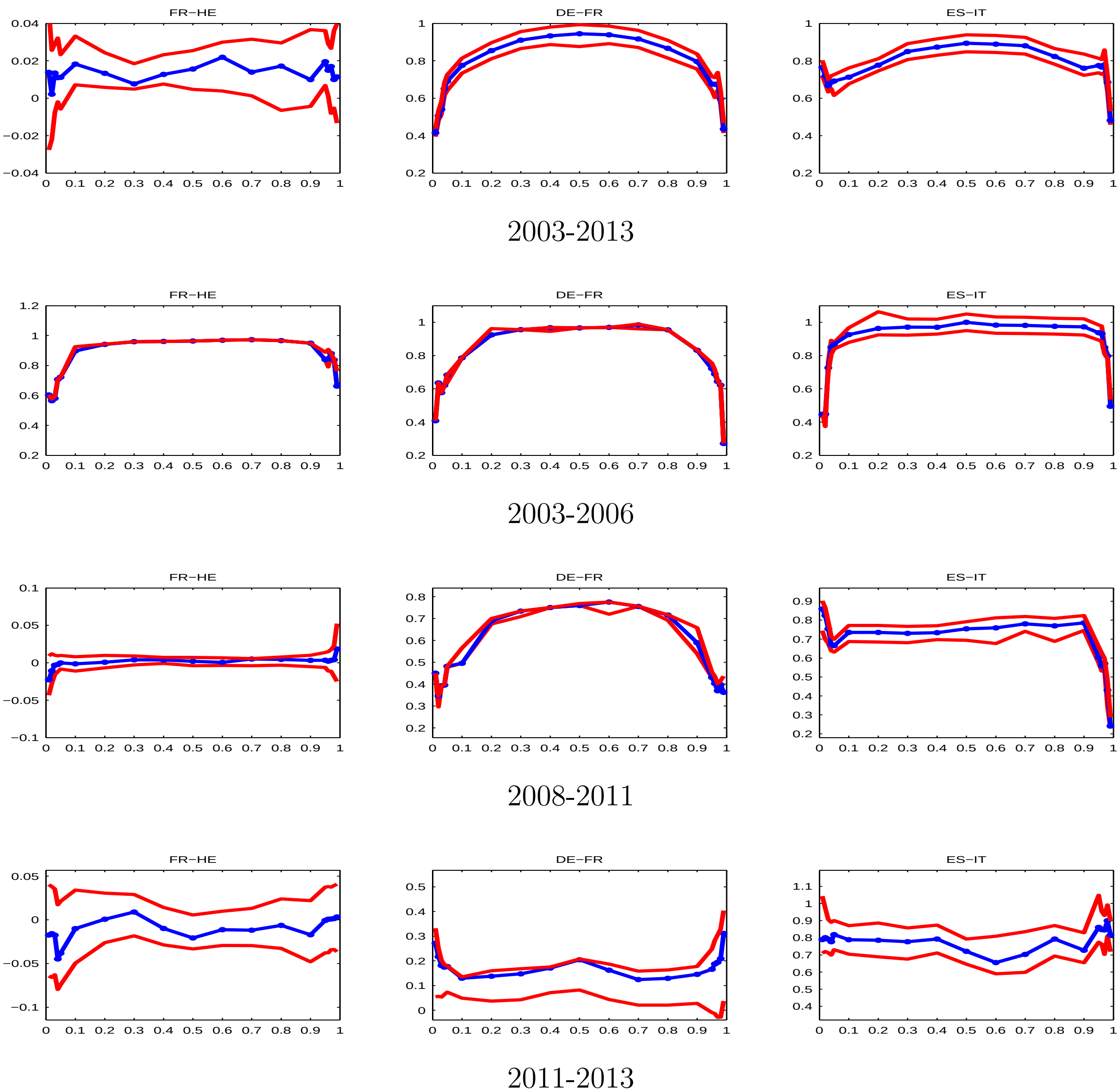
This figure shows the directed relationship network that derives from the estimated Quantile Regression coefficients $\widehat{\beta}_{1,\tau}$ for the sample period 2008-Nov2011. The arrows start from country j and reach country i. The color and the thickness of each arrow represent the level of the 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 8: **Network Graphs 2011-2013**



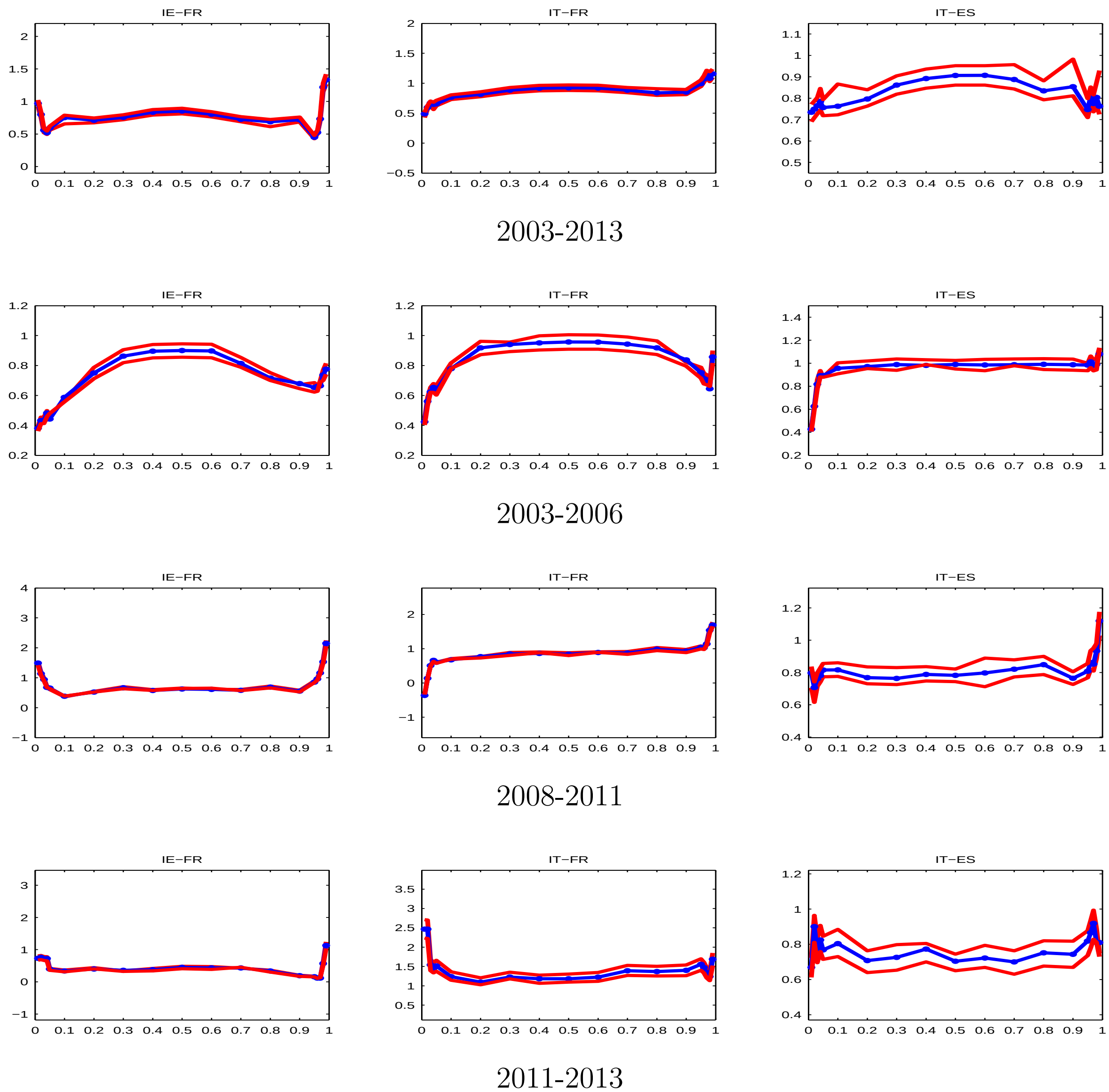
This figure shows the directed relationship network that derives from the estimated Quantile Regression coefficients $\widehat{\beta}_{1,\tau}$ for the sample period Dec 2011-Apr2013. The arrows start from country j and reach country i. The color and the thickness of each arrow represent the level of 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 9: **Samples of Quantile Regression Coefficients with Heteroskedasticity for Different Bond Spreads.**



This figure shows the estimated coefficients $\widehat{\beta}_{1,\tau}$ of the Bayesian Quantile regression with heteroskedasticity 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 (FR), 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 10: **Samples of Quantile Regression Coefficients with Heteroskedasticity for Different Bond Spreads.**



This figure shows the estimated coefficients $\widehat{\beta}_{1,\tau}$ of the Bayesian Quantile regression with heterosledasticity 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.D.	Min	Max	Med.	Mean	St.D.	Min	Max	Med.
	2003-2013					2003-2006				
France	0.02	3.71	-22.50	31.90	160	0.01	2.58	-18.55	15.82	120
Germany	-0.03	3.35	-20.20	25.30	150	0.01	2.27	-12.10	13.00	115
Greece	1.86	28.66	-657.95	428.20	205	0.02	2.70	-20.05	29.10	115
Ireland	0.31	11.57	-140.15	102.20	250	-0.01	2.94	-17.70	37.10	140
Italy	0.24	6.74	-70.85	88.60	175	0.01	2.49	-15.65	22.70	110
Portugal	0.68	15.25	-321.65	258.00	190	0.00	2.80	-17.45	51.90	115
Spain	0.17	6.16	-87.25	47.70	180	0.01	2.49	-14.15	34.50	115
U.K.	-0.02	2.92	-14.24	41.40	120	0.00	1.70	-7.90	7.55	90
Eur.	0.00	0.01	-0.12	0.10	30	0.00	0.01	-0.09	0.09	20
L.R.	0.00	0.02	-0.18	0.16	40	0.00	0.01	-0.03	0.02	30
R.A.	-0.01	2.68	-24.53	24.60	0.91	-0.02	1.60	-11.78	7.19	0.67
	2008-2011					2011-2013				
France	0.09	4.66	-22.50	31.90	220	-0.08	4.59	-18.20	16.90	240
Germany	-0.01	3.94	-20.20	19.05	193	0.13	2.63	-11.00	14.60	160
Greece	5.27	48.45	-657.95	428.20	850	-0.38	82.71	-1464.20	223.40	260
Ireland	0.87	18.24	-140.15	102.20	551	-1.48	10.40	-78.60	60.90	420
Italy	0.65	10.64	-70.85	88.60	360	-0.75	14.84	-83.30	65.10	700
Portugal	1.96	25.57	-321.65	258.00	530	-3.20	38.80	-207.40	265.20	1300
Spain	0.52	9.59	-87.25	47.70	398	-0.23	14.82	-70.50	57.15	685
U.K.	0.01	3.90	-14.24	41.40	160	0.13	3.01	-8.75	38.30	105
Eur.	0.00	0.01	-0.12	0.06	30	0.00	0.01	-0.09	0.01	20
L.R.	0.00	0.02	-0.18	0.14	70	0.00	0.01	-0.04	0.03	20
R.A.	0.01	3.12	-23.80	14.44	1.30	-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 full sample and the three sub-sample periods: January 1, 2003 to April 30, 2013; 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.D.), minimum and maximum values (Min and Max), and median values of the absolute spreads in basis points (Med.) (Eur., L.R. and R.A. are in %).

	FR	DE	HE	IE	IT	PT	ES	UK	Eur.	L.R.	FR	DE	HE	IE	IT	PT	ES	UK	Eur.	L.R.
	Sample: January 2003 - April 2013										Sample: January 2003 - December 2006									
Germany	0.75										0.72									
Greece	0.07	-0.02									0.77	0.72								
Ireland	0.24	0.16	0.41								0.59	0.56	0.54							
Italy	0.45	0.26	0.31	0.45							0.80	0.71	0.75	0.59						
Portugal	0.11	0.10	0.44	0.6	0.39						0.72	0.73	0.85	0.52	0.72					
Spain	0.48	0.32	0.35	0.48	0.77	0.43					0.79	0.77	0.85	0.56	0.76	0.93				
UK	0.23	0.27	0.01	0.08	0.06	0.04	0.11				0.48	0.46	0.46	0.34	0.50	0.40	0.46			
Eur.	0.02	0.02	-0.01	0.01	0	0.01	0	-0.03			0.01	0.00	0.03	0.07	0.02	0.02	0.01	0.04		
L.R.	-0.06	-0.13	0.08	-0.04	0.03	-0.01	0.01	-0.05	0.3		0.01	0.00	-0.01	0.01	0.01	0.01	0.01	0.04	0.04	
R.A.	-0.10	-0.18	0.11	0.09	0.11	0.11	0.07	-0.07	0.01	0.07	0.02	0.04	0.03	0.05	0.03	0.03	0.04	0.01	-0.05	0.05
	Sample: November 2008 - November 2011										Sample: December 2011 - April 2013									
Germany	0.65										0.30									
Greece	0.03	-0.11									-0.00	-0.02								
Ireland	0.17	0.05	0.42								0.17	0.01	-0.01							
Italy	0.34	0.07	0.30	0.45							0.45	-0.09	0.03	0.35						
Portugal	0.02	-0.01	0.42	0.63	0.37						0.08	-0.10	0.06	0.15	0.12					
Spain	0.36	0.11	0.35	0.48	0.76	0.41					0.36	-0.12	0.02	0.34	0.76	0.08				
UK	0.11	0.17	-0.01	0.03	-0.03	-0.00	0.03				0.03	0.00	0.11	0.02	-0.07	-0.02	-0.05			
Eur.	0.03	0.05	0.00	0.01	-0.00	0.04	-0.00	-0.07			0.11	0.06	-0.05	0.05	-0.05	-0.03	-0.12	-0.04		
L.R.	-0.07	-0.17	0.11	-0.04	0.04	0.00	0.04	-0.05	0.12		-0.00	0.08	-0.04	0.02	-0.05	0.01	-0.09	-0.15	0.60	
R.A.	-0.00	-0.14	0.17	0.18	0.24	0.19	0.20	-0.05	-0.01	0.04	0.18	-0.15	-0.01	0.23	0.35	0.08	0.34	0.02	-0.02	-0.03

Table 2: This table presents unconditional correlations on the full sample and 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	$H1$	$H2$	$H3$	y_i	y_j	$H1$	$H2$	$H3$
France	Germany	0.03	0.05	0.07	Italy	France	0.22	0.67	0.12
France	UK	0.82	0.92	0.67	Italy	Germany	0	0	0
France	Spain	0.00	0.00	0.00	Italy	UK	0.03	0.04	0.06
France	Italy	0.00	0.00	0.00	Italy	Spain	0.26	0.13	0.34
France	Ireland	0.82	0.93	0.69	Italy	Ireland	0.69	0.72	0.56
France	Portugal	0.18	0.04	0.10	Italy	Portugal	0.00	0.00	0.02
France	Greece	0.95	0.88	0.88	Italy	Greece	0.99	0.98	0.99
Germany	France	0.00	0.00	0.00	Ireland	France	0.17	0.07	0.27
Germany	UK	0.94	0.83	0.89	Ireland	Germany	0.00	0.00	0.00
Germany	Spain	0.00	0.00	0.00	Ireland	UK	0.91	0.81	0.98
Germany	Italy	0.00	0.00	0.00	Ireland	Spain	0.93	0.82	0.82
Germany	Ireland	0.78	0.67	0.58	Ireland	Italy	0.92	0.86	0.94
Germany	Portugal	0.57	0.39	0.58	Ireland	Portugal	0.28	0.27	0.48
Germany	Greece	0.82	0.64	0.64	Ireland	Greece	0.93	0.95	0.84
UK	France	0.37	0.21	0.23	Portugal	France	0.07	0.04	0.09
UK	Germany	0.93	0.95	0.82	Portugal	Germany	0.00	0.01	0.00
UK	Spain	0.64	0.85	0.48	Portugal	UK	0.10	0.07	0.05
UK	Italy	0.74	0.53	0.54	Portugal	Spain	0.58	0.53	0.81
UK	Ireland	0.45	0.75	0.27	Portugal	Italy	0.88	0.83	0.76
UK	Portugal	0.67	0.89	0.5	Portugal	Ireland	0.60	0.36	0.78
UK	Greece	0.97	0.96	0.96	Portugal	Greece	0.67	0.84	0.56
Spain	France	0.03	0.64	0.01	Greece	France	0.01	0.00	0.1
Spain	Germany	0.00	0.01	0.00	Greece	Germany	0.00	0.00	0.00
Spain	UK	0.23	0.12	0.16	Greece	UK	0.01	0.25	0.01
Spain	Italy	0.00	0.01	0.00	Greece	Spain	0.98	0.90	0.98
Spain	Ireland	0.22	0.45	0.11	Greece	Italy	0.56	0.99	0.36
Spain	Portugal	0.03	0.01	0.07	Greece	Ireland	0.66	0.45	0.46
Spain	Greece	0.09	0.06	0.95	Greece	Portugal	0.22	0.53	0.12

Table 3: 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 April 30, 2013. 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	0.185	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 4: 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 5: 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 6: 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 ($H3$) $H_0 : \widehat{\beta}_{1,0.95} = \widehat{\beta}_{1,0.90} = \widehat{\beta}_{1,0.50}$.

APPENDIX

This appendix provides detailed data figures; describes several robustness tests; and presents methodological details.

A. Testing shift-contagion with quantile regression

Let leave aside for a while the shift-contagion case due to an economic event (the special case of a structural break), and assume for the moment that economic events do not cause a change in the transmission mechanism, but only a change in the distribution of the shocks (or residuals). We thus focus on shift-contagion occurrence in association with the size/sign of shocks (small/large or positive/negative) or with market phases (tranquil/crisis). First, it is important to recognize that in most macroeconomic events in which we are interested, there is significant heteroskedasticity and, indeed, most of the crisis events involve large negative shocks. The simple test is to realize that, if the parameters are stable conditional on the size and sign of the shocks, then we can conclude that there is no shift-contagion in any of its forms. In other words, conditional on a large negative shock, if there exist endogeneity, omitted variables, or non-linearity, the coefficient in a simple OLS regression should be different from the estimates conditional on a small shock or on a large positive shock. Also, notice that market phases (tranquil/crises) are generally associated with heteroskedasticity issues, and thus by conditioning on shocks sign and size we jointly deal with both shift-contagion conditional on market phase and shocks sign. However, size and sign of shocks can be associated with the size and sign of the modelled variables, and thus with different quantiles of their distributions. This implies that a quantile-based approach is well designed to deal with the problem at hand.

In fact, quantile regression can be used to test for differences in the β-coefficients across quantiles (thus across size and sign of shocks and market phases) and therefore to identify positive shifts in the relationship between bond spread changes in country i versus country j. We stress that the main focus we pursue is the search of parameter stability, and thus the null hypothesis is the absence of shift-contagion.

In the rest of this section we explore simple models to highlight the conditions in which a simple quantile approach is able to uncover the possible presence of shift-contagion even when OLS is biased due to misspecification problems.[27]

The simplest example is a factor model – or omitted variable framework. To develop the intuition lets assume that $y_{i,t}$ and $y_{j,t}$ are the sovereign yields of two countries, and assume the macroeconomic event we are interested is a "crisis" – either sovereign, financial, or currency. An affine omitted variable model is

$$\begin{aligned} y_{i,t} &= \beta y_{j,t} + \gamma X_t + \varepsilon_t, \\ y_{j,t} &= X_t + \eta_t, \end{aligned} \tag{10}$$

where X_t is the factor that is zero in tranquil times and appears during the crisis. We stress that, if the factor is observable,[28] the model is equivalent to an omitted variable case. We assume that the structural shocks are uncorrelated. So, ε_t, η_t and X_t are uncorrelated. In addition, assume that X_t is not observable. So, it cannot be partial led out. We denote X_t as the "crisis factor". Because X_t is not observable, without loss of generality we can normalize the variable to have a coefficient of one for country $y_{j,t}$. So, the nuisance factor enters $y_{j,t}$ with the same weight as its structural shocks. Therefore, the difference in the propagation mechanisms is fully captured by γ – it actually reflects how the factor X_t affects $y_{i,t}$ differently from $y_{j,t}$. Notice that γ could be positive or negative so instances of shift-contagion could be associated with larger strengths in the propagation mechanism, but also a lowering of the impact is allowed by the model. In our empirical application, we interpret the latter 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.

Imagine the true model is (10) but the econometrician estimates (1) in tranquil and crisis

[27] For a significant discussion on some of these issues see Rigobon (2001)

[28] In general, factor models of this form deal with latent factors.

periods – which is implicitly what the quantile regression does by conditioning on large and small shocks – as well as on positive and negative shocks. The OLS coefficient when the X_t is zero is

$$\hat{b}_{tranquil} = \beta$$

On the other hand, the estimate when the factor is present is

$$\hat{b}_{crisis} = \beta + \gamma \frac{\sigma_X^2}{\sigma_X^2 + \sigma_\eta^2}$$

As it can be very simply proven, $\hat{b}_{crisis} = \hat{b}_{tranquil}$ only when $\gamma = 0$ or $\sigma_X^2 = 0$.[29]

In other words, the parameters are stable ONLY if there is no crisis factor, or if the crisis factor has nothing particularly different from the usual shocks – except maybe larger realizations. On the contrary, if there exists a crisis factor, or if shocks are showing heteroskedasticity, $\hat{b}_{crisis} \neq \hat{b}_{tranquil}$. Distinguishing between the two possible motivations leading to changes in the coefficients might be difficult. Nevertheless, by resorting to quantile regressions we can tackle this issue.

The quantile regression approach we implement in this paper slices the space in hundred of conditional OLS regressions. If all those coefficients are statistically equal we can conclude that there is no change in the propagation mechanism due to the presence of omitted variables/factors, which is the first of the elements possibly causing changes in the coefficients.[30]

[29] There is another uninteresting circumstance in which the coefficients are the same – the case of near identification – when σ_η^2 is infinity.

[30] The simplified model we adopt in this section is similar to Corsetti, Pericoli and Sbracia (2005). However, in our model the presence of shift-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 shift-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 (2014). However, their model is based on observed factors and therefore differs from our approach based on latent factors.

The case of endogeneity is very similar. Assume that there are two countries whose yields are given by

$$
\begin{aligned}
y_{i,t} &= \beta y_{j,t} + \varepsilon_t, \\
y_{j,t} &= \alpha y_{i,t} + \eta_t
\end{aligned} \tag{11}
$$

The OLS coefficient from estimating (1) when the underlying model in (11) is

$$
\hat{b} = \beta + \alpha \left(1 - \alpha\beta\right) \frac{\sigma_\varepsilon^2}{\alpha^2 \sigma_\varepsilon^2 + \sigma_\eta^2} \tag{12}
$$

In this model, shift-contagion occurs when the β coefficient changes (increases) in comparing small versus large shocks or tranquil versus crisis. However, the $\hat{b}$ may increase both because of a change in β, and thus when we have shift-contagion, but may also change because of the endogeneity bias (the second term in (12)). In fact, by conditioning on shocks sign and size, we might have that the variance ratio $\frac{\sigma_\varepsilon^2}{\alpha^2\sigma_\varepsilon^2+\sigma_\eta^2}$ changes (it is different across the various slices of the space considered by quantile regression) and induces a change in $\hat{b}$ even when β is constant.

Therefore, if shift-contagion is not present, running a quantile regression when there is endogeneity implies that the actual coefficient shifts around if and only if the different quantiles exhibit differences in the variance ratios. In other words, conditional on the fact that there is heteroskedasticity, the estimates of $\hat{b}_q$ for quantile q are likely to change if the variance shifts across quantiles. Notice that, as previously stated, this is likely to happen when during crisis we observe large negative shocks and thus, conditioning on size and sign of shocks, we can expect to have different variances across quantiles.

In this model, in the presence of heteroskedasticity, the only way the parameters are stable are in those circumstances in which the propagation of shocks is stable (absence of shift-contagion) and the variance ratios are constant. The latter corresponds, for instance, to the case in which countries simultaneously enter into, say, a high volatility regime. As a consequence, despite the presence of endogeneity biases, the absence of shift-contagion can be associated to a null of parameter stability. If parameters are stable, there is no shift-contagion. If parameters are unstable, there might be shift-contagion or heteroskedasticity could be present. The latter doubt can be easily solved by extending quantile regression with the introduction of heteroskedasticity in the shocks, as we do with the Bayesian Quantile Regression.

Indeed, cross sectional information (the separate estimation of both equations in the system) provides further elements to assess the endogeneity issues. In fact, if α and β are stable, Rigobon (2003) shows that the heteroskedasticity in the data is enough to obtain identification of the structural parameters. In that case the identification is obtained by splitting the sample across heteroskedastic regimes – by directly looking at the conditional volatility of $y_{i,t}$ and $y_{j,t}$ – jointly affecting all modelled variables. Furthermore, if there are more than two regimes then the system is over identified and the assumption of parameter stability can be tested.[31] In the case of the quantile regression the conditioning is between large versus small, and positive versus negative realizations. And there are not only two regimes but hundreds. In the end, if crises are associated with larger volatility then the implicit conditioning in the quantile regression is equivalent to condition on several heteroskedastic regimes. This is the reason why quantile regression are better able to verify stability in the parameter estimation.

The final example is when the relationship is of lower intensity for small shocks versus large shocks, that is shift-contagion. In this case it is trivial that asymmetries in the size and sign of the shocks will produce different OLS estimates and this is the evidence that we are looking for with our investigation of shift-contagion. Quantile regression again will capture the presence of shift-contagion.

In summary, from the simple OLS regression perspective, empirical evidence suggesting the presence of shift-contagion can be the outcome of endogeneity, omitted variables, and of a true change in the intensity of the transmission. However, as we discussed above, quantile regression

[31]This analyis can be performed using the DCC test proposed in Rigobon (2003) used recently also in the microstructure context by Chaboud, Chiquoine, Hjalmarsson, and Vega (2014). For a synthetic description of the test see Appendix D.

(run with and without heteroskedasticity) is able to identify the absence of shift-contagion both in factor/omitted variables models, in endogenous regressions and in the true presence of a change in the intensity of shock transmission. In the latter case, to be identified, the size of the positive shift in the coefficients has to be large enough to be empirically relevant. The quantile regression is flexible in its assumption on instability of the coefficients, and regarding the country in which the crisis starts, but its ability to detect shift-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.[32]

B. Additional Figures

Figure B.1 shows the 5-year redemption yields for the eight countries; and Figures B.2 and B.3 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 B.2 indicates that the differences are not due to swap rates. The UK yield 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 re-converge and only stops in spring 2012, when the European Union,

[32] In the Appendix C, we also report results for the test developed in Rigobon (2000), and used in Rigobon (2003), called the DCC test. This approach is specifically designed to deal with simultaneous equations and omitted variables biases when there is heteroskedasticity in the data. The disadvantage of such a 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 shift-contagion 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 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. The DCC test could thus be seen as a robustness check of the results given by Quantile Regression-based methods, where we are not conditioning on the crisis timing.

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 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 increase after that. Rates are more moderate in the last few months of the sample.

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 to 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.

C. Detailed Robustness Analysis

In order to verify the results reported in this paper, we run a number of checks. In particular, we consider additional subsamples and a different estimation method for the quantile regression. We also run the same analysis using three different approaches to evaluate the possible presence of nonlinearities in the relationships between the bond spreads: two nonparametric methods, the rolling evaluation of the linear correlation and the exceedance correlation measures proposed by Longin and Solnik (2001); and a linear regression model. We estimate the latter one adding

GARCH residuals and adding non-linear terms. For the linear model, we also consider other forms of time-varying volatility and instrumental variables. Then, we apply our analysis to the change in country CDS. Finally, we apply a test for parameter stability under omitted variables and simultaneous equations.

C.1. Additional Subsamples

For most of the analyses in the text we focused on the full sample and three subsamples. Further checks are performed by extending the crisis period to include the ECB intervention, specifically up to the Greek restructuring and exit from the markets on July 31, 2012, and up to the end of the sample period on April 30, 2013. Results for the subsamples 2008-2012 and 2008-2013 are in the Supplementary online material, and confirm the findings obtained with the subsample 2008-2011.

C.2. Different Estimation Method for QR: IVQR

A possible strategy for avoiding the biases due to endogeneity issues when dealing with quantile regressions is to estimate the model by means of instrumental variable approaches; see Chernozhukov and Hansen (2005 and 2006). We thus follow that approach and consider as instruments the lagged endogenous variables and the covariates. We report the quantile estimates across subsamples and for each pair of countries, again testing for the stability of the quantile coefficients. The results, reported in the Supplementary online material, are comparable for those of the standard quantile regression reported in the paper. Nevertheless, we note that the quantile processes are characterised by wider confidence intervals than those of the classical quantile regression. This signals that there is a lot of uncertainty in the estimations, but this might be due to the selected instruments. Overall, standard tests of endogeneity and tests on the information content of the selected instruments suggest that the use of instrumental variables is needed, that the instruments are not endogenous, but that there are cases where the informative content of the instruments is limited. Summarizing, despite some limitations implicit in the instruments, the use of instrumental variables quantile regression confirms our results.

C.3. Correlation Analysis

As an initial evaluation of the 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 C.1 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 C.1 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).

C.4. Exceedance Correlation Measures Proposed by Longin and Solnik (2001)

To evaluate the possible presence of nonlinearities in the relationships between the bond spreads, we consider the exceedance correlation measures proposed by Longin and Solnik (2001). Given a quantile level q, we compute the exceedance correlations as follows:

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

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

where $y_{i,t}$ indicates changes in the bond yield spreads, i, j denote any two different countries, and F_i and F_j are the cumulative density functions of the corresponding bond yield spreads variations. Note that we deviate from the original definition of Longin and Solnik (2001) since we condition the correlation on a single variable rather than a joint conditioning (both variables in their upper/lower quantile). This choice is made for two reasons: First, it is consistent with our interest in the quantile regression framework, where the reference quantile is that of the dependent variable (while the explanatory can assume any value over its support). Second, it matches the sources of nonlinearities that we are interested in, that is, those associated to extreme values (on the higher/lower quantiles) of a given variable. The exceedance correlation ρ^- measures the association between two given spread changes when one variable is located in its lower q quantile, while ρ^+ refers to the linear dependence when one variable lies above its $1 - q$ quantile. As a consequence, the instability of exceedance correlations across quantiles can be interpreted as evidence of nonlinearity. In fact, it detects a change in the association between a potentially dependent variable (the one driving the conditioning) and an explanatory variable. By construction, the quantile q assume values in the range $(0, 0.5]$. For the purposes of this study, the quantity ρ^+ is more interesting.

Note that from this point onward we will comment on the subsamples mentioned above, focusing in most cases on January-2003 to December-2006, November-2008 to November 2011, and December-2011 to April 2013.

Figure C.3 reports five different panels that summarize the exceedance correlation analysis. The panels refer to the different periods we consider. Each panel reports the average exceedance correlation and the 10% and 90% empirical quantiles.[33] The various panels ρ^- and ρ^+ report on the left and right sides, respectively. The 2003-2006 period shows evidence of a marked decrease in ρ^+ for increasing quantiles. A similar pattern, but less evident, is present for ρ^-. If we contrast the 2003-2006 outcomes to those of the other subsamples we observe two relevant differences: the average level of exceedance correlations is smaller, about one third of the 2003-2006 period (20% for 2011-2013 compared to 2003-2006); the decreasing pattern for increasing quantiles is less evident. These effects might be a by-product of the crisis, which has induced a change in the relationships between countries. Nevertheless, while in 2003-2006 we have relevant

[33] Averages and quantiles are computed with respect to the cross-sectional dimension. With the 8 countries we consider, we have 56 possible pairs for computing the exceedance correlations as defined in the text. The 10% and 90% quantiles correspond to ranks 6 and 51 in the ordered exceedance correlations.

evidence of nonlinearities, the latter becoming a little weaker from 2008 onward. Regardless, the change in exceedance correlations across quantiles and the country-specific results suggest that nonlinearities might still be present in the data.

Despite being interesting, exceedance correlation measure has a drawback: it is affected by the changes in the marginal densities of the variables. Moreover, it suffers from the problem highlighted by Forbes and Rigobon (2002): the bond spread volatility might differ during turbulent market periods compared to the volatility that occurs during tranquil market periods, and these changes may bias the correlation measure. This problem clearly emerges when looking at Figure 5, where the volatility tends to increase during 2010. For this reason these exceedance correlation measures cannot be used to investigate the sovereign risk spillover among countries.

C.5. Drawing Inference using Linear and Nonlinear 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:

$$y_{i,t} = \beta_{ij,0} + \beta_{ij,1} y_{j,t} + \gamma_{ij}' X_{t-1} + \sigma_{ij,t} \varepsilon_{ij,t} \tag{C.3}$$

$$\varepsilon_{ij,t} | I^{t-1} \sim D(0,1) \tag{C.4}$$

$$\sigma_{ij,t}^2 = \theta_{ij,0} + \theta_{ij,1} e_{ij,t-1}^2 + \theta_{ij,2} \sigma_{ij,t-1}^2, \tag{C.5}$$

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, $e_{ij,t-1} = \sigma_{ij,t}\varepsilon_{ij,t}$.[34] Moreover, the parameters in the GARCH equation (C.5) must satisfy the constraints leading to variance positivity and covariance stationarity, namely $\theta_{ij,0} > 0$, $\theta_{ij,1} \geq 0$, $\theta_{ij,2} \geq 0$, and , $\theta_{ij,1} + \theta_{ij,2} \leq 1$. The parameters in equation (C.3) 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 extended model:

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

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

The coefficients of the powers in equation (C.6), 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

[34] We repeated the same analysis using as covariates the variables adopted by Ang and Longstaff (2013), 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.

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 the Supplementary online material 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.

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. However, 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 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 (C.6). 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 C.2 reports the time series of the median p-value and of the 25% and 75% quantiles (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.

C.6. Different Estimation Methods for the Regression Models

We consider two alternative approaches. In the first case, we remove the GARCH component from the model and estimate the model coefficients with OLS and Newey-West standard errors. The results, in the Supplementary online material, confirm our findings: there is evidence of nonlinearity; the economic impact of the quadratic and cubic terms is limited. Some negligible differences emerge when focusing on the economic impact of the powers, as, expressed in basis points, they have higher values, in particular during the 2003-2006 period. However, they remain limited, being in most cases less than 0.01 basis points (values are derived using the median of the absolute change in bond yield spreads).

As a second check, we estimate the model using instrumental variables; see Supplementary online material. The reference model used considers the covariates as instruments. The lagged values of the explanatory variables and of their powers are also included in the instruments set. We note that the instruments are informative in many cases, and uncorrelated with the error term, which supports their use in the analysis. Moreover, there is evidence of endogeneity. The estimation using IV methods again confirms the existence of nonlinearities and their limited economic relevance. With respect to the OLS-based estimations, we note that the IV results suggest a somewhat lower lever of interaction across countries since the number of statistically significant coefficients is smaller.

C.7. Different Dependent Variables: Change in Sovereign CDS

We also consider a different dependent variable to measure the links between the sovereign risks of the European countries analysed. For that purpose we focus on country CDS. A CDS contract obliges the seller of the CDS to compensate the buyer in the event of a loan default; see definitions in Duffie (1999), Longstaff, Mithal, and Neis (2005), Pan and Singleton (2008), Longstaff, Pan, Pedersen, and Singleton (2011), among others. It is basically a swap agreement because, in the event of default, the buyer of the CDS receives money (usually the face value of the bond), and the seller of the CDS receives the defaulted bond. For the present study, we obtain five-year sovereign CDS spreads from Datastream. We consider daily data for the euro denominated CDS for the same eight European countries analysed in the bond spread case. The sample covers the period from November 2008 to April 2013. The beginning of this sample period is dictated by the availability of CDS data for all of the countries in the study. The subsample of 2003-2006 is not available for CDS changes. We perform the analysis for the same two subsamples proposed in the paper: 2008-Nov2011 and Dec2011-Apr2013.[35]

The values of the estimations of the beta coefficients as well as the results of the stability tests (both reported in the Supplementary online material) are very similar to the results presented in the previous sections on bond spreads. One element that is partially different is

[35]We also consider the two additional subsamples of 2008-2012 and 2008-2013 discussed in a previous robustness check.

the size of the confidence intervals (the uncertainty), which are narrower than those estimated for the bond spread. This is a by-product of the different volatility levels of the two sets of time series. Besides the different uncertainty levels, our results suggest that the propagation of shocks within the subsamples is similar for the bond and CDS markets.

C.8. Testing for Parameter Stability under Omitted Variables and Simultaneous Equations

Problems of omitted variables and simultaneous equations can bias the coefficient estimates of linear equations. Such bias is a function of the relative variances of the shocks, and the bias tends to shift with the heteroskedasticity in the data. To investigate this issue more deeply, in this section we apply the DCC (Determinant of the Change in the Covariance matrix) test highlighted in Rigobon (2000, 2003), and Dungey et al. (2005).

The key idea of this test is to use heteroskedasticity as a tool to solve the identification issues and evaluate the presence of contagion within a system. In that case, heteroskedasticity is a driver of information and allows testing the presence of stability in relations across countries.

The DCC is a simple test for parameter stability when the model suffers from biases related to simultaneous equations and omitted variables. These are exactly the types of problems that arise in the estimation of contagion and systemic risk. This test, however, only determines whether the relationship is stable, and not its strength.[36] Appendix B.2 reports some details on the DCC test and on the interpretation of the test outcomes.

As discussed in section D, in order to apply the DCC test, the only necessary assumption is that some of the structural shocks are homoskedastic within a certain estimation window. In the case of Europe, it is reasonable to assume that when Greece is heading toward a fiscal crisis and its shocks become more volatile, the shocks in Germany are homoskedastic, which implies that all the observed heteroskedasticity in Germany is coming from the heteroskedasticity in the shocks to the periphery. This applies to the subsamples 2008-2011 and 2011-2013.[37]

[36] For an evaluation of the properties of the DCC as compared to other parameter stability tests see Rigobon (2001).

[37] Remember that Greece is excluded from the dataset from July 2012 onward.

Alternatively, we can assume that the core countries were homoskedastic during the 2003-2006 period. Therefore, running the DCC test within the cited subsamples allows us to detecting changes in the transmission mechanism during a stable period (2003-2006) or during a turbulent period (2008-2011 during the crisis, and 2011-2013 with the ECB interventions). Note that, in those cases, within each subsample, we can identify high/low volatility regimes and verify whether the transmission mechanism changes when the volatility, within a given subsample, changes. On the contrary, when applying the test to compare the whole 2003-2006 subsample to the crisis period (say, 2008-2011), we clearly expect a rejection of the null hypothesis.[38] However, such a rejection would be uninformative as the two periods are characterised by heteroskedasticity on all shocks, and the structural relations bwtween the countries can be assumed to be different (but we cannot test that with the DCC).

Therefore, for the recent eurozone fiscal crisis, it is assumed that either the crisis is driven by shocks to some of the countries – a subset of the structural shocks – or the crisis is driven by the common shocks.[39]

With our data we first estimate a simple VAR(5) where we include as exogenous variables the same set used in the quantile regression framework. These exogenous variables, the Euribor rate, the liquidity risk, and the risk appetite, enter the regression with the same lags as the dependent variables (that is, lags from 1 to 5) and are not included as contemporaneous variables. The choice of using 5 lags is a compromise between the different suggestions regarding lag length selection criteria. Some suggest 1 to 3 lags, other more than 10. We thus decided to include lags of up to one full week of data.

We then recover the residuals from that generalized regression model and estimate the 60-day rolling covariance matrices. Figure C.4 reports the cross-sectional average across the square

[38] In that case, the subsample are themselves two regimes, and we are aiming at verifying that the transmission mechanism changes between subsamples.

[39] These assumptions are perfectly reasonable, but to provide evidence of the robustness of our results even without the hypothesis that we know the country (or countries) in which the crisis started, see results for a quantile regression with instrumental variables.

roots of the diagonal elements of the rolling covariances (that is, we take only the volatilities). This graphical representation allows us to identifying periods of high and low volatility within one of the subsamples we consider. Moreover, we include the subsamples in the figure (shaded areas). Within each subsample, high- and low-volatility regimes are identified by means of a thresholds. That is, given a known threshold level, each day is labelled as high (low) volatility if the average variance is above (below) the threshold. Then, we compute the determinant of the change in the variance-covariance matrix across the high and low volatility regimes. The basic idea is to split the data between high and low conditional volatility phases. One of the advantages of the DCC is that the test is linear on the covariance matrices, so that minor misspecifications on the "regimes" will only reduce the power of the test. In order to control for this possibility we try different thresholds.

If we consider the subsamples defined in section (3), the DCC provides a strong rejection of the null when the 2003-2006 period is compared to the 2008-2011 and 2011-2013 periods.[40] This is, however, expected, as the two periods compared are characterized by completely different variance levels, see Figure C.4, supporting thus the presence of heteroskedasticity. As a consequence, we do not know whether the rejection is due only to heteroskedasticity or to a real change in the transmission mechanism. On the contrary, when comparing the 2008-2011 and 2011-2013 subsamples, the null is now accepted, and we have evidences of parameter stability. Note that this also suggests that some of the underlying structural shocks or common shocks are homoskedastic in the two subsamples. As we argued previously, this might happen for Germany.

If we take a different viewpoint, and analyse the stability within each of the three regimes previously analysed, the results are different. In this case, we have to fix thresholds to define high/low volatilities. We set the thresholds to the deciles of the average volatilities within each subsample. Table C.1 reports the thresholds, for the deciles from 10% to 90% (thus we have at

[40] Only in 0.3% of the simulations we have a null determinant.

least 10% of the data in the high/low regimes), the estimated DCC quantity and the one-sided p-value.

The results clearly indicate that the parameters are stable within each subsample. Therefore, the heteroskedasticity in the data is the outcome of the heteroskedasticity from a subset of the shocks. The DCC test statistics are all well below the 95% confidence intervals. This suggests that within each subsample we do have parameter stability, and therefore we do have evidence of linearities. In contrast, if we perform the comparison between subsamples, we cannot attribute the violations of the test statistic to nonlinearity.

The necessary and sufficient condition for this test is that one country should be homoskedastic in the sample of interest. In our data set, this can be assumed for the subsamples but not in the whole sample. Such a limitation prevents the test from being used to analyse the presence of parameter stability in a range where heteroskedasticity is a certainty, such as in our full-sample data. However, when the modeling framework of Rigobon is generalized to allow for multiple volatility regimes across countries, as in Bacchiocchi (2015), the results show evidence for parameter stability and no contagion. See Bacchiocchi (2015) for further details.

D. Methodological Details

D.1. Bayesian Quantile Regression with Heteroskedasticity

The relation between the bond spread of country i with country j and the other covariates is modeled as:

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

$$\varepsilon_{ij,t}|I^{t-1} \sim D(0,1) \tag{D.2}$$

$$\sigma^2_{ij,t} = \theta_{ij,0} + \theta_{ij,1}e^2_{ij,t-1} + \theta_{ij,2}\sigma^2_{ij,t-1} \tag{D.3}$$

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

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

Chen, Gerlack, and Wei (2009) shows that if the residual $\varepsilon_{ij,t-1}$ in equation (D.1) is assumed to be skewed Laplace distributed, *i.i.d.*, and has been standardized to have variance of one, the likelihood of the model in (D.1)-(D.3) is:

$$l(\Delta CDS_i|\Theta, \alpha) = \sqrt{1-2\tau+2\tau^2}\left(\prod_{t=1}^{T}(\rho_\tau(\sigma_{ij,t}))^{-1}\right)\exp\left(\sum_{t=1}^{T}\frac{\sqrt{1-2\tau+2\tau^2}(\Delta CDS_{i,t}-\beta_{0,\tau}-\beta_{1,\tau}\Delta CDS_{j,t}-\gamma'_\tau X_{t-1})}{\rho_\tau(\sigma_{ij,t})}\right), \tag{D.4}$$

where $\rho_\tau(a)$ is the *check* function for quantile τ defined as $\rho_\tau(a) = a \times (\tau - I(a<0))$, $\Theta = \{\Theta_\tau\}_\tau = \{\beta_{0,\tau}, \beta_{1,\tau}, \gamma'_\tau\}_\tau$ and $\alpha = \{\alpha_\tau\}_\tau = \{\theta_{ij,0,\tau}, \theta_{ij,1,\tau}, \theta_{ij,2,\tau}\}_\tau$. The maximum likelihood estimates from equation (D.4) for Θ_τ are mathematically equivalent to the heteroskedastic quantile estimators of

$$min_{\Theta_\tau,\alpha_\tau}\sum_{t=1}^{T}\left(\frac{\rho_\tau\left(y_{i,t}-\beta_{ij,0}-\beta_{ij,1}y_{j,t}-\gamma'_{ij}X_{t-1}\right)}{\sigma_{ij,t}(\tau)} + log(\sigma_{ij,t}(\tau))\right) \tag{D.5}$$

Then, define the vector $\Phi_\tau = (\beta_{0,\tau}, \beta_{1,\tau}, \gamma_\tau, \theta_{0,\tau}, \theta_{1,\tau}, \theta_{2,\tau})$ and $\Phi_{j,\tau}$ the j-th element of the vector. The sampling scheme consists of the following iterative steps, where the subscript τ is deleted to easier reading: Step 1: at iteration i, generate a point Φ^*_j from the random walk kernel

(RW-MH)

$$\Phi_j^* = \Phi_j^{i-1} + \epsilon_j \;\; \epsilon \sim N(0, \Sigma), \tag{D.6}$$

where Σ is a diagonal matrix and σ_j^2 is its j-th diagonal element, and Φ_j^{i-1} is the $(i-1)$th iteration of Φ_j. We accept Φ_j^* as Φ_j^i with probability $p = min\left[1, f(\Phi_j^*)/f(\Phi_j^{i-1})\right]$, where $f()$ is the likelihood in equation (D.4) multiplied by the priors. Otherwise, set $\Phi_j^* = \Phi_j^{i-1}$. The elements of Σ are set by monitoring the acceptance rate to lie between 25% and 50%. Step 2: After M iterations, we apply the following independent kernel (IK-MH) algorithm. Generate Φ_j^* from

$$\Phi_j^* = \mu_{\Phi_j}^{i-1} + \epsilon_j \;\; \epsilon \sim N(0, \Sigma_{\Phi_j}), \tag{D.7}$$

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

$$p = min\left[1, \frac{f(\Phi_j^*)g(\Phi_j^{i-1})}{f(\Phi_j^{i-1})g(\Phi_j^*)}\right], \tag{D.8}$$

where $g()$ is the Gaussian proposal density in (D.7).

As regards to the number of iterations, we should say that the choice of the initial sample size and the convergence detection of the Gibbs sampler remain open issues (see Robert and Casella (1999)). In our application we choose the sample size on the basis of both a graphical inspection of the MCMC progressive averages and the application of the convergence diagnostic (CD) statistics proposed in Geweke (1992). The posterior distributions of the model parameters are approximated through a kernel density estimator applied to a sample of 10000 random draws from the posterior. In order to generate 10000 i.i.d. samples from the posterior, we run the RW-MH sampler for 30000 iterations, discard the first 10000 draws to avoid dependence on the initial condition, and apply a thinning procedure with a factor of 4 samples, to reduce the dependence between consecutive Markov-chain draws. Then, we produce 20000 iterations from step 2 and again apply a thinning procedure with factor 4.

D.2. The DCC Test of Rigobon (2000)

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

$$\eta_t A' = Z_t \Gamma' + \varepsilon_t, \tag{D.9}$$

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

$$\begin{aligned}
E[\varepsilon_t] &= 0 \;\; E[\varepsilon_{i,t}\varepsilon_{j,t}] = 0 \; \forall i \neq j \\
E[z_t] &= 0 \;\; E[z_{i,t} z_{j,t}] = 0 \; \forall i \neq j \\
E[\varepsilon_t z_t] &= 0 \\
E[\varepsilon_t' \varepsilon_t] &= \Omega_t^{\varepsilon} \;\; E[Z_t' Z_t] = \Omega_t^Z,
\end{aligned} \tag{D.10}$$

where both Ω_t^Z and Ω_t^{ε} are diagonal. Assume A and Γ are non-triangular matrices that have been normalized as follows:[41]

$$A = \begin{pmatrix} 1 & a_{12} & \cdots & a_{1N} \\ a_{21} & 1 & & \\ \vdots & & \ddots & \vdots \\ a_{N1} & & \cdots & 1 \end{pmatrix}, \tag{D.11}$$

$$\Gamma = \begin{pmatrix} 1 & 1 & \cdots & 1 \\ \gamma_{21} & \gamma_{22} & \cdots & \gamma_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{N1} & \gamma_{N2} & \cdots & \gamma_{Nk} \end{pmatrix}. \tag{D.12}$$

Finally, without loss of generality, assume that η_t has a zero mean and is serially uncorrelated.[42]

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

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

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

In this model, the question of interest is the stability of the parameters (A or/and Γ). However, it is well-known that equation (D.9) cannot be estimated. Hence, inference on the coefficients cannot be made without further information. Indeed, from equations (D.9) to (D.12) the only statistic that can be computed is the covariance matrix of the reduced form of η_t:

$$\Omega_t = A^{-1}\Gamma\Omega_t^Z\Gamma' A'^{-1} + A^{-1}\Omega_t^\varepsilon A'^{-1} \tag{D.13}$$

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

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

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

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

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

Then,

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

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

Therefore, a null determinant might be the outcome of a shock affecting a subset of the common (systemic) shocks or a subset of the idiosyncratic shocks. As a consequence, the test has a joint null hypothesis: the heteroskedasticity derives from a subset of shocks, and the structural parameters are stable in the two periods considered. The test will provide a non-zero outcome in two circumstances: (1) all the shocks are heteroskedastic; (2) the structural parameter changes. This suggests a fundamental prerequisite for interpreting the DCC test as a parameter (in)stability test: we must have a subset of shocks that is known to be homoskedastic in the periods considered. If this is not the case, rejections of the null hypothesis cannot be attributed to parameter instability. In fact, they might be a by-product of heteroskedasticity in all shocks.

From a practical viewpoint, the test implementation proceeds as follow. At first, a general structural model is considered

$$AY_t = \mu + \Phi\left(L\right)Y_t + \Theta\left(L\right)X_t + \Gamma Z_t + \varepsilon_t, \tag{D.14}$$

where Y_t is the set of endogenous variables, X_t is a set of predetermined and/or exogenous variables, Z_t is the set of common unobservable shocks and ε_t is the vector of structural shocks.

The model can easily be recast into a reduced form

$$Y_t = A^{-1}\mu + A^{-1}\Phi\left(L\right)Y_t + A^{-1}\Theta\left(L\right)X_t + \eta_t, \tag{D.15}$$

where

$$A\eta_t = \Gamma Z_t + \varepsilon_t \tag{D.16}$$

Note that equation (D.15) can be estimated using a VAR, while equation (D.16) exactly corresponds to the baseline equation for the DCC test (D.9). The previous representation offers a strategy for the evaluation of the DCC test, that goes through the following steps:[43]

i Estimate the VAR model in (D.15) on the full sample and store reduced-form residuals.

ii Define two subsamples/regimes of the residuals using some given criteria; these two subsamples/regimes can be associated with, say, high and low volatility, or crisis and stability.

iii Compute the reduced-form residual covariances on the two subsamples/regimes, Ω_1^{η} and Ω_2^{η}, and estimate the DCC, $det\Delta\Omega = det\left(\Omega_2^{\eta} - \Omega_1^{\eta}\right)$.

iv Compute the simulated distribution of the DCC test using bootstrap methods.

We employ the following procedure for recovering the bootstrapped distribution:

1 Within each subsample/regime generate a new set of reduced-form residuals by circular block-bootstrap (see Romano and Politis, 1992);

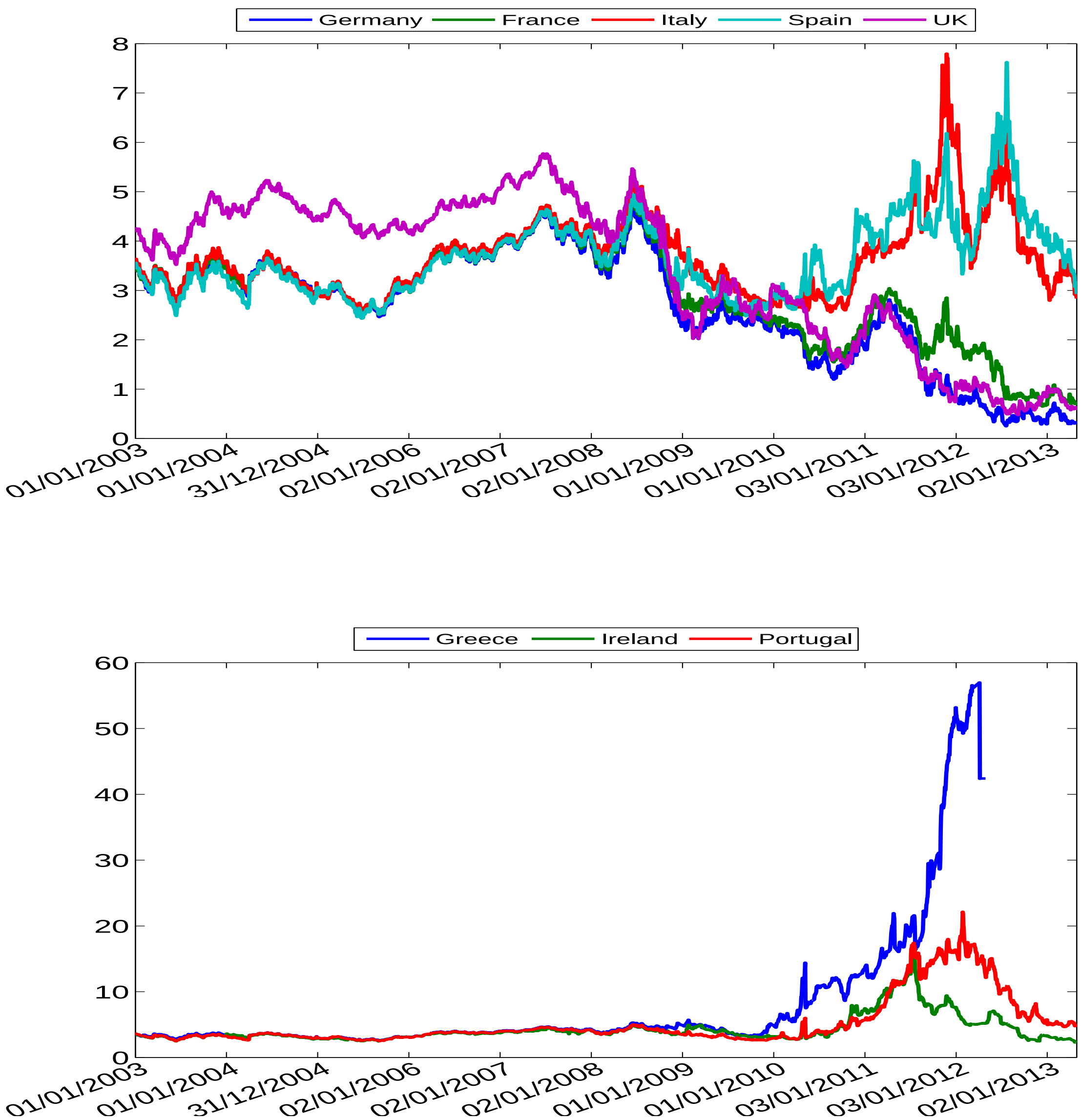
2 Using the regime-specific simulated reduced form residuals of step 1, compute the covariance matrices of the subsamples/regimes and the DCC.

3 Repeat steps 1 and 2 for M times.

The bootstrap scheme reported above assumes that the covariance matrices are independent in the two subsamples or regimes. In the present paper we fix $M = 1000$ and use blocks of size 5, that is one week. To evaluate the null hypothesis, we determine whether, across the replications, there is a mass of simulated DCC values that are above zero. If the test is rejected, then the rejection can be associated with parameter instability only in the case of there being structural or common shocks that are homoskedastic.

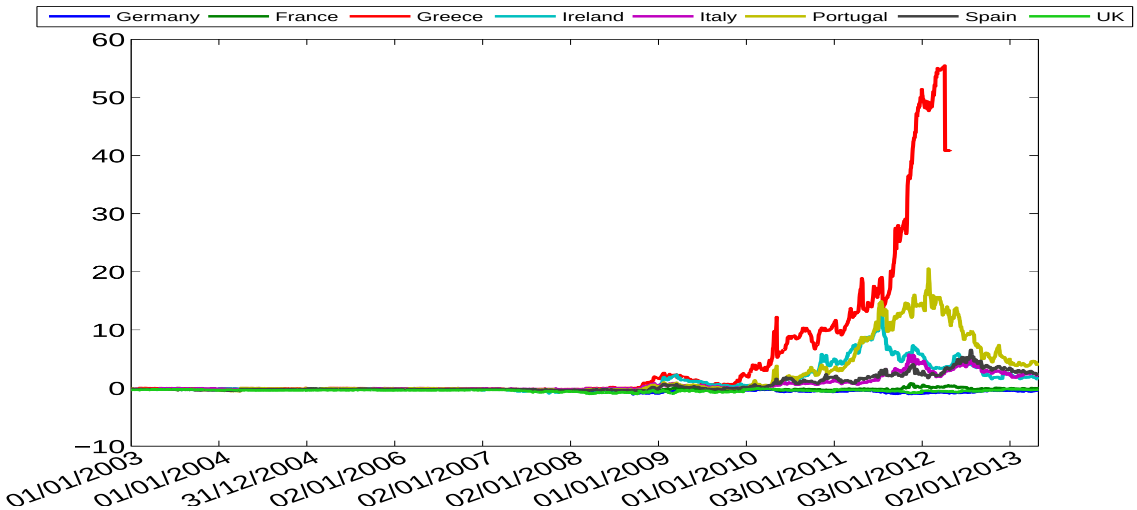
[43] Additional details can be found in Rigobon (2000, 2003).

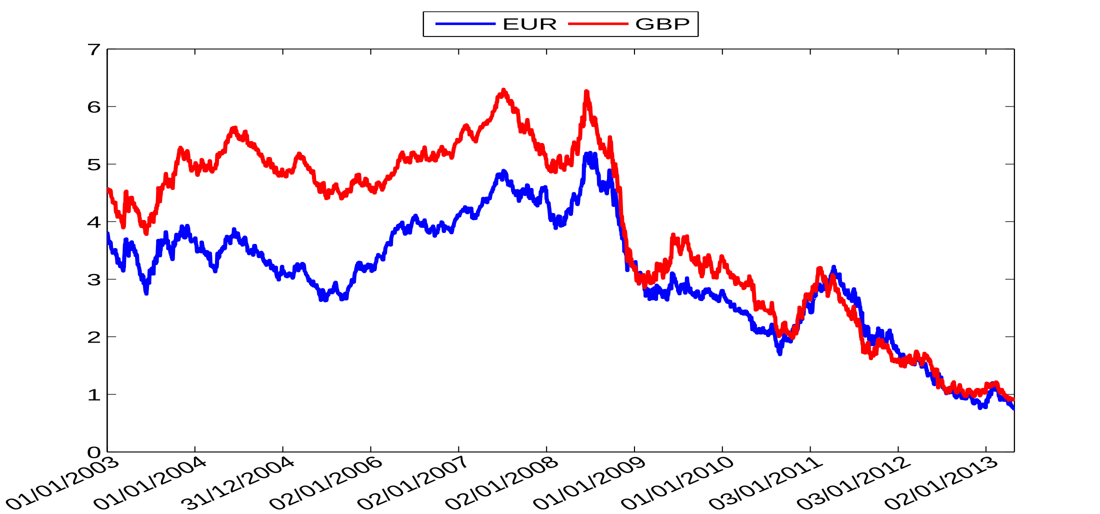
Figure B.1: **5 years Bond Redemption Yields**



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).

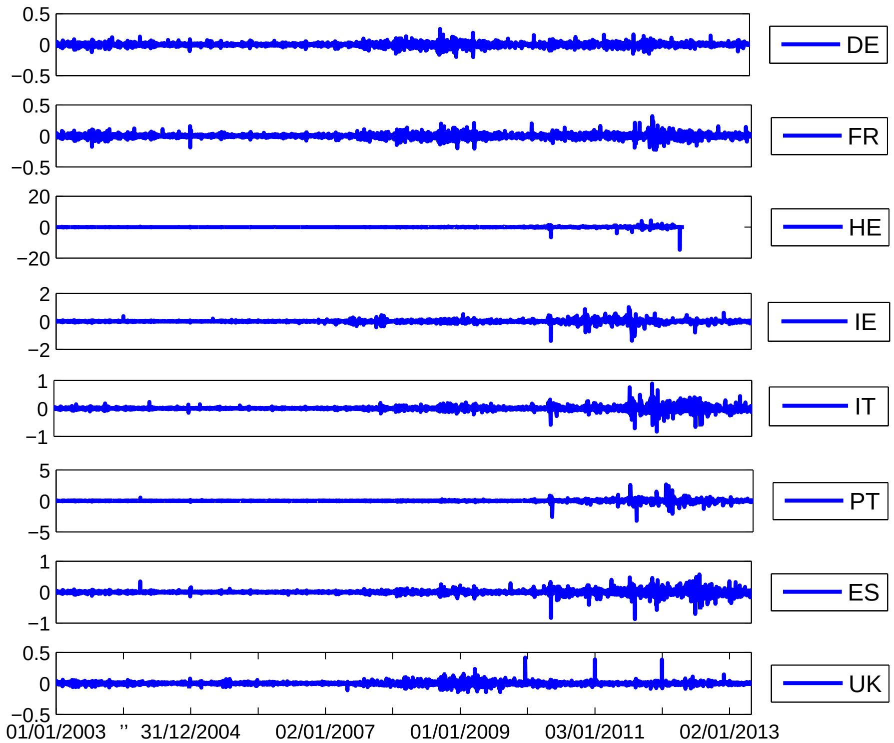
Figure B.2: **5 years Bond Yield Spreads**





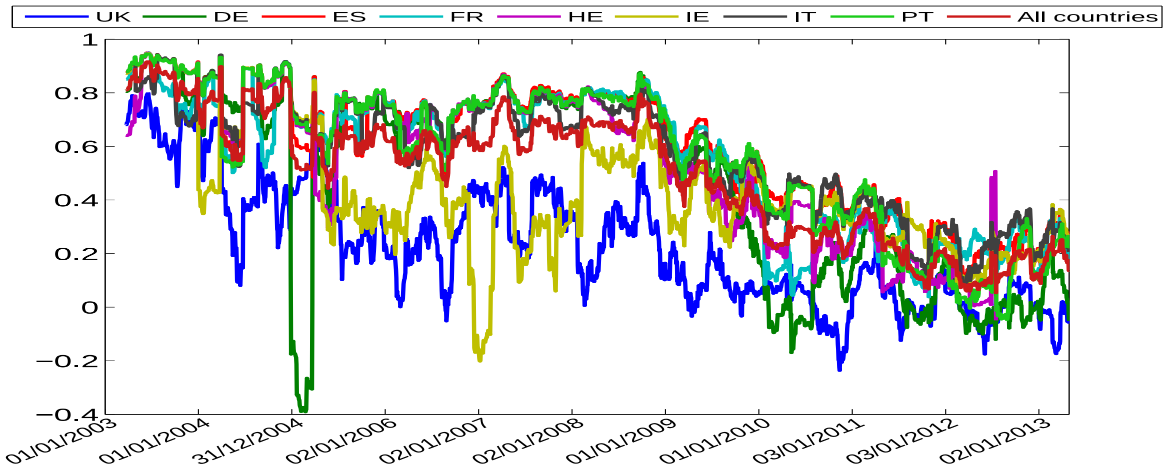
The first panel of this figure shows the daily 5 years bond yield spreads calculated as the difference between the 5 years Bond redemption yields and the 5 years euro swap rate for the eurozone countries and the British pound swap rate for UK. The sample period considered ranges from January 1, 2003 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.

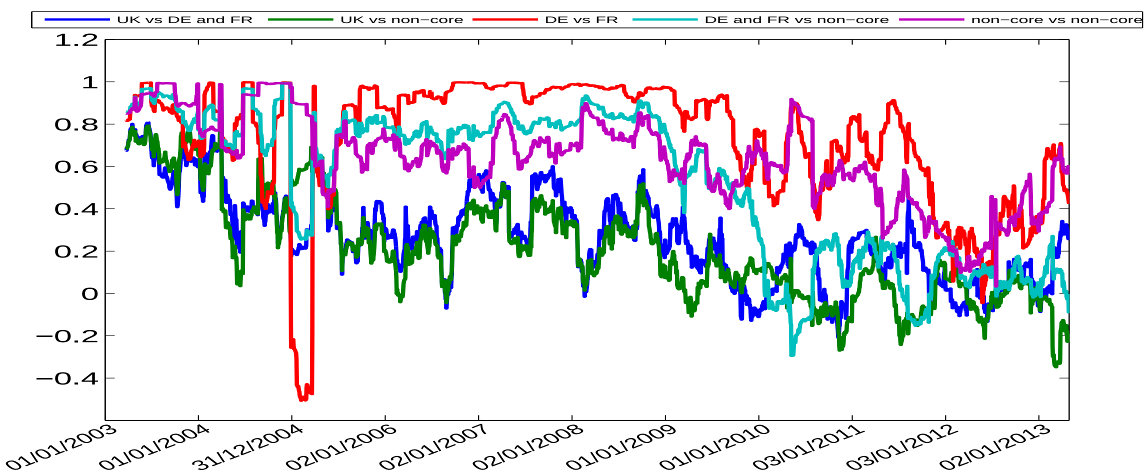
Figure B.3: **Changes in 5 years Bond Yield Spreads**



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.

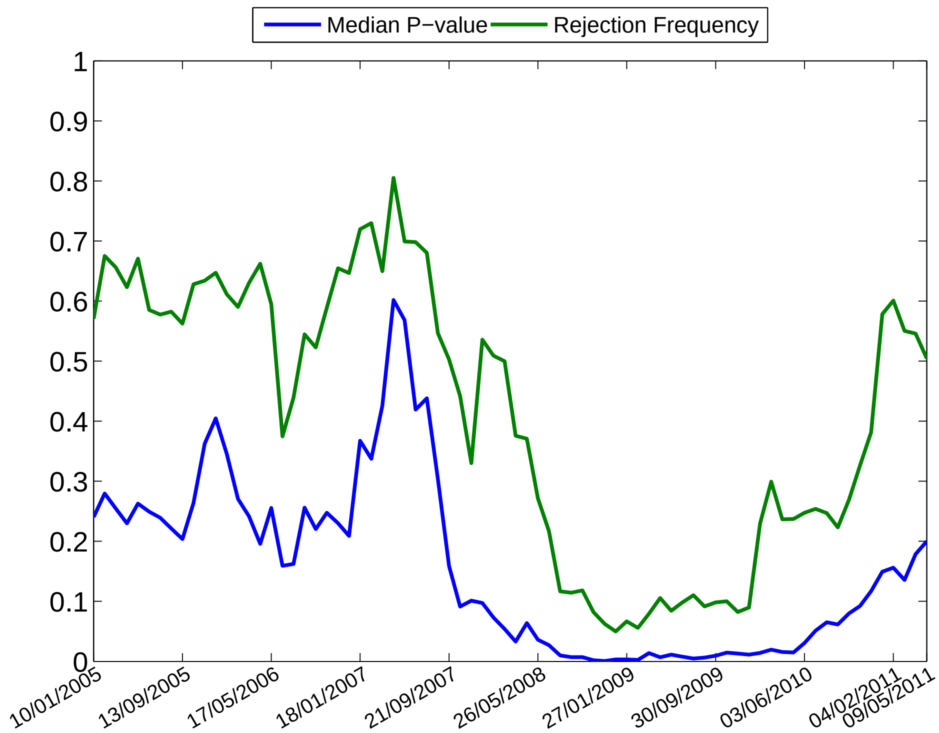
Figure C.1: **Average Rolling Correlations on Yield-Spread Changes**





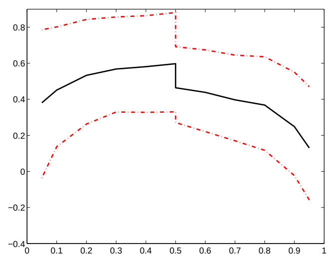
The first panel of this figure plots the average of the pairwise rolling correlation of 5 years yield spread changes of the 7 eurozone countries considered: France (FR), Germany (DE), Greece (GR), Ireland (IE), Italy (IT), Portugal (PT) and Spain (ES) and the United Kingdom (UK). The Red line reports 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 C.2: **Structural Instability in the Linear Regression**

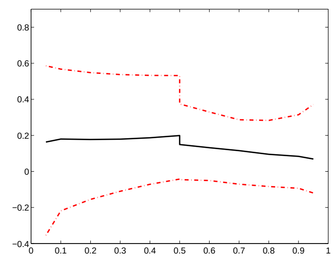


This figure shows the results of the Chow-type test for a structural break in the coefficient β_1 in the linear relation (C.6). The test is performed on a rolling window of four years, testing for a break occurring after the end of the second year. The lines report median p-values (Blue line) and the 75% quantile (Green line) over the 56 cross-country regressions.

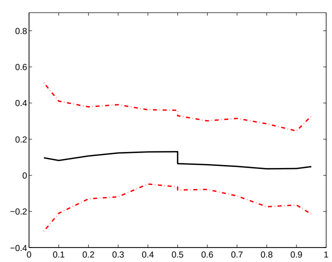
Figure C.3: **Exceedance correlations**



(a) 2003-2006



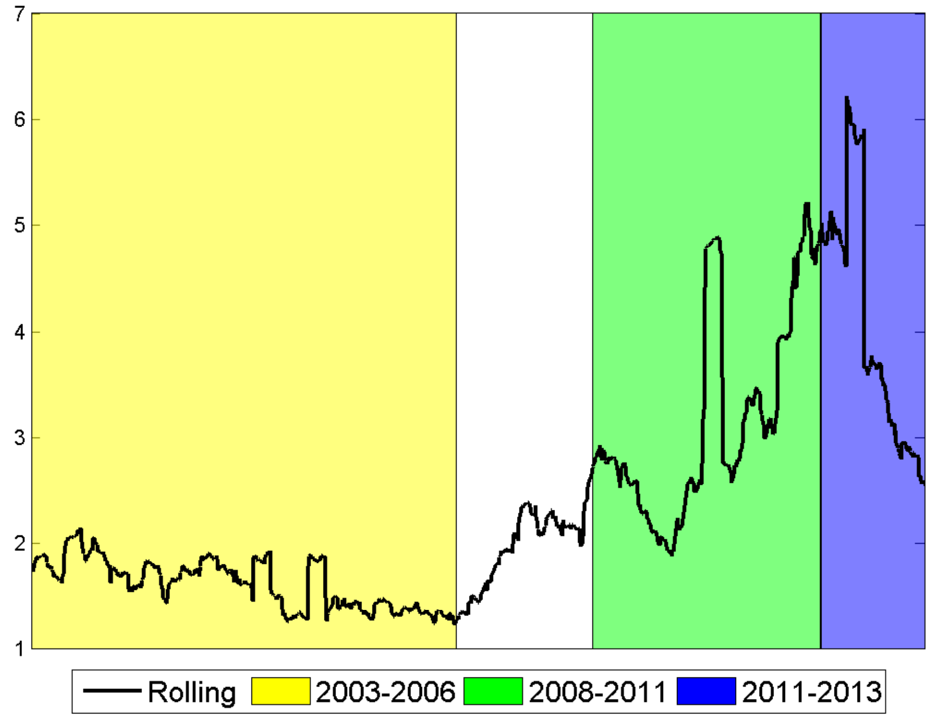
(b) 2008-2011



(c) 2011-2013

The graph reports the exceedance correlations for the subsamples defined in Section 3. Correlations refer to upper quantile correlation for values above 0.5 and to lower quantile correlation for values below 0.5. At the 0.5 point, two exceedance correlations (above/below the median) are reported.

Figure C.4: **Average Rolling Covariances**



This graph shows the cross-sectional average across the square roots of the diagonal elements of the rolling covariances.

2003-2006			2008-2011			2011-2013		
Threshold	DCC	P-value	Threshold	DCC	P-value	Threshold	DCC	P-value
1.274	0.557	0.153	2.13	0.829	0.978	2.628	0.046	0.550
1.343	0.114	0.470	2.40	0.254	0.343	2.851	0.201	0.482
1.412	0.112	0.484	2.67	0.052	0.391	3.073	0.516	0.599
1.481	0.108	0.466	2.94	0.089	0.681	3.296	0.305	0.503
1.550	0.063	0.610	3.21	0.354	0.520	3.518	0.466	0.420
1.619	0.065	0.487	3.48	0.842	0.302	3.741	0.472	0.426
1.688	0.014	0.508	3.75	0.683	0.293	3.963	0.464	0.381
1.757	0.047	0.524	4.02	0.006	0.634	4.186	0.009	0.260
1.826	0.038	0.419	4.29	0.106	0.533	4.409	0.408	0.597

Table C.1: This table presents the results of the DCC test to three different subsamples. For each subsample the first column reports the thresholds used to separate the subsamples into high/low volatility periods. The thresholds are deciles of the subsample 60-day rolling average volatility, from 10% up to 90%. The second and third columns present the DCC test and the associated p-value obtained with a circular block-bootstrap.