Distributional linkages between European sovereign bond and bank asset returns*

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Abstract

We analyse the dependence between sovereign bonds' and banks' asset return distributions with a large panel of European data from 2001 to 2013. Using quantile regressions, we identify nonlinear contemporaneous and lagged dependence. As a result, shocks to crisis-hit sovereign bonds have contemporaneous effects on the whole distribution of banks' returns, as well as a persistent impact in the tails. Our results offer relevant insights about the relationship between banking and sovereign crises. In particular, during the recent financial crisis, banks' asset return distributions have lower means and fatter tails than in the absence of a simultaneous sovereign crisis.

Keywords: Quantile regressions, nonlinear dependence, counterfactual analyses, systemic risk.

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1 Introduction

The European financial and sovereign debt crises have generated interest in the relationship between sovereign credit risk and financial sector risk, as investor concerns on sovereign creditworthiness and bank solvency continue to plague European Union (EU) member countries on the periphery (Greece, Ireland, Italy, Portugal, and Spain - hereafter known as GIIPS). The crisis, which manifested in early August 2007, became full-blown with the collapse of Lehman Brothers in mid-September 2008. The credit crunch then hit Europe's banking sector nearly two weeks after, and precipitated a wave of bank rescue and stimulus packages that were initiated by major EU governments to shore up their economies. Meanwhile, another crisis arose as several European Monetary Union (EMU) member countries, and in particular, the GIIPS, ran budget deficits due to increased government spending and weak tax revenues. The rising amount of sovereign debt led to a widening differential between the GIIPS countries and the more stable EMU countries like Germany, as illustrated in Figure 1. Investors became concerned about the ability of these countries to cover maturing debt and interest payments, which resulted in credit rating downgrades; the euro depreciated, and share prices further declined as a response.

In light of the financial crisis, numerous empirical studies have placed considerable attention to the interdependence between sovereign bonds and banks' asset returns. Alter and Schüler (2012) find that prior to the banking crisis, contagion disperses from banks to the sovereign credit default swap (CDS) market, while after the banking crisis, a financial sector shock affects the sovereign more strongly in the short run than in the long run. Ejsing and Lemke (2011) study the relationship between bank and sovereign CDS premia and find that the variation between the two can be explained by a single common risk factor. Dieckmann and Plank (2012), meanwhile, find negative correlation between financial sector and sovereign CDS spreads while rescue packages are being instituted, and a positive correlation afterwards. Acharya and Steffen (2014) argue that bank risks reflect a "carry trade" behavior in that banks appeared to have taken long positions in GIIPS sovereign bonds, which were funded by short-term lending in wholesale markets. Finally, Gennaioli et al. (2013) find that the correlation between sovereign bonds and future bank loans are positive in normal times, while negative in crisis times.

The studies mentioned earlier have relied on standard regression techniques to analyse this effect, which implies that they have only considered the conditional mean of bank and bond return distributions. The main objective of this paper, in contrast, is to investigate this interdependence on the whole distribution of bank asset returns and sovereign bond returns. There are two reasons for focusing on distributions of bank and bond returns as opposed to focusing just on the conditional mean. First, considerable research has shown that investor preferences go beyond mean and variance in their portfolio optimisation decisions to higher-order moments. In particular, investors care about potential portfolio losses, more known as downside risk, which is a function of higher-order moments such as skewness and kurtosis.[1] Second, the recent financial crisis has emphasised the need to quantify systemic risk. While numerous quantitative measures have been developed in response, the more prominent ones focus on the tails of the asset returns' distributions, a feature that cannot be captured by standard regressions.[2] Though we do not propose a systemic risk measure, our empirical analysis aims to capture the transmission of risk from sovereign bonds across the conditional distribution of bank returns, and similarly, from bank returns across the conditional distribution of sovereign bond returns.

In this regard, we employ a multivariate quantile regression model to directly study the contemporaneous linkages between European sovereign bond and bank return distributions. We consider an extensive database with weekly data from 2001 to 2013, covering 27 major European banks and the sovereign returns from their countries. Quantile regression offers the following advantages over the standard regression framework. First, as it is a semi-parametric technique, it does not require a distributional assumption on bank asset returns and sovereign bond returns; this implies that the regression results are robust to non-normality and to outliers. Second, quantile methods are efficient in the use of data. Third, the flexibility of quantile regression methods permits a more comprehensive analysis of the impact of bond returns on the entire conditional distribution of bank asset returns, and vice-versa.

[1]Harvey and Siddique (2000) argue that investors like positive skews (big returns) and dislike negative skews (big losses), and that these must be taken into account when making investment decisions. Harvey et al. (2010) provide an analysis of portfolio choice taking into account higher-order moments in the utility function of investors. Kelly and Jiang (2014), meanwhile, analyse the impact of tail risk on asset prices.

[2]Prominent tail risk measures include CoVaR by Adrian and Brunnermeier (2011), Marginal Expected Shortfall by Acharya et al. (2012) and its dynamic counterpart proposed by Brownlees and Engle (2010).

The results of the quantile regression estimates indicate that there exists nonlinear dependence between sovereign bond and bank asset returns, a feature not captured by standard regression techniques. Specifically, the results suggest a contagion effect from the peripheral sovereign bond returns across the return distribution of banks headquartered in non-GIIPS countries. Moreover, the results capture a strong transmission of risk from sovereign bond to bank asset returns of GIIPS countries. We then recover the the conditional distributions of bank returns, and analyse how they shift in response to shocks from bond returns. We find that a negative shock on the GIIPS sovereign bonds yields for non-GIIPS banks a lower expected return, and a distribution that is more negatively skewed and has fatter left tails. We take this as evidence of contagion from the GIIPS sovereign bonds to non-GIIPS banks' asset returns.

We extend the analysis to study the evolution of the conditional distributions over time through a quantile vector autoregressive framework. The quantile regression results confirm the importance of contemporaneous dependence between sovereign bond and bank asset returns; we also find that the past history of bond returns influences the shape of the distribution of bank asset returns. We then analyse the impact of multi-period negative sovereign shocks on the conditional quantile functions, and in turn, the conditional distribution of bank asset returns over time. We find that a negative shock to the peripheral sovereign bonds yields an increase in the volatility of bank asset returns over the long run. In contrast, a negative shock on the German bond returns only shifts banks' return distributions in the short run. We finally analyse the sensitivity to the crisis of our results. We find that the transmission of risk between peripheral sovereign bond returns to bank asset returns of non-GIIPS countries was stronger during crisis periods compared to non-crisis periods. We then compute for the unconditional marginal density of a bank's asset returns in the scenario that the sovereign crisis had not occurred. In general, the crisis increased banks' exposure to risk, as shown by return distributions that had lower expected returns, higher volatility and fatter tails.

The rest of the paper is as follows. In Section 2, we discuss the data used and provide summary statistics. We analyse the contemporaneous linkages between sovereign bond and bank asset returns in Section 3. We also discuss the kernel interpolation methodology and the sensitivity analysis performed. We consider an autoregressive framework in Section 4 and analyse the evolution of return distributions over time. In Section 5, we analyse the sensitivity of the results we have obtained to crisis and non-crisis periods. Finally, Section 6 concludes. Some technical discussion of the methods used for the empirical analysis pursued in this paper are gathered in appendices.

2 Data and summary statistics

2.1 Dataset construction

We construct a dataset with information obtained from Datastream and Bloomberg to compute bank asset returns and sovereign bond returns. The information covers the period from January 3, 2001 to November 6, 2013. The data comprises 27 major cross-border banks in Europe, a list of which is provided in Appendix A. Out of the banks in the sample, ten are headquartered in peripheral countries, while 17 are headquartered outside of the GIIPS countries. There are 14 countries represented in the dataset; ten are in the Eurozone,[3] while the remaining countries are Denmark, Sweden, Switzerland, and the United Kingdom.[4]

We compute weekly bank asset returns from publicly available market information such as bank equity prices, market-to-book equity ratio, and the book value of total assets from Datastream.[5] We follow Adrian and Brunnermeier (2011) in specifying bank asset returns as the return of market-valued total financial assets denominated in euros through the following definition. Denote by ME_{t,B_i} the market value of bank i's total equity, and by LEV_{t,B_i} the ratio of total assets to book equity. We define the daily return of market-valued total assets, y_{t,B_i} by

$$y_{t,B_i} = \frac{A_{t,B_i} - A_{t-1,B_i}}{A_{t-1,B_i}}$$

where $A_{t,B_i} = ME_{t,B_i} \cdot LEV_{t,B_i}$. Note that $LEV_{t,B_i} = BA_{t,B_i}/BE_{t,B_i}$, where BA_{t,B_i} is the book-valued total assets of the institution and BE_{t,B_i} is the book value of a bank's equity; hence, $A_{t,B_i} = ME_{t,B_i} \cdot LEV_{t,B_i} = BA_{t,B_i} \cdot (ME_{t,B_i}/BE_{t,B_i})$. Thus, we can apply

[3]The Euro area countries included in the sample are: the GIIPS countries, Austria, Belgium, France, Germany, and the Netherlands.

[4]We calculate the euro-denominated returns of non-Euro area banks and sovereign bonds by converting the relevant variables into euros using spot exchange rate data obtained from the Pacific Exchange Rate database.

[5]Save for the book value of total assets, which we observe at a quarterly frequency, we observe the rest at a daily frequency and take the observations on Wednesday to create the variable. We compute weekly bank asset returns as some equity prices were illiquid during certain periods.

the market-to-book equity ratio to transform book-valued total assets into market-valued total assets.

Meanwhile, we construct euro-denominated sovereign bond returns for the countries in the dataset by a first-order approximation using ten-year weekly sovereign bond yields obtained from Datastream and bond duration data obtained from Bloomberg. More formally, we denote by Dur_{t,S_j} the duration, and by Z_{t,S_j}, the yield on the ten-year sovereign bond of country j. We first compute for the modified duration of the bond, $ModD_{t,S_j}$ as

$$ModD_{t,S_j} = \frac{Dur_{t,S_j}}{\left(1 + Z_{t,S_j}/100\right)}$$

We finally calculate weekly sovereign bond returns, y_{t,S_j} from the following formula:

$$y_{t,S_j} = -ModD_{t-1,S_j} \cdot \left(Z_{t,S_j} - Z_{t-1,S_j}\right)$$

2.2 Summary statistics

Tables 1 and 2 show some summary statistics about sovereign bond returns. From Table 1, we observe that GIIPS countries generally have bond return distributions with negative means, negative skewness, and fat tails. Non-GIIPS countries, on the other hand, generally have bond return distributions with positive means, negative skewness and tails that are less fat than those of GIIPS sovereign bond returns.[6] Table 2 shows the correlations between the GIIPS and the German sovereign bonds, divided into three phases: the pre-banking crisis phase, which is the period prior to August 2007, the onset of the banking crisis in Europe; the banking crisis phase, which is from August 2007 to November 2009, when the newly-elected Greek government disclosed a deficit that doubled the previous official figure; and the sovereign crisis phase, which, for parsimony, we compute until the first bailout of Greece by the troika[7]. The table shows that before the financial crisis occurred, German and peripheral sovereign bonds were highly correlated, which might suggest that investors perceived those bonds as similar despite major economic differences. As the banking crisis unfolded, however, German sovereign bonds and peripheral sovereign bonds became less correlated. Finally, when the sovereign debt

[6]Performing the Jarque-Bera test for normality confirms the intuition that bond return distributions are non-Gaussian.

[7]The troika is composed of the European Community (EC), the International Monetary Fund (IMF), and the European Central Bank (ECB).

crisis occurred, we see that the correlations between German sovereign bonds and the periphery turned negative, showing the divergence of the countries within the Euro area.

Finally, Figure 2 shows the predicted GARCH(1,1) asset return volatilities of BNP Paribas, Deutsche Bank and Banco Santander, and the corresponding sovereign bond yields of the countries these banks are headquartered in. The figure highlights the relationship between banks' asset returns and movements in the sovereign debt market. In particular, we find that the volatility of banks' asset returns reflects two crises: the global financial crisis (from 2008 to 2009), and the sovereign debt crisis (from 2011 to 2012), each with a different impact for different banks. On the one hand, French and German sovereign bond yields exhibit a decreasing trend; on the other hand, the sovereign yields from peripheral sovereign countries, here represented by Spain, started increasing in the financial crisis, but they did not reach huge levels until the sovereign crisis exploded. We observe that, save for Deutsche Bank, bank asset return volatilities have a similar evolution. In contrast, some countries suffer higher yields while others enjoy increasingly cheaper access to credit.

3 Contemporaneous dependence between bank and bond returns

As the goal of the paper is to study the linkages across sovereign bond and bank return distributions, it is relevant to consider the joint distribution of bank and bond returns, $f_{B,S}(\mathbf{y}_{t,B}, \mathbf{y}_{t,S}|I_{t-1})$, where $\mathbf{y}_{t,B}$ and $\mathbf{y}_{t,S}$ denote the vectors of banks and bonds returns, respectively, and I_{t-1} denotes the information known at time $t-1$. We can decompose the joint distribution as follows:

$$f_{B,S}(\mathbf{y}_{t,B}, \mathbf{y}_{t,S}|I_{t-1}) = g_{B|S}(\mathbf{y}_{t,B}|\mathbf{y}_{t,S}, I_{t-1})h_S(\mathbf{y}_{t,S}|I_{t-1}), \quad (1)$$

$$= g_{S|B}(\mathbf{y}_{t,S}|\mathbf{y}_{t,B}, I_{t-1})h_B(\mathbf{y}_{t,B}|I_{t-1}), \quad (2)$$

where $g_{B|S}(\cdot)$ ($g_{S|B}(\cdot)$) is the conditional distribution of bank asset returns given sovereign bond returns (and vice-versa), and $h_B(\cdot)$, $h_S(\cdot)$ are the corresponding marginal distributions for banks and bonds, respectively. Thus, to analyse the dependence between bank and bond returns, the decomposition suggests that we can focus on the conditional distribution of bank asset returns given sovereign bond returns (and vice-versa).

In this section, we study the contemporaneous dependence between $\mathbf{y}_{t,B}$ and $\mathbf{y}_{t,S}$

by characterising the quantiles of the conditional distributions in (1) and (2) through quantile regressions. We then recover the conditional distribution of bank asset returns from the quantile regressions through a weighted kernel density interpolation. Finally, we analyse how changes in some key variables shift the conditional distribution of bank asset returns.

3.1 Baseline model specification and estimation results

To characterise the conditional distributions, we specify the following affine quantile functions:

$$\mathbf{q}_{t,B}(\theta) = \mathbf{c}_B(\theta) + \mathbf{A}_{bs}(\theta)\mathbf{y}_{t,S} + \nu(\theta)\mathbf{y}_{t-1,B}, \quad (3)$$

$$\mathbf{q}_{t,S}(\theta) = \mathbf{c}_S(\theta) + \mathbf{A}_{sb}(\theta)\mathbf{y}_{t,B} + \mathbf{A}_{ss}(\theta)\mathbf{y}_{t,S} + \phi(\theta)\mathbf{y}_{t-1,S}, \quad (4)$$

where $\mathbf{q}_{t,B}(\theta)$ ($\mathbf{q}_{t,S}(\theta)$) is the vector of θ-th quantiles of banks (sovereign bond) returns. This specification takes into account the interplay between bank and bond returns through the parameterisation of matrices $\mathbf{A}_{bs}(\theta)$, $\mathbf{A}_{sb}(\theta)$ and $\mathbf{A}_{ss}(\theta)$. The vectors of coefficients $\mathbf{c}_B(\theta)$ and $\mathbf{c}_S(\theta)$, the matrices $\mathbf{A}_{bs}(\theta)$, $\mathbf{A}_{sb}(\theta)$ and $\mathbf{A}_{ss}(\theta)$, and the scalar parameters $\nu(\theta)$ and $\phi(\theta)$ are all constant for a given quantile level θ. However, we consider different constant parameters for each quantile level. Notice that the linear dependence implied by the Gaussian distribution would yield constant parameters across quantiles, except for the intercept. In this sense, we can argue that there is nonlinear dependence if our estimates differ from those of a standard regression. We can interpret quantile models (3) and (4) as the Exposure CoVaR of banks conditional on the situation of the sovereign for (3), and the Exposure CoVaR of sovereign bonds conditional on the situation of the banking system for (4), respectively.[8] As opposed to Exposure CoVaR, which focuses on the tail of the distribution of bank asset returns conditional on sovereign bond returns, we consider the entire distribution of bank asset returns conditional on sovereign bond returns (and vice-versa). By characterising the conditional distributions, we can analyse how shocks on key variables have an impact on the shape of the distribution, which we discuss in section 3.2.

[8] As in Adrian and Brunnermeier (2011), we define $CoVaR_q^{i|\mathbb{C}(X^j)}$ as the Value-at-Risk (VaR) of institution i conditioning on some event $\mathbb{C}(X^j)$ of an institution j. That is, $CoVaR_\theta^{i|\mathbb{C}(X^j)}$ is implicitly defined by the q-quantile of the conditional probability distribution $\Pr[X^i \leq CoVaR_\theta^{i|\mathbb{C}(X^j)}|\mathbb{C}(X^j)] = \theta$.

For parsimony, we parameterise the matrices $\mathbf{A}_{bs}(\theta)$, $\mathbf{A}_{sb}(\theta)$ and $\mathbf{A}_{ss}(\theta)$ as sparse matrices; that is, we focus on the most relevant effects, and set the remaining elements of the matrices to zero. In addition, we employ a panel structure by which each effect has a common coefficient across the cross-sections of banks and bonds. The dimensions of $\mathbf{A}_{bs}(\theta)$, $\mathbf{A}_{sb}(\theta)$ and $\mathbf{A}_{ss}(\theta)$ are $n \times m$, $m \times n$, and $m \times m$, respectively, as there are n banks and m bonds in the sample. We consider different coefficients depending on whether the countries are GIIPS or not. In addition, we allow German sovereign bonds and banks to have an additional impact on all other banks and countries. The developments in the German market have been widely perceived as a relevant fear gauge during the crisis, as noted by Acharya and Steffen (2014) and Angeloni and Wolff (2012). For instance, flight-to-quality movements out of crisis-hit markets and into German assets have been common at the points when the crisis aggravated.

We first outline the effects that enter in $\mathbf{A}_{bs}(\theta)$:

- GIIPS bond returns to non-GIIPS bank returns: α.
- German bond returns to non-German bank returns: β.
- Own bond effect to banks headquartered in the country**:** γ on the cells of non-GIIPS banks and τ for GIIPS banks' returns.

The effects captured in $\mathbf{A}_{sb}(\theta)$ can be summarised as:

- GIIPS banks to non-GIIPS bond returns: η.
- German banks to non-German bond returns: ω.
- Effect of banks headquartered in a country to their own sovereign bond: κ on the cells of non-GIIPS bonds and π for GIIPS bonds.

Lastly, $\mathbf{A}_{ss}(\theta)$ only contains the contemporaneous effect of GIIPS bonds on non-GIIPS bonds (ψ).

Figure 3 graphically summarises the effects that we consider on GIIPS countries, Germany and non-GIIPS countries, respectively. With this specification, we substantially extend those employed by previous empirical studies to study dependence on the whole conditional distribution, and not just on its conditional mean.

To focus the discussion, consider a simplified version of quantile models (3) and (4) with only three countries with one bank at each of them. The countries would be a non-GIIPS country, Germany, and a GIIPS country, ordered in this way in the matrices. Then, we would have

$$\mathbf{A}_{bs}(\theta) = \begin{bmatrix} \gamma & \beta & \alpha \\ 0 & \gamma & \alpha \\ 0 & \beta & \tau \end{bmatrix}, \mathbf{A}_{sb}(\theta) = \begin{bmatrix} \kappa & \omega & \eta \\ 0 & \kappa & \eta \\ 0 & \omega & \pi \end{bmatrix}, \mathbf{A}_{ss}(\theta) = \begin{bmatrix} 0 & 0 & \psi \\ 0 & 0 & \psi \\ 0 & 0 & 0 \end{bmatrix}.$$

Once again, it is important to stress that most of the effects we attempt to capture are homogeneous within each of the categories we classified earlier (i.e., the effect of the German sovereign bond is the same for a French-headquartered bank and a Spanish-headquartered bank). In principle, we could allow for the effects we are capturing to vary across individual banks (and in turn, individual sovereigns); this, however, would increase the computational burden of estimating the system we consider in this empirical study. Moreover, following the empirical studies earlier mentioned, we are interested in common effects across the European financial system, not in the particular determinants of one particular bank. These common effects are directly related to systemic risk, as they may bring a collapse of the whole financial system.

We consider a panel of 41 dependent variables across the time period earlier specified (as we have 27 banks headquartered in 14 countries). We use the whole sample for all countries except for Greece, Ireland and Portugal. For these latter countries, we only use data prior to their respective bailouts by the troika to avoid using data from intervened economies.[9] As usual in quantile regressions, we estimate the parameters by exploiting the quasi maximum likelihood properties of the asymmetric double exponential distribution (see White et al., 2013).[10] This permits us to explicitly study the dependence structure for each bank and sovereign, and analyse how changes in each of the effects of interest affect the conditional distribution. We estimate the parameters of interest by performing quantile regressions from the 10^{th} to the 90^{th} deciles. We then compare the resulting estimates to those of an equivalent OLS regression. In the subsequent discussion of results, we refer to (3) and (4) as the bank and bond quantile models, respectively.

[9]The troika first bailed out these countries on the following dates: 2nd May 2010 (Greece), 28th November 2010 (Ireland), and 16th May 2011 (Portugal).

[10]Appendix B.1 explains in more detail the econometric model specification and the estimation procedure.

Tables 3 and 4 present the results for the bank quantile model and the bond quantile model, respectively. For brevity, we present the results of the OLS regression, and five different quantiles that provide a depiction of the whole conditional distribution of returns. We focus first on Table 3, which discusses the results for the bank equation (3). Both the OLS and quantile regressions suggest that non-GIIPS banks have a positive and significant exposure to peripheral sovereign bonds, while non-German banks have a negative and significant exposure to German bonds. Hence, a deterioration of peripheral sovereign debt is directly propagated across the financial system. In contrast, it is a rise in German bond returns that deteriorates the return distributions of non-German banks. This latter effect seems to be more related to flight-to-quality effects: banks returns increase when German sovereign prices fall, probably as demand for a safe asset diminishes. The own bond effect for non-GIIPS banks is also negative and significant, which seems to imply that banks in these countries have a negative and significant exposure to their own bond, in line with what happens to the German bond effect. Meanwhile, the own bond effect for GIIPS banks is positive and significant; moreover, the magnitude of this dependence is bigger (in absolute value) than the same effect for non-GIIPS banks.

The results obtained suggest that nonlinear dependence emerges when we consider the distributional impact of sovereign bond returns on bank asset returns. For instance, the GIIPS bond effect on non-GIIPS banks is weaker at the extreme left tail. This result suggests that a negative shock to GIIPS countries reduces the likelihood of positive gains in non-GIIPS banks returns more than it increases the likelihood of extreme negative returns. We can assess nonlinearities in greater detail in Figure 4, which shows the graphs of the OLS and quantile regression coefficients for each of the effects of interest in the bank equation, with the corresponding 90% confidence intervals. The differences between the coefficients from OLS and quantile regressions confirm that sovereign bond returns have a nonlinear impact across the distribution of bank asset returns, though the precise form varies depending on the coefficient. For instance, the graphs indicate that for the German bond effect and the own bond effects, the plots are somewhat hump-shaped, while for the GIIPS bond effect, the graph is weakly increasing.

We now turn on to Table 4, which shows that the dependence of bond returns on bank returns is weaker than that of bank returns on bond returns. Only three channels turn out to be significant: the German bank effect, the own bank effect for non-GIIPS countries, and the GIIPS bond to non-GIIPS bond effect. The former two exhibit the same negative sign as that of the corresponding bond effect in the bank equation. Thus, flight-to-quality effects seem to be at play in non-GIIPS countries, but not in peripheral Euro area countries. The coefficients of GIIPS to non-GIIPS bonds, meanwhile, are positive and significant throughout the distribution. This result suggests that there is a contagion effect from GIIPS to non-GIIPS sovereigns. Figure 5, meanwhile, shows the graphs of the OLS and quantile regression coefficients in the bond equation (4), with the corresponding 90% confidence intervals. For the GIIPS bank effect and the own bank effect for GIIPS countries, we find that the graphs are almost flat, and close to the OLS estimates, as opposed to the corresponding effects in the bank equation. As for the other coefficients, we find that the graphs are clearly nonlinear, and are significantly different from OLS estimates. The precise form of nonlinearities, as in the bank equation (3), depends on the coefficient. The German bank effect, for instance, has a graph that is relatively constant. The graphs of the own bank effect for non-GIIPS countries, and the GIIPS bond to non-GIIPS bond effects, meanwhile, appear to have a hump shape. Many of the graphs, though, have steeper slopes at the extreme tails of the distribution, which clearly suggests that the dependence is stronger at the extreme tails than at the rest of the distribution.

3.2 Conditional densities and impulse responses

The main insight from the quantile regression results is that sovereign bond returns have a significant, and in some cases, nonlinear impact across the whole conditional distribution of bank asset returns. In order to understand the implications of these effects, it is interesting to recover the cumulative distribution function of bank asset returns conditional on sovereign bond returns from the conditional quantile functions.[11] We could then analyse more easily the response of the distribution to changes in some key variables that figured in the financial crisis.

There are several alternatives by which one could recover the conditional density of a bank's asset returns. For instance, one could perform quantile regressions on a

[11] An issue that comes up with recovering the conditional distribution is the quantile crossing problem, of which a solution is provided by Chernozhukov et al. (2010); this method involves a monotone rearrangement of the conditional quantile functions. For most of the banks and bonds in the sample, quantile crossings occur up to at most 0.03 percent of the time.

sufficiently large number of quantiles. Another procedure would be to perform cubic interpolation on the conditional quantile functions. In both cases, however, the resulting conditional cumulative distribution function (c.d.f.) might not be monotone. With these in mind, we prefer to resort to a weighted kernel interpolation methodology where we find the kernel that best fits the grid of quantile points in our estimation.[12] Specifically, we consider the kernel c.d.f.

$$G_{B_i|S}(x|\mathbf{y}_{t,S}, I_{t-1}) = \sum_{j=1}^{n_p} w_j \Phi\left(\frac{x - q_{t,B_i}(\theta_j)}{h}\right), \tag{5}$$

where $\Phi(\cdot)$ is the standard Gaussian c.d.f., n_p is the number of points and h is the smoothing parameter.[13] We calculate the weights $\boldsymbol{w}_{B_i} = (w_1, \ldots, w_{n_p})'$ that minimise the squared distance between the quantile level and its associated c.d.f.:

$$\hat{\boldsymbol{w}}_{B_i} = \arg\min_{\boldsymbol{w}_{B_i}} \sum_{k=1}^{n_p} \left[\theta_k - G_{B_i|S}(q_{t,B_i}(\theta_k)|\mathbf{y}_{t,S}, I_{t-1})\right]^2 \quad \text{such that} \sum_{j=1}^{n_p} w_j = 1. \tag{6}$$

Finally, by differentiation of (5), we obtain the conditional density

$$g_{B_i|S}(x|\mathbf{y}_{t,S}, I_{t-1}) = \frac{1}{h}\sum_{j=1}^{n_p} \hat{w}_j \phi\left(\frac{x - q_{t,B_i}(\theta_j)}{h}\right), \tag{7}$$

where $\phi(\cdot)$ is the standard normal density function. One advantage of our methodology is that, by construction, the conditional c.d.f. is smooth and monotone, which alleviates the worry that differentiation will result in an unstable probability density function.

We use this methodology to analyse the impact of sovereign bond returns on the conditional density of a bank's asset returns at two different dates: a pre-crisis date (June 2007, two months before the beginning of the financial crisis), and a crisis date (December 2009, after the Greek unexpected debt announcement). The analysis consists of the following procedure. First, we obtain the actual conditional density of a given bank on these two dates, $g_{B_i|S}(x|\mathbf{y}_{t,S}, I_{t-1})$, by setting $\mathbf{y}_{t,S}$ to the actual values of the covariates on these dates. Second, we compute a stressed conditional density, $g_{B_i|S}(x|\tilde{\mathbf{y}}_{t,S}, I_{t-1})$, where $\tilde{\mathbf{y}}_{t,S} = \mathbf{y}_{t,S} - \hat{\sigma}e'$; $\hat{\sigma}$ is the magnitude of the shock, while e is a vector with ones

[12] Gallant et al. (1992) compute unconditional densities and moments implied by these densities using kernel-based methods to analyse contemporaneous movements in stock prices and trading volume; as opposed to our study, they are not interested in specific channels by which these comovements occur. Escanciano and Goh (2014), meanwhile, use kernel-based methods to perform specification tests for linear quantile regressions.

[13] We compute the bandwidth as: $h = 1.06\min\{\hat{s}, \hat{r}\}n_p^{-1/5}$, where $\hat{s}$ is the standard deviation and $\hat{r}$, the interquartile range, of the quantile functions.

on the elements where the shock is applied, and zeros otherwise. We finally compare the two conditional densities graphically. The interest is on studying the impact of the following shocks: (i.) a negative shock on the GIIPS sovereign bonds; (ii.) a negative shock on the German sovereign; and (iii.) a negative shock on the home sovereign bond.

Figure 6 illustrates the results for BNP Paribas, as the results for other non-GIIPS banks are similar. In general, the crisis conditional densities (right panels) have clearly shifted to lower returns with respect to the pre-crisis ones (left panels). Figures 6a and 6b show the change in the density of BNP Paribas if there is a simultaneous negative shock to all the GIIPS sovereign bond returns equal to their historical standard deviation, weighted by the relative economic size of each country.[14] We find that the return distribution shifts to the left (implying a lower expected return). The effect is slightly asymmetric, as the density on the right tail decreases more than the left tail increases. The results, hence, suggest a small contagion effect from peripheral sovereign debt to non-GIIPS banks. Figure 6c and 6d, meanwhile, show the impact of a negative shock of the German bond. We find that a negative shock on the German bond shifts the distribution to the right and reduces the left tail of the distribution. This effect is clearly larger than the impact of the GIIPS shock. Finally, the last two panels show the impact of the French sovereign bond return on BNP Paribas. The results obtained show that a negative shock on the home sovereign bond does not seem to have a significant impact on non-GIIPS bank returns distributions. This result stands in contrast to Figure 7, which illustrates that a shock on the own bond for Banco Santander has a larger impact on its return distribution.

4 Modelling persistence with autoregressive quantiles

It is well-established in the empirical finance literature that financial time series exhibit time-varying volatility. Hence, one might be interested in analysing how the conditional distributions of bank asset returns (and similarly, of sovereign bond returns) evolve over time. In this section, we extend the model that we earlier analysed into a quantile vector autoregressive framework, and study how shocks in the key variables

[14]The contribution of each GIIPS country to the GIIPS bond shock is proportional to its real gross domestic product (GDP), which we obtained from Eurostats.

analysed in the previous section have an impact on the conditional distribution of bank asset returns.

4.1 Quantile autoregressive model specification and estimation results

We consider the following quantile autoregressive model:

$$\mathbf{q}_{t,B}(\theta) = \mathbf{c}_B(\theta) + \nu_1(\theta)\mathbf{y}_{t-1,B} + \mathbf{A}_{bs}(\theta)\mathbf{y}_{t,S} + \nu_2(\theta)\mathbf{q}_{t-1,B}(\theta) + \mathbf{B}_{bs}(\theta)\mathbf{q}_{t-1,S}(\theta), \quad (8)$$

$$\mathbf{q}_{t,S}(\theta) = \mathbf{c}_S(\theta) + \phi_1(\theta)\mathbf{y}_{t-1,S} + \mathbf{A}_{sb}(\theta)\mathbf{y}_{t,B} + \mathbf{A}_{ss}(\theta)\mathbf{y}_{t,S} + \phi_2(\theta)\mathbf{q}_{t-1,S}(\theta) + \mathbf{B}_{sb}(\theta)\mathbf{q}_{t-1,B}(\theta) + \mathbf{B}_{ss}(\theta)\mathbf{q}_{t-1,S}(\theta), \quad (9)$$

where $\mathbf{q}_{t,B}(\theta)$ ($\mathbf{q}_{t,S}(\theta)$) is the vector of θ-th quantiles of banks (sovereign bond) returns. This model belongs to the family of quantile autoregressive models studied by White et al. (2013).[15] As in Section 3, the matrices $\mathbf{A}_{bs}(\theta)$, $\mathbf{A}_{sb}(\theta)$ and $\mathbf{A}_{ss}(\theta)$ characterise contemporaneous dependence between $\mathbf{y}_{t,B}$ and $\mathbf{y}_{t,S}$, and are parameterised with the same channels studied previously. Meanwhile, $\mathbf{B}_{bs}(\theta)$, $\mathbf{B}_{sb}(\theta)$ and $\mathbf{B}_{ss}(\theta)$, which are matrices that capture autoregressive effects, are parametrised with the same channels as the contemporaneous matrices. Analogously, we introduce $\nu_2(\theta)$ and $\phi_2(\theta)$ to capture the effect of the own lagged quantiles. This parameterisation implies a consistency between the quantile models in that the same effects are studied in both specifications. We compute quantile regressions from the 10^{th} to the 90^{th} deciles, as in Section 3. Similarly, we refer to (8) and (9) as the bank and bond models, respectively.

By introducing autoregressive quantile effects to conditional quantile functions (3) and (4), models (8) and (9) now follow a GARCH(1,1)-like process as in Bollerslev (1986). Controlling for the lagged quantiles not only enables us to take into account the entire past history of the variables in the regressions, but also allows us to capture time-varying features of the return distributions such as volatility. Hence, (8) and (9) permit an analysis of the evolution of the conditional quantile functions, and in turn, the conditional distribution, over time. Moreover, the flexibility and parsimony that this specification provides makes it preferable over a quantile model with only a finite number of lags. However, a stationarity condition is needed to prevent the conditional quantile functions from becoming explosive (see Appendix B.2).

[15] Other examples of quantile autoregressive models present in the literature include Gouriéroux and Jasiak (2008) and Chen et al. (2009).

Table 5 presents the results for the bank quantile model. The results underscore the importance of contemporaneous dependence between bond and bank asset returns. We find that the nonlinear impact of GIIPS sovereign bonds across the conditional distribution of non-GIIPS banks still holds. The German bond effect also remains negative and significant. Meanwhile, the same is not observed for the own bond effect for non-GIIPS countries. At the left tail of the distribution, the own bond effect for non-GIIPS countries is insignificant. Perhaps, this result is because part of this effect is now captured by the lagged quantiles. In contrast, the contemporaneous own bond effect for GIIPS-headquartered banks is still significant throughout the distribution; this result suggests that GIIPS banks are more quickly affected by shocks to the bonds of GIIPS countries than other banks. The coefficients on the lagged quantiles, meanwhile, suggest the importance of past history in analysing the evolution over time of the conditional quantile functions. Looking at the lagged quantile parameters, we find that the GIIPS bond effect is significantly positive and persistent at the extreme left tail of the conditional distribution of bank asset returns. This suggests that, over the long-term, persistence only occurs at periods when returns are extremely negative. Meanwhile, the German bond effect is stronger and significantly negative at the extreme left tail. Interestingly, we find that the own bond effects are strongly significant, implying that they are long-term phenomena. They are particularly significant at the tails, but the coefficients on GIIPS and non-GIIPS countries differ in the middle of the distribution. On the one hand, the own bond effect for non-GIIPS countries is positive and significant, and stronger at the extreme right tail than at the extreme left tail. On the other hand, the analogous effect for the GIIPS is stronger at the extreme left tail. These results, hence, suggest that persistence occurs at extreme events. They also indicate that dependence between banks and sovereign bonds is activated more quickly in GIIPS countries (contemporaneous effects), while in non-GIIPS countries it is mainly introduced through lags.

Table 6 presents the results, meanwhile, for the bond quantile model. After controlling for autoregressive quantile effects, in general, bank asset returns do not seem to have a strong contemporaneous impact on the distribution of sovereign bond returns. Interestingly, the impact of the autoregressive quantiles of own sovereign bond returns is significant across the distribution. This shows that quantiles tend to be much more persistent for sovereign bonds than for banks.

4.2 Evolution of conditional quantile functions over time

The results in the previous subsection suggest the importance of the past history of sovereign bond returns to analyse the evolution over time of the conditional distributions of bank asset returns. In this subsection, we analyse the impact of a negative shock in some key variables on the evolution over time of conditional quantile functions of a bank $q_{t,B_i}(\theta_j)$, and infer the evolution of the conditional distributions.

To do this, we select a reference time period t_0, and the number of periods ahead, N, from which we will trace the path of the conditional quantile function $q_{t,B_i}(\theta_j)$. With this reference period, we compare two conditional quantile functions of y_{t,B_i}, where the difference is in the realisations of $\mathbf{y}_{t,S}$. The first is the original realisation without the shock, $\mathbf{y}_{t,S} = \mathbf{y}_{t_0,S}\ \forall t$, while the second is the realisation with the shock, $\tilde{\mathbf{y}}_{t,S}$, introduced through the following step function:

$$\tilde{\mathbf{y}}_{t,S} = \begin{cases} \mathbf{y}_{t_0,S} & t \leq t_0 \\ \mathbf{y}_{t_0,S} - \hat{\sigma} e' & t \geq t_0 \end{cases}, \tag{10}$$

where $\hat{\sigma}$ and e are the same as in Section 3.2; that is, $\hat{\sigma}$ is the shock, and e is a vector of ones that signify the variables where we apply the shock. We then compute $q_{t,B_i}(\theta_j)$, the conditional quantile function without applying the shock, and $\tilde{q}_{t,B_i}(\theta_j)$, the conditional quantile function with the shock over the time horizon specified, following the processes in quantile models (8) and (9). As in Section 3.2, the effects we study are shocks on the peripheral sovereign bonds, the German bund, and the home country sovereign bond. We consider short and long time horizons to be able to analyse the short-run and long-run impacts of the channels considered; in the results that follow, the short time horizon corresponds to a month after the application of the shock, while the long time horizon corresponds to a year after the shock.

Figure 8 shows the graph of the conditional quantile functions $q_{t,B_i}(\theta_j)$ and $\tilde{q}_{t,B_i}(\theta_j)$ of BNP Paribas; we select August 2007 as the reference period. The graphs demonstrate that contemporaneous dependence dominates in the short term: the graphs in the left panels show that a negative shock to each of the bonds considered produces a level shift of the conditional quantile functions. Depending on the shock, however, the magnitude and direction of the shift is different. For instance, we find that for the GIIPS bond effect, the conditional quantile function shifts downward at a one-month horizon. This translates to a corresponding shift of the conditional density of BNP Paribas to the left (lower returns). Meanwhile, a negative shock to the German sovereign translates to an upward shift of the conditional quantile functions. A negative shock to the French bond, interestingly, leads to a much smaller movement of the conditional quantile functions over the short run.

At the one year horizon, we observe that the impact from the lagged quantiles varies for each bond effect considered. On the one hand, as illustrated in Figure 8b, a shock on the GIIPS bonds produces a downward shift of the left part of the c.d.f. and an upward shift of the right part. This outcome implies that the negative shock results in a distribution with fatter tails, while the center does not seem to be affected much. On the other hand, Figure 8d shows that the impact of the German bond seems to be much smaller over the long run than the one-month effect. In the case of a negative shock on the French bond, the conditional quantile functions are almost overlapping, except on the extreme tails. We take this as confirmation of the results that persistence only occurs in extreme events.

5 Sensitivity to the crisis

The results presented thus far have been obtained with common parameters at each quantile for the whole sample, as we want to consider how dependence changes throughout the whole conditional distributions of sovereign bond and bank asset returns, respectively. Table 2 shows, however, that the correlations between GIIPS and non-GIIPS sovereign bonds changed during the sovereign crisis. The difference might suggest that perhaps, analysing the dependence between bonds and banks should incorporate the possibility of a regime change between pre-crisis and crisis periods. Doing so leads to introducing different dependence structures for parts of the conditional distribution: the returns in the pre-crisis sample mainly cover the right part of the distribution, while the returns from the crisis sample come mainly from the left part of the distribution. In this sense, it might be of interest to consider the extent to which the interdependencies found earlier are due to a particular subperiod. Toward this end, we estimate a quantile model that allows for a regime change in the dependence of some key channels. We also calculate the marginal distribution of bank asset returns, and analyse a counterfactual scenario in which the sovereign crisis would not have occurred.

5.1 Pre-crisis model specification and estimation results

In this subsection, we introduce interactions of the matrices $\mathbf{A}_{bs}(\theta)$, $\mathbf{A}_{sb}(\theta)$ and $\mathbf{A}_{ss}(\theta)$ from (3) and (4) with two time dummies that equal one before and during the crisis, respectively. We designate the first week of August 2007, the beginning of the banking crisis, as the starting point for the crisis period.[16] For parsimony, we only allow four parameters to be different prior to and during the crisis: the GIIPS bond effect, the own bond effects (both for GIIPS and non-GIIPS countries), and the GIIPS bond to the non-GIIPS bond effect. Like in the previous sections, we estimate quantile regressions from the 10^{th} to the 90^{th} deciles, separately.

We focus the discussion on the channels with pre-crisis and crisis parameters, as the other results remain the same. Table 7 presents the results for the bank quantile model. The results indicate that for the GIIPS bond effect, the dependence prior to the crisis was only significant in the middle of the distribution. As the crisis occurred, the dependence spread through most of the distribution of a non-GIIPS bank's asset returns and became stronger at reducing the right tail. A negative shock on the GIIPS bonds, hence, results in a spillover effect to non-GIIPS banks' asset return distributions during the crisis times; the same spillover only occurs at the middle of the distribution during normal times. We find significantly negative dependence from non-GIIPS bonds to their respective banks during the pre-crisis period; however, this dependence is not significant during the crisis. Hence, the flight-to-quality phenomenon in non-GIIPS countries disappears during the crisis. In practice, this feature implies a reduction of diversification opportunities in these countries. Meanwhile, the dependence between GIIPS bonds and banks was already positive but limited to the middle of the distribution prior to the crisis. Then, it has intensified during the crisis and extended to the whole distribution. Table 8, meanwhile, presents the results for the bond quantile model. We find that, prior to the crisis, there was a strong contemporaneous dependence between GIIPS and non-GIIPS bonds across the whole distribution. During the crisis, however, we only observe the dependence at the tails of the distribution. This result suggests that non-GIIPS bonds were able to elude the contagion from GIIPS bonds, except at the most extreme moments of the crisis.

[16] We perform the same analysis with a different starting point (in this case, the first week of December 2009), and the results are the same.

5.2 Counterfactual distributions

The previous subsection highlighted the differences in the impact of key variables on the conditional distribution during pre-crisis and crisis periods. A natural question to consider, hence, is the following: *"What could have happened to the return distribution of these banks if there had been no sovereign debt crisis?"* In this subsection, we exploit the flexibility of quantile regressions and perform a counterfactual analysis. Specifically, we apply the kernel interpolation methodology proposed in Section 3.2 to obtain the unconditional density of a bank in the absence of the sovereign crisis, but still maintaining the financial crisis. We compare this density to the actual unconditional density, which incorporates the impact of both the sovereign and financial crises. We adapt this exercise, which has been standard in the labour literature to analyse wage distributions, to study changes in bank asset return distributions.[17]

More formally, we aim to recover the marginal density of a bank, $h_{B_i}(y_{t,B_i}|I_{t-1})$, from the joint distribution of bank and bond returns $f_{B,S}(\mathbf{y}_{t,B}, \mathbf{y}_{t,S}|I_{t-1})$. Using the decomposition in (1) of Section 3 and integrating over the distribution of sovereign bonds $h_S(\mathbf{y}_{t,S} = x|I_{t-1})$, we obtain $h_{B_i}(\cdot)$:

$$h_{B_i}(y_{t,B_i}|I_{t-1}) = \int_{-\infty}^{\infty} g_{B_i|S}(\mathbf{y}_{t,B_i}|\mathbf{y}_{t,S} = x, I_{t-1}) h_S(\mathbf{y}_{t,S} = x|I_{t-1})\, dx \tag{11}$$

The decomposition above requires two important objects for the analysis performed in this section. The first is $g_{B_i|S}(\cdot)$, the conditional density of bank asset returns, which we obtain by the kernel density interpolation described in section 3.2. The second is $h_S(\cdot)$, the marginal density of sovereign bond returns. By assuming that $h_S(\cdot)$ is multivariate Normal, we obtain a closed-form solution for the marginal density of a bank, $h_{B_i}(\cdot)$, which we outline in detail in Appendix C. Specifically, we obtain the actual marginal density of bank i by integrating over the crisis marginal distribution of sovereign bonds: $\mathbf{y}_{t,S} \sim \mathcal{N}(\boldsymbol{\mu}_C, \boldsymbol{\Sigma}_C)$, estimated with the crisis sub-sample. In contrast, to obtain the counterfactual marginal density of bank i, we integrate over the pre-crisis marginal distribution of sovereign bonds, $\mathbf{y}_{t,S} \sim \mathcal{N}(\boldsymbol{\mu}_{PC}, \boldsymbol{\Sigma}_{PC})$, estimated with the pre-crisis sub-sample.

[17]Counterfactual decompositions have been standard in the labour literature to analyse the role of institutional and labour market factors in accounting for changes in wage distributions. Prominent examples include Dinardo et al. (1996), Gosling et al. (2000), and Machado and Mata (2005). The latter two papers use quantile regressions. More recently, Chernozhukov et al. (2013) provide estimation and inference procedures for a class of regression-based methods used to analyse counterfactual distributions; in particular, they provide results for quantile regressions.

In both cases we use the crisis conditional distribution $g_{B_i|S}(\cdot)$, whose parameters are shown in Table 7.

Figure 9 presents the plots of the actual and counterfactual densities in December 2009 for three banks: BNP Paribas, Deutsche Bank, and Banco Santander. The higher peaks at the center of the three counterfactual distributions indicate that the actual densities are much more volatile and probably have fatter tails. In addition, the actual densities for BNP Paribas and Banco Santander seem to have fatter left tails than those of the counterfactual estimations. Table 9 presents the moments of the marginal densities, plus two often-used risk measures, the Value-at-Risk (VaR) and Expected Shortfall (ES). We find that, for BNP and Banco Santander, the counterfactual densities have positive mean returns, while the actual densities have negative mean returns. The standard deviations confirm that the counterfactual distributions are less volatile than the actual distributions. Meanwhile, Deutsche Bank seems to have suffered a reduction in its expected return, but the volatility of its distribution has been less affected by the sovereign crisis. The tail risk measures that correspond to the actual densities of BNP and Santander are also much higher than the counterfactual densities; these risk measures appear to be more insensitive to the sovereign crisis in the case of Deutsche Bank, however. In sum, the results suggest that GIIPS and non-GIIPS banks were strongly exposed to the financial crisis, while German banks, though they were hit, were more insulated from the crisis.

6 Conclusions

With the European financial and sovereign debt crisis as the context, we investigate the distributional linkages between sovereign bond returns and bank asset returns. Results from quantile regression estimates suggest that sovereign bond returns exhibit a nonlinear contemporaneous dependence on the whole distribution of bank asset returns; this feature is not captured by standard regressions, which focus on the conditional mean of the distribution of bank asset returns. Specifically, we find positive, nonlinear dependence from GIIPS sovereign bonds to banks headquartered in GIIPS countries. We also observe evidence of positive, nonlinear dependence from peripheral sovereign bonds to the entire distribution of non-peripheral sovereign bond returns. These results suggest that there is contagion from peripheral to non-peripheral sovereign bonds. There is also evidence of smaller dependence of bank returns on sovereign bond returns, although we still find a significant impact of home bank returns on their country's sovereign bond returns for non-peripheral countries.

We then analyse the response of the conditional densities of banks to shocks in some sovereign bond returns. To do so, we propose a weighted kernel density interpolation methodology to recover conditional densities of bank asset returns given sovereign bond returns. The results show that a negative shock to the peripheral sovereign bond returns during crisis periods shifted the distribution of bank asset returns to the left (implying a lower expected return), and increased negative skewness by reducing the right tail of the distribution. The impact seems to be stronger on GIIPS banks.

In addition, we analyse how the conditional distributions evolve over time by extending the quantile model into a quantile vector autoregressive framework. The results show that not only does the contemporaneous dependence from bond to bank returns still hold, but also that this dependence is strongly persistent at the tails of the distribution of bank asset returns. However, the contemporaneous link from bonds to banks seems to be stronger on GIIPS banks, while non-GIIPS banks are more affected by lagged dependence. We then study the evolution of the conditional distributions of bank asset returns over time in response to a perturbation in some sovereign bond returns. The results indicate that the contemporaneous dependence has a more dominant impact in the short run, which generates a level shift in banks' asset returns conditional distributions. In the long run, however, the main effect is an increase in the probability mass at the tails.

We finally analyse the sensitivity of our results to the crisis by allowing the most relevant parameters to change during the crisis. The results indicate that the dependence between the peripheral sovereign bonds and non-peripheral bank asset returns is stronger in crisis periods than in non-crisis periods. The same observation also holds true for spillovers from own country bond to bank returns for GIIPS countries. We analyse a scenario where we obtain the marginal density of a bank in the case that the sovereign crisis had not occurred. The results indicate that, had the sovereign crisis not occurred, bank returns would have had a higher expected return and a distribution with lower volatility and thinner tails. Once again, the impact is particularly strong for GIIPS banks, and weaker in relative terms for German banks.

The results provide evidence of the importance of higher-order moments when assessing dependence between financial variables. Though it is apparent from the crisis that there exists a feedback mechanism between sovereign bond and bank returns, which has been referred to as the "diabolic loop" between sovereign bonds and banks (see Acharya et al., 2014, Bolton and Jeanne, 2011, and Gennaioli et al., 2014 for theoretical papers), our results do not have a causal interpretation. In particular, we do not study what causes the sovereign-bank link, which may well be due to determinants from the real economy (see Castro and Mencía, 2014). Nevertheless, our results provide useful information for market analysts and financial regulators, who are becoming increasingly concerned about the systemic risk implications of multivariate dependence in the market. Finally, our findings contain relevant insights for the literature on the relationship between banking and sovereign crises, (see e.g. Reinhart and Rogoff, 2011). In particular, we show that the dependence between banks' returns and sovereign debt behaves in a highly nonlinear fashion. For instance, a bank's return and a sovereign bond may be negatively correlated in normal times, but their dependence may become positive during a crisis. Hence, we quantify how the bank-sovereign link intensifies as the sovereign bond moves to the tail of its return distribution.

Our results open some interesting questions for future research. It would be interesting to explore the impact of the real economy on the non-linear dependence between sovereign debt and banks' returns. It might also be useful to extend our analysis to consider quantile-based measures of higher-order moments and study which market factors affect the evolution of asset return distributions over time, given that the literature has established the importance of higher-order moments in asset pricing (see e.g. Harvey and Siddique, 2000). Moreover, it could be helpful to extend the quantile regression framework to analyse, in a more flexible manner, the impact of uncertainty in asset pricing dynamics, as in Bansal and Yaron (2004). Lastly, it also might be interesting to consider how government policy interventions have an impact on these conditional distributions.

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A List of Banks

This is a list of banks that are included in the dataset. The banks are classified according to the country of its headquarters. We also include the identifier in Datastream for each of the banks in the sample.

Bank	**Identifier**	**Country**
Erste Group Bank A.G.	ERS	Austria
KBC Group N.V.	KB	Belgium
Danske Bank	DAB	Denmark
BNP Paribas	BNP	France
Societe Generale	SGE	France
Deustche Bank A.G.	DBK	Germany
Commerzbank A.G.	CBK	Germany
National Bank of Greece	ETE	Greece
Alpha Bank	PIST	Greece
Piraeus Bank Group	PEIR	Greece
Allied Irish Banks plc	ALBK	Ireland
Bank of Ireland	BKIR	Ireland
Intesa Sanpaolo S.p.A	ISP	Italy
Unicredit S.p.A	UCG	Italy
ING Bank N.V.	ING	Netherlands
Banco Comercial Portugues, S.A.	BCG	Portugal
Banco Santander S.A.	SCH	Spain
Banco Bilbao Vizcaya Argentaria S.A.	BBVA	Spain
Nordea Bank A.B.	NDA	Sweden
Skandinaviska Enskilda Banken A.B.	SEA	Sweden
Svenska Handelsbanken A.B.	SVK	Sweden
Swedbank A.B.	SWED	Sweden
Credit Suisse Group A.G.	CS	Switzerland
UBS A.G.	UBS	Switzerland
Royal Bank of Scotland Group plc	RBS	United Kingdom
HSBC Holdings plc	HSBC	United Kingdom
Barclays plc	BARC	United Kingdom

B Model specification and estimation

B.1 Baseline model

We can write the matrices in (3) and (4) as $\mathbf{A_{bb}} = \nu \mathbf{I_n}$, $\mathbf{A_{bs}} = \alpha \mathbf{A_{11}} + \beta \mathbf{A_{21}} + \gamma \mathbf{A_{31}} + \tau \mathbf{A_{41}}$, $\mathbf{A_{sb}} = \kappa \mathbf{A_{12}} + \pi \mathbf{A_{22}} + \eta \mathbf{A_{32}} + \omega \mathbf{A_{42}}$, and $\mathbf{A_{ss}} = \phi \mathbf{I_m} + \psi \mathbf{A_{52}}$. These expressions are based on auxiliar matrices, which are defined as follows:

1. GIIPS sovereign bond effect on non-GIIPS banks' returns: $\mathbf{A_{11}}$ is an $n \times m$ matrix such that $\mathbf{A_{11}}(i,j) = 1$ if country (bank i) $\notin$ GIIPS but country $j \in$ GIIPS, and zero otherwise.

2. German sovereign bond effect on non-German banks' returns: $\mathbf{A_{21}}$ is an $n \times m$ matrix such that $\mathbf{A_{21}}(i,j) = 1$ if country (bank i) $\notin$ DE but country $j =$ DE, and zero otherwise.

3. Own country effect on banks' returns for non-GIIPS countries: $\mathbf{A_{31}}$ is an $n \times m$ matrix such that $\mathbf{A_{31}}(i,j) = 1$ if country (bank i) $=$ country j, and country $j \notin$ GIIPS, and zero otherwise.

4. Own country effect on banks' returns for GIIPS countries: $\mathbf{A_{41}}$ is an $n \times m$ matrix such that $\mathbf{A_{41}}(i,j) = 1$ if country (bank i) $=$ country j, and country $j \in$ GIIPS, and zero otherwise.

5. Own bank effect on sovereign bond returns for non-GIIPS countries: $\mathbf{A_{12}}$ is an $m \times n$ matrix such that $\mathbf{A_{12}}(i,j) = 1$ if country $i =$ country (bank j), and country $j \notin$ GIIPS, and zero otherwise.

6. Own bank effect on sovereign bond returns for GIIPS countries: $\mathbf{A_{22}}$ is an $m \times n$ matrix such that $\mathbf{A_{22}}(i,j) = 1$ if country $i =$ country (bank j), and country $j \in$ GIIPS, and zero otherwise.

7. GIIPS banks effect on non-GIIPS sovereign bond returns: $\mathbf{A_{32}}$ is an $m \times n$ matrix such that $\mathbf{A_{32}}(i,j) = 1$ if country $i \notin$ GIIPS, but country (bank j) $\in$ GIIPS, and zero otherwise.

8. German bank effect on non-German sovereign bond returns: $\mathbf{A_{42}}$ is an $m \times n$ matrix such that $\mathbf{A_{42}}(i,j) = 1$ if country $i \notin$ GIIPS, but country (bank j) $=$ DE, and zero otherwise.

9. GIIPS sovereign effect on non-GIIPS sovereign bond returns: $\mathbf{A_{52}}$ is an $m \times m$ matrix such that $\mathbf{A_{52}}(i,j) = 1$ if country $i \notin$ GIIPS, but country $j \in$ GIIPS, and zero otherwise.

Hence, we can rewrite (3) and (4), respectively, as:

$$\mathbf{q_{bt}}(\theta) = \mathbf{c_b} + \nu \mathbf{y_{bt-1}} + \alpha \mathbf{A_{11}} \mathbf{y_{st}} + \beta \mathbf{A_{21}} \mathbf{y_{st}} + \gamma \mathbf{A_{31}} \mathbf{y_{st}} + \tau \mathbf{A_{41}} \mathbf{y_{st}}, \tag{B1}$$

and

$$\mathbf{q_{st}}(\theta) = \mathbf{c_s} + \phi \mathbf{y_{st-1}} + \kappa \mathbf{A_{12}} \mathbf{y_{bt}} + \pi \mathbf{A_{22}} \mathbf{y_{bt}} + \eta \mathbf{A_{32}} \mathbf{y_{bt}} + \omega \mathbf{A_{42}} \mathbf{y_{bt}} + \psi \mathbf{A_{52}} \mathbf{y_{st}}. \tag{B2}$$

As in most quantile regression procedures, we solve the following optimisation problem:

$$\min_{\boldsymbol{\alpha}} S_T(\boldsymbol{\alpha}) := T^{-1} \sum_{t=1}^{T} \left\{ \sum_{i=1}^{n} \rho_{\theta_{i,t}} (y_{it} - q_{i,t}(\boldsymbol{\alpha})) \right\} \tag{B3}$$

where $\boldsymbol{\alpha}$ is the vector of parameters we are estimating, $\rho_\theta(e) = e\psi_\theta(e)$ is the standard check function, defined through the quantile step function, $\psi_\theta(e) = \theta - 1_{[e \leq 0]}$. Under suitable regularity assumptions, White et al. (2013) shows that the solution to this problem is consistent and asymptotically normal. White et al. (2013) minimise (B3) from 40 different initial parameter values using a search method based on the simplex algorithm. However, due to the dimensions of the problem we are estimating, the simplex method may yield local minima. Moreover, as Koenker (2005) notes, in large sample sizes interior-point methods are more appropriate and more efficient to find the optimal parameter estimates. In this regard, we perform the following two-step algorithm:

1. In the first step, using an initial guess, we minimise optimisation problem (B3) with a smoothed approximation to the step function, $\psi_\theta(e)$:

   $$H(x) = \theta - \left(\frac{1}{2} + \frac{1}{2} \tanh(kx) \right), \tag{B4}$$

   where k is a smoothing parameter, which we set as $k = 1000$. Another paper that used smoothed approximations to the quantile objective function is Gosling et al. (2000), who works with a smoothed linear absolute deviations estimator proposed by Horowitz (1998).

2. In the second step, we use the parameter estimates obtained in the previous step as an initial guess, and solve the optimisation problem (B3) using the non-smoothed step function $\psi_\theta(e)$.

We then take as the optimal parameter estimate the vector of parameters that yielded the smallest objective function value.

B.2 Extension to an autoregressive model

In Section 4, we extend the baseline quantile model to include autoregressive terms:

$$\mathbf{q_t}(\theta) = \mathbf{c}(\theta) + \mathbf{A}(\theta)\mathbf{y_t} + \mathbf{B}(\theta)\mathbf{q_{t-1}}(\theta) \tag{B5}$$

It is easy to notice that we can rewrite equation (B5) as:

$$(1 - \mathbf{B}(\theta)L)\mathbf{q_t}(\theta) = \mathbf{c}(\theta) + \mathbf{A}(\theta)\mathbf{y_t} \tag{B6}$$

where L is the lagged operator. An implication of this is that we need to impose restrictions as to the parameter values that $\mathbf{B}(\theta)$ could take in order for $q_t(\theta)$ not to become explosive. Hence, we impose the following condition: $\max(|\mathbf{eig}(\mathbf{B}(\theta))|) < 1$. This constraint, however, implies that to get numerically stable solutions, we must work with the smoothed approximation to $\psi_\theta(e)$, equation (B4).

C Derivation of the marginal density of a bank

If we introduce (7) in (11), we obtain:

$$h_{B_i}(y_{t,B_i}|I_{t-1}) = \int \frac{1}{h}\sum_{j=1}^{n_p} w_j \phi\left(\frac{y - q_{t,B_i}(\theta_j)}{h}\right) h_S(\mathbf{y}_{t,S} = \mathbf{x}|I_{t-1})\, d\mathbf{x}$$

For the sake of simplicity, we can write $q_{t,B_i}(\theta_j) = c_{B_j} + \nu_j y_{t-1,B_i} + \mathbf{a}'_{bsj}\mathbf{x}$, so that we have

$$h_{B_i}(y_{t,B_i}|I_{t-1}) = \sum_{j=1}^{n_p} w_j \int \frac{1}{h}\phi\left(\frac{y - c_{B_j} - \nu_j y_{t-1,B_i} - \mathbf{a}'_{bsj}\mathbf{x}}{h}\right) h_S(\mathbf{y}_{t,S} = \mathbf{x}|I_{t-1})\, d\mathbf{x}. \tag{C7}$$

Since $\mathbf{y}_{t,S} \sim N(\boldsymbol{\mu}_S, \boldsymbol{\Sigma}_S)$, we can easily introduce its density function in the integrand of (C7), which yields

$$\frac{1}{h}\phi\left(\frac{y - c_{B_j} - \nu_j y_{t-1,B_i} - \mathbf{a}'_{bsj}\mathbf{x}}{h}\right) h_S(\mathbf{y}_{t,S} = \mathbf{x}|I_{t-1})\, d\mathbf{x} = \frac{1}{(2\pi)^{(m+1)/2}|\boldsymbol{\Sigma}_S|^{1/2}h} \times \exp\left[-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu}_S)'\boldsymbol{\Sigma}_S^{-1}(\mathbf{x} - \boldsymbol{\mu}_S) - \frac{1}{2}\frac{(y - c_{B_j} - \nu_j y_{t-1,B_i} - \mathbf{a}'_{bsj}\mathbf{x})^2}{h^2}\right]. \tag{C8}$$

It is straightforward to show that

$$(\mathbf{x}-\boldsymbol{\mu})'\boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})+(a-\mathbf{b}'\mathbf{x})^2 = (\mathbf{x}-\boldsymbol{\mu}^*)'\boldsymbol{\Sigma}^{*-1}(\mathbf{x}-\boldsymbol{\mu}^*)-\boldsymbol{\mu}^{*\prime}\boldsymbol{\Sigma}^{*-1}\boldsymbol{\mu}^* + a^2+\boldsymbol{\mu}'\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu},$$

where $\boldsymbol{\mu}^* = \boldsymbol{\Sigma}^* \left(\boldsymbol{\Sigma}^{-1}\,\boldsymbol{\mu}+ a\mathbf{b}\right)$ and $\boldsymbol{\Sigma}^* = \left(\boldsymbol{\Sigma}^{-1}+\mathbf{b}\mathbf{b}'\right)^{-1}$. Using this result, we can rewrite (C8) as

$$\frac{1}{(2\pi)^{m/2}|\boldsymbol{\Sigma}_S^*|^{1/2}}\exp\left[-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_{Sj}^*)'\boldsymbol{\Sigma}_{Sj}^{*-1}(\mathbf{x}-\boldsymbol{\mu}_{Sj}^*)\right]$$
$$\times\exp\left[\frac{1}{2}\boldsymbol{\mu}_{Sj}^{*\prime}\boldsymbol{\Sigma}_{Sj}^{*-1}\boldsymbol{\mu}_{Sj}^*-\frac{1}{2}a_j^2-\frac{1}{2}\boldsymbol{\mu}_S'\boldsymbol{\Sigma}_S^{-1}\boldsymbol{\mu}_S\right]\frac{|\boldsymbol{\Sigma}_S^*|^{1/2}}{|\boldsymbol{\Sigma}_S|^{1/2}}\frac{1}{h\sqrt{2\pi}}$$

where $\boldsymbol{\mu}_{Sj}^* = \boldsymbol{\Sigma}_{Sj}^*\left(\boldsymbol{\Sigma}_S^{-1}\boldsymbol{\mu}_S + a_j\mathbf{b}_j\right)$, $\boldsymbol{\Sigma}_{Sj}^* = \left(\boldsymbol{\Sigma}_S^{-1}+\mathbf{b}_j\mathbf{b}_j'\right)^{-1}$, $a_j = (y - c_{B_j} - \nu_j y_{t-1,B_i})/h$ and $\mathbf{b}_j = (\mathbf{a}_{bsj})/h$. Finally, if we introduce these results in (C7), we obtain

$$h_{B_i}(y_{t,B_i}|I_{t-1}) = \sum_{j=1}^{n_p} w_j\exp\left[\frac{1}{2}\boldsymbol{\mu}_{Sj}^{*\prime}\boldsymbol{\Sigma}_{Sj}^{*-1}\boldsymbol{\mu}_{Sj}^*-\frac{1}{2}a_j^2-\frac{1}{2}\boldsymbol{\mu}_S'\boldsymbol{\Sigma}_S^{-1}\boldsymbol{\mu}_S\right]\frac{|\boldsymbol{\Sigma}_S^*|^{1/2}}{|\boldsymbol{\Sigma}_S|^{1/2}}\frac{1}{h\sqrt{2\pi}},$$

which corresponds to a mixture of univariate normal variables.

Table 1. Weekly Return Sovereign Bond Data, 2001-2013

	GIIPS				
	Greece	Ireland	Italy	Portugal	Spain
Mean	-0.074	-0.054	0.010	-0.058	0.008
SD	1.224	1.122	1.096	1.095	1.109
Skewness	-4.678***	-1.547***	0.407***	-0.403***	1.212***
Kurtosis	54.573***	17.163***	15.886***	16.702***	12.782***
	Non-GIIPS				
	Germany	France	Netherlands	Switzerland	UK
Mean	0.037	0.031	0.034	0.021	0.027
SD	0.822	0.752	0.622	0.469	1.117
Skewness	-0.128***	-0.412***	-0.301***	-0.321***	0.054***
Kurtosis	3.601***	4.612***	3.673***	4.656***	4.146***

Note: The table provides summary statistics for GIIPS and selected non-GIIPS sovereign bond returns. The sample period for these statistics is January 2, 2001 - November 6, 2013, with the exception of Greece, Ireland, and Portugal. In the case of these countries, the summary statistics were computed until the week when each of these countries were bailed out by the troika of the IMF, EMU, and EC. Normality tests were performed using the Jarque-Bera test. Significance levels are indicated by the following: *** - 1%,** - 5%, * - 10%.

Table 2. Correlations: Weekly Sovereign Bond Returns, 2001-2010

	Germany	Greece	Ireland	Italy	Portugal	Spain
			Pre-crisis (2001/01-2008/02)			
Germany	1					
Greece	0.980	1				
Ireland	0.971	0.959	1			
Italy	0.970	0.967	0.951	1		
Portugal	0.979	0.969	0.959	0.966	1	
Spain	0.981	0.970	0.959	0.959	0.968	1
			Banking Crisis (2007/08-2009/11)			
Germany	1					
Greece	-0.039	1				
Ireland	0.117	0.377	1			
Italy	0.298	0.334	0.366	1		
Portugal	0.157	0.386	0.650	0.395	1	
Spain	0.360	0.340	0.460	0.706	0.355	1
			Sovereign Crisis (2009/12-2010/05)			
Germany	1					
Greece	-0.221	1				
Ireland	-0.381	0.688	1			
Italy	0.245	0.519	0.455	1		
Portugal	-0.108	0.778	0.657	0.514	1	
Spain	0.015	0.686	0.756	0.634	0.664	1

Note: Sample period: January 2, 2001 - May 2, 2010. This table describes the correlation between Germany and the GIIPS sovereign bonds. The sample was divided into three: a pre-crisis sample, a sample reflecting the onset of the banking crisis, and a sample reflecting the onset of the sovereign debt crisis. We took the following dates as turning points: August 7, 2007, the closure of three investment funds by BNP Paribas, and November 30, 2009, the announcement by the Greek government of its €30 billion sovereign debt. To compute the correlations for the third period, we only consider data up to the first bailout of the Greek sovereign, May 2, 2010.

Table 3. OLS and quantile regressions, bank equation, weekly data

Effect	**OLS**	**Quantile**				
		0.10	0.30	0.50	0.70	0.90
GIIPS bond to	0.057***	0.042	0.052***	0.068***	0.079***	0.093*
non-GIIPS bank (α)	(0.007)	(0.028)	(0.017)	(0.014)	(0.023)	(0.047)
German bond to	-2.229***	-2.483***	-2.229***	-2.092***	-2.153***	-2.865***
non-German bank (β)	(0.276)	(0.394)	(0.182)	(0.166)	(0.190)	(0.389)
own bond effect	-0.506*	-0.401	-0.307**	-0.193	-0.338**	-0.507*
for non-GIIPS (γ)	(0.283)	(0.295)	(0.126)	(0.130)	(0.144)	(0.297)
own bond effect	0.109	0.989***	1.166***	1.178***	1.168***	1.166***
for GIIPS (τ)	(0.084)	(0.271)	(0.121)	(0.148)	(0.187)	(0.238)
lagged bank returns (ν)	-0.007	-0.015	-0.043***	-0.052***	-0.064***	-0.069***
	(0.007)	(0.048)	(0.015)	(0.018)	(0.015)	(0.003)
Intercept	0.661**	-5.803***	-1.854***	0.130**	2.165***	6.135***
	(0.328)	(0.267)	(0.127)	(0.107)	(0.119)	(0.245)
T	670	670	670	670	670	670

Note: The table provides OLS and quantile regression results for the bank equation (3). The dependent variables in these regressions are bank asset returns. The first column corresponds to the effect of interest. The second column corresponds to the OLS regression, while the third to last columns correspond to a particular quantile. All regressions were under the time period from January 3, 2001-November 6, 2013, except for Greece, Ireland and Portugal. Standard errors are in parentheses, and are computed by using a sandwich formula as outlined in White et al. (2013), and robust standard errors for OLS. Significance levels are indicated by the following: *** - 1%,** - 5%, * - 10%.

Table 4. OLS and quantile regressions, bond equation, weekly data

Effect	**OLS**	**Quantile**				
		0.10	0.30	0.50	0.70	0.90
GIIPS bank to	-0.0000	0.0003	0.0001	0.0002	0.0003	0.0002
non-GIIPS bond (η)	(0.0001)	(0.0001)	(0.0002)	(0.0003)	(0.0004)	(0.0002)
German bank to	0.0003	-0.0065***	-0.0080***	-0.0060***	-0.0076***	-0.0064***
non-German bond (ω)	(0.0028)	(0.0020)	(0.0022)	(0.0027)	(0.0026)	(0.0024)
own bank effect	-0.0092***	-0.0138***	-0.0064***	-0.0051***	-0.0087***	-0.0104***
for non-GIIPS (κ)	(0.0029)	(0.0015)	(0.0011)	(0.0013)	(0.0013)	(0.0010)
own bank effect	0.0004	0.0021	-0.0001	-0.0004	0.0009	0.0024***
for GIIPS (π)	(0.0005)	(0.0026)	(0.0008)	(0.0010)	(0.0013)	(0.0006)
GIIPS bonds	0.0120***	0.0113***	0.0243***	0.0183***	0.0170***	0.0186***
to non-GIIPS bond (ψ)	(0.0000)	(0.0019)	(0.0042)	(0.0034)	(0.0033)	(0.0039)
lagged bond returns (ϕ)	-0.0507	0.0081	0.0047	0.0196	0.0017	-0.0015
	(0.1012)	(0.0607)	(0.0462)	(0.0425)	(0.0317)	(0.0297)
Intercept	0.0221	-0.8561***	-0.2452***	0.0267	0.3113***	0.8748***
	(0.0275)	(0.0274)	(0.0307)	(0.0329)	(0.0312)	(0.0249)
T	670	670	670	670	670	670

Note: The table provides OLS and quantile regression results for the bond equation (4) The dependent variables in these regressions are sovereign bond returns. The first column corresponds to the effect of interest. The second column corresponds to the OLS regression, while the third to last columns correspond to a particular quantile. All regressions were under the time period from January 3, 2001-November 6, 2013, except for Greece, Ireland and Portugal. Standard errors are in parentheses, and are computed by using a sandwich formula as outlined in White et al. (2013), and robust standard errors for OLS. Significance levels are indicated by the following: *** - 1%,** - 5%, * - 10%.

Table 5. Quantile autoregressive model, bank equation, weekly data

Effect	**Quantile**				
	0.10	0.30	0.50	0.70	0.90
	Contemporaneous Parameters				
GIIPS bond to	0.056	0.051**	0.067***	0.091***	0.076**
non-GIIPS bank (α_1)	(0.044)	(0.024)	(0.014)	(0.019)	(0.037)
German bond to	-2.190***	-2.270***	-2.093***	-2.093***	-2.741***
non-German bank (β_1)	(0.332)	(0.183)	(0.161)	(0.177)	(0.292)
own bond effect	-0.184	0.063	-0.147	-0.587***	-0.305
for non-GIIPS (γ_1)	(0.297)	(0.139)	(0.127)	(0.129)	(0.246)
own bond effect	0.918***	1.240***	1.185***	1.167***	1.427***
for GIIPS (τ_1)	(0.287)	(0.116)	(0.139)	(0.180)	(0.211)
lagged bank returns (ν_1)	-0.015	-0.041***	-0.036***	-0.066**	-0.081*
	(0.021)	(0.005)	(0.011)	(0.013)	(0.046)
	Lagged Quantile Parameters				
GIIPS bond to	0.366***	-1.200***	-0.823	-0.1265	0.117
non-GIIPS bank (α_2)	(0.138)	(0.281)	(0.525)	(0.223)	(0.082)
German bond to	-4.695***	1.078	4.879**	0.496	0.645*
non-German bank (β_2)	(1.084)	(0.825)	(1.413)	(0.381)	(0.454)
own bond effect	2.033***	4.032***	4.498***	4.696***	4.188***
for non-GIIPS (γ_2)	(0.543)	(1.350)	(1.467)	(0.737)	(0.660)
own bond effect	4.984***	-4.138***	-2.976	1.427	2.596***
for GIIPS (τ_2)	(1.055)	(1.251)	(2.084)	(0.923)	(0.489)
lagged bank returns (ν_2)	0.006	-0.036	-0.002	-0.003	0.053
	(0.139)	(0.069)	(0.062)	(0.058)	(0.090)
Intercept	-4.878***	-3.095***	-0.174	1.477***	2.247***
	(0.918)	(0.781)	(1.068)	(0.299)	(0.446)
T	670	670	670	670	670

Note: The table provides regression results for the bank equation (8), the quantile vector autoregressive model. The dependent variables in these regressions are bank asset returns. The first column corresponds to the effect of interest. The second to the last columns correspond to a particular quantile. All regressions were under the time period from January 3, 2001-November 6, 2013, except for Greece, Ireland and Portugal. Standard errors are in parentheses, and are computed by using a sandwich formula as outlined in White et al. (2013). Significance levels are indicated by the following: *** - 1%,** - 5%, * - 10%.

Table 6. Quantile autoregressive model, bond equation, weekly data

Effect	**Quantile**				
	0.10	0.30	0.50	0.70	0.90
	Contemporaneous Parameters				
GIIPS bank to	0.0001	0.0002	0.0001	0.0000	0.0001
non-GIIPS bond (η_1)	(0.0004)	(0.0002)	(0.0001)	(0.0000)	(0.0001)
German bank to	0.0049	-0.0065***	-0.0037	-0.0026	-0.0072***
non-German bond (ω_1)	(0.0031)	(0.0021)	(0.0026)	(0.0026)	(0.0027)
own bank effect	-0.0015	-0.0032**	-0.0020	-0.0010	-0.0023
for non-GIIPS (κ_1)	(0.0030)	(0.0016)	(0.0013)	(0.0016)	(0.0022)
own bank effect	-0.0001	0.0010	0.0010	0.0001	0.0009
for GIIPS (π_1)	(0.0028)	(0.0007)	(0.0010)	(0.0012)	(0.0016)
GIIPS bonds	-0.0005	0.0016	0.0002	0.0005	0.0010
to non-GIIPS bond (ψ_1)	(0.0026)	(0.0028)	(0.0050)	(0.0022)	(0.0030)
lagged bond returns (ϕ_1)	0.0578	-0.0078	-0.0258	-0.0102	-0.0481
	(0.0442)	(0.0405)	(0.0417)	(0.0425)	(0.0383)
	Lagged Quantile Parameters				
GIIPS bank to	0.0009	0.0006	0.0002	-0.0007	0.0006
non-GIIPS bond (η_2)	(0.0014)	(0.0008)	(0.0018)	(0.0011)	(0.0005)
German bank to	0.0005	-0.0352**	0.0168	0.0002	-0.0001
non-German bond (ω_2)	(0.0041)	(0.0165)	(0.0334)	(0.0090)	(0.0036)
own bank effect	-0.0005	-0.0010	-0.0043	-0.0002	-0.0003
for non-GIIPS (κ_2)	(0.0039)	(0.0045)	(0.0066)	(0.0036)	(0.0021)
own bank effect	0.0003	0.0067	0.0055	0.0029	0.0012
for GIIPS (π_2)	(0.0047)	(0.0102)	(0.0144)	(0.0103)	(0.0050)
GIIPS bonds	-0.0100	-0.0611*	-0.1589	0.0134	0.0091
to non-GIIPS bond (ψ_2)	(0.0183)	(0.0324)	(0.0997)	(0.0327)	(0.0246)
lagged bond returns (ϕ_2)	0.9816***	0.4695***	0.4710***	0.9745***	0.9795***
	(0.0023)	(0.1188)	(0.2048)	(0.0051)	(0.0016)
Intercept	-0.0073	-0.3556**	-0.0253	0.0012	0.0141
	(0.1315)	(0.1551)	(0.0412)	(0.0816)	(0.0912)
T	670	670	670	670	670

Note: The table provides regression results for the bond equation (9), the quantile vector autoregressive model. The dependent variables in these regressions are sovereign bond returns. The first column corresponds to the effect of interest. The second to the last columns correspond to a particular quantile. All regressions were under the time period from January 3, 2001-November 6, 2013, except for Greece, Ireland and Portugal. Standard errors are in parentheses, and are computed by using a sandwich formula as outlined in White et al. (2013). Significance levels are indicated by the following: *** - 1%,** - 5%, * - 10%.

Table 7. Pre-crisis regressions, bank equation, weekly data

Effect	**Quantile**				
	0.10	0.30	0.50	0.70	0.90
GIIPS bond to	0.040	0.142^{*}	0.170^{**}	0.128^{*}	0.126
non-GIIPS bank (α_{PC})	(0.173)	(0.076)	(0.066)	(0.072)	(0.186)
GIIPS bond to	0.044	0.052^{***}	0.062^{***}	0.075^{***}	0.109^{***}
non-GIIPS bank (α_{C})	(0.028)	(0.018)	(0.015)	(0.025)	(0.043)
German bond to	-2.291^{***}	-2.186^{***}	-2.131^{***}	-2.134^{***}	-2.861^{***}
non-German bank (β)	(0.500)	(0.266)	(0.222)	(0.253)	(0.472)
own bond effect	-1.116^{*}	-0.729^{***}	-0.546^{***}	-0.558^{***}	-1.145^{**}
for non-GIIPS (γ_{PC})	(0.660)	(0.176)	(0.164)	(0.173)	(0.704)
own bond effect	-0.254	-0.330^{*}	-0.221	-0.310	-0.230
for non-GIIPS (γ_{C})	(0.386)	(0.189)	(0.233)	(0.218)	(0.348)
own bond effect	0.086	0.826^{**}	0.997^{***}	0.852^{***}	0.689
for GIIPS (τ_{PC})	(0.753)	(0.364)	(0.291)	(0.323)	(0.593)
own bond effect	1.155^{***}	1.272^{**}	1.257^{***}	1.285^{***}	1.359^{***}
for GIIPS (τ_{C})	(0.342)	(0.149)	(0.159)	(0.268)	(0.263)
lagged bank returns (ν)	-0.015	-0.044^{***}	-0.052^{***}	-0.065^{***}	-0.035^{***}
	(0.052)	(0.015)	(0.018)	(0.015)	(0.004)
Intercept	-5.804^{***}	-1.847^{***}	0.123	2.177^{***}	6.142^{***}
	(0.019)	(0.023)	(0.025)	(0.023)	(0.020)
T	670	670	670	670	670

Note: The table provides regression results for the bank equation

$$\begin{aligned} \mathbf{q}_{t,B}(\theta) &= \mathbf{c}_B(\theta) + \mathbf{A}_{bs,PC}(\theta)\mathbf{y}_{t,S} \cdot 1(t < T) \\ &\quad + \mathbf{A}_{bs,C}(\theta)\mathbf{y}_{t,S} \cdot 1(t \geq T) + \nu(\theta)\mathbf{y}_{t-1,B}, \end{aligned}$$

which denotes a quantile regression with pre-crisis (PC) and crisis (C) parameters for three effects: GIIPS bond to non-GIIPS bank, and the own bond effects for both GIIPS and non-GIIPS countries. The dependent variables in these regressions are bank asset returns. The first column corresponds to the effect of interest, while the second to the last columns correspond to a particular quantile. The starting period for crisis times was designated as the first week of August 2007 (T in the equation). All regressions were under the time period from January 3, 2001-November 6, 2013, except for Greece, Ireland and Portugal. Standard errors are in parentheses, and are computed by using a sandwich formula as outlined in White et al. (2013). Significance levels are indicated by the following: *** - 1%,** - 5%, * - 10%.

Table 8. Pre-crisis regressions, bond equation, weekly data

Effect	**Quantile**				
	0.10	0.30	0.50	0.70	0.90
GIIPS bank to	-0.0001	0.0002	0.0001	0.0002	-0.0002
non-GIIPS bond (η)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
German bank to	-0.0005	-0.0052***	-0.0032	-0.0052**	0.0014
non-German bond (ω)	(0.0018)	(0.0019)	(0.0024)	(0.0022)	(0.0024)
own bank effect	-0.0083***	-0.0035***	-0.0025***	-0.0041***	-0.0105***
for non-GIIPS (κ)	(0.0012)	(0.0012)	(0.0016)	(0.0013)	(0.0013)
own bank effect	0.0001	-0.0005	0.0000	0.0004	-0.0011
for GIIPS (π)	(0.0026)	(0.0008)	(0.0010)	(0.0013)	(0.0007)
GIIPS bonds	0.1499***	0.1637***	0.1903***	0.1524***	0.1208***
to non-GIIPS bond (ψ_{PC})	(0.0044)	(0.0071)	(0.0088)	(0.0075)	(0.0049)
GIIPS bonds	0.0033**	0.0024	0.0018	0.0027	0.0063*
to non-GIIPS bond (ψ_C)	(0.0014)	(0.0036)	(0.0032)	(0.0025)	(0.0035)
Intercept	-0.7656***	-0.1854***	0.0123	0.2241***	0.7907***
	(0.0199)	(0.0230)	(0.0252)	(0.0238)	(0.0206)
T	670	670	670	670	670

Note: The table provides regression results for the bond equation

$$\begin{aligned}\mathbf{q}_{t,S}(\theta) &= \mathbf{c}_S(\theta) + \mathbf{A}_{sb}(\theta)\mathbf{y}_{t,B} + \mathbf{A}_{ss,PC}(\theta)\mathbf{y}_{t,S} \cdot 1(t < T) \\ &\quad + \mathbf{A}_{ss,C}(\theta)\mathbf{y}_{t,S} \cdot 1(t \geq T) + \phi(\theta)\mathbf{y}_{t-1,S},\end{aligned}$$

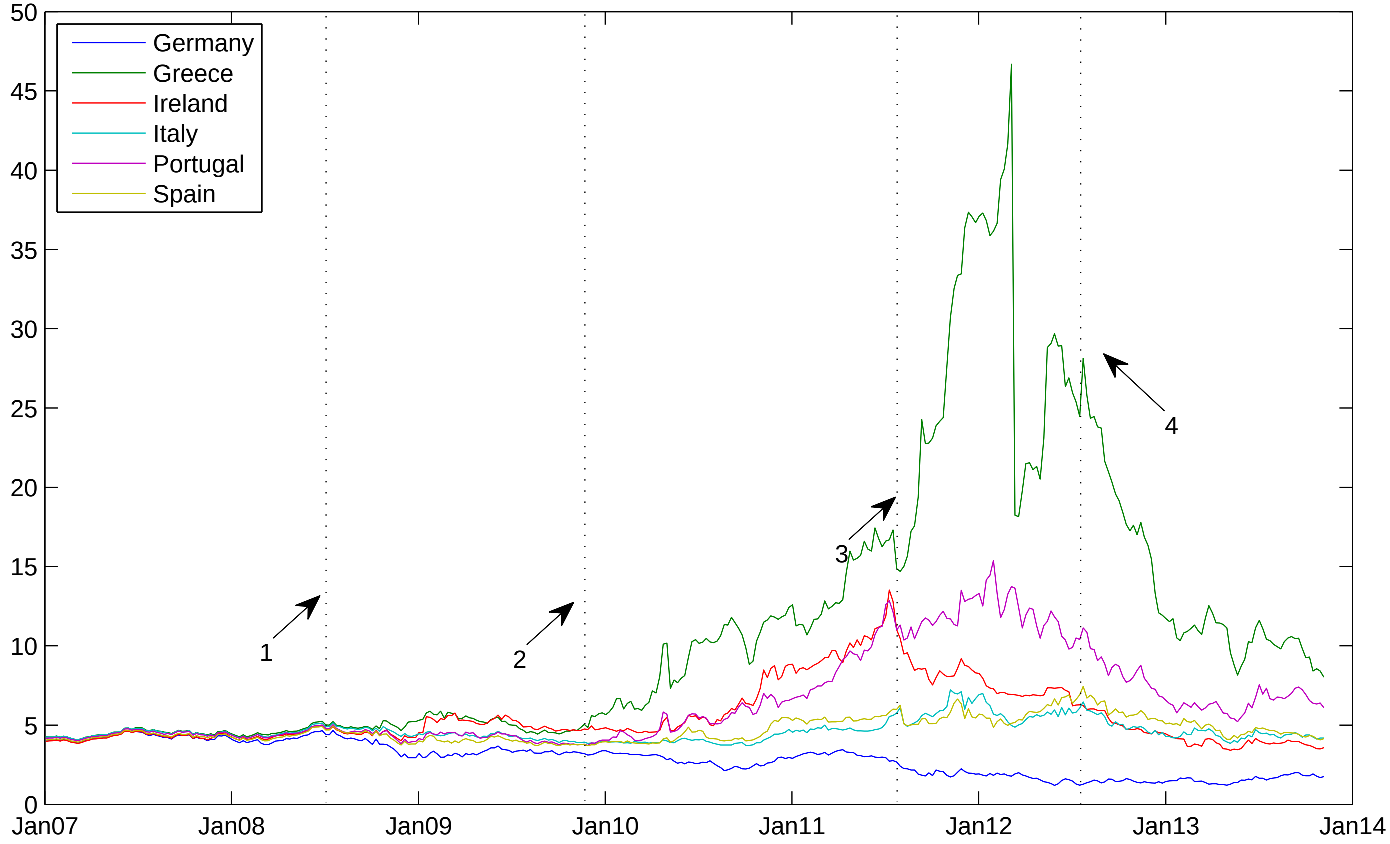
which denotes a quantile regression with pre-crisis (PC) and crisis (C) parameters for the GIIPS bond to non-GIIPS bond effect. The dependent variables in these regressions are bank asset returns. The first column corresponds to the effect of interest, while the second to the last columns correspond to a particular quantile. The starting period for crisis times was designated as the first week of August 2007 (T in the equation). All regressions were under the time period from January 3, 2001-November 6, 2013, except for Greece, Ireland and Portugal. Standard errors are in parentheses, and are computed by using a sandwich formula as outlined in White et al. (2013). Significance levels are indicated by the following: *** - 1%,** - 5%, * - 10%.

Table 9. Moments of the Marginal Densities and Risk Measures

	BNP Paribas		Deutsche Bank		Santander	
	Actual	Counterfactual	Actual	Counterfactual	Actual	Counterfactual
Mean	-0.0129	0.0266	0.0057	0.0464	-0.0111	0.0360
Std. Dev.	3.5367	2.9030	2.5844	2.3967	3.3728	2.6591
95% - VaR	5.8345	4.8439	4.3462	4.1056	5.5765	4.4701
95% - ES	7.4341	5.8994	5.3521	4.7994	6.9487	5.3291

Note: This table shows the moments and some often-used risk measures of the actual and counterfactual densities of the following banks: BNP Paribas, Deutsche Bank, and Banco Santander. The date chosen for the analysis is December 2009.

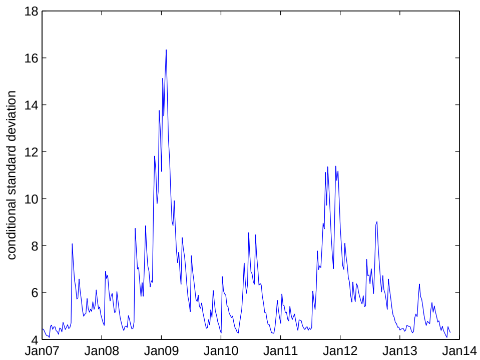
Figure 1: Sovereign Bond Returns of Germany and GIIPS countries, 2007-2013



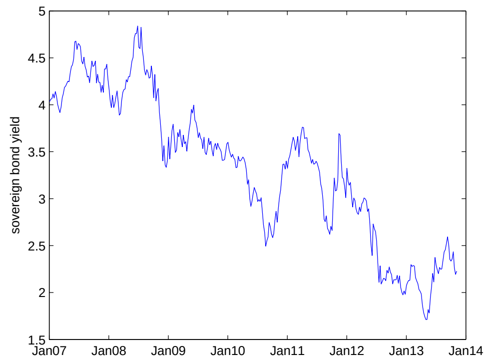
Note: Sample period: January 3, 2007 - November 6, 2013. This illustrates the divergence between German and GIIPS 10-year sovereign bond yields during the sovereign debt crisis, which began in late 2009. The dashed lines indicate significant periods in the financial and sovereign debt crises, marked with numbers: (1) the Lehman brothers collapse, (2) the announcement of a 300-billion euro sovereign debt by Greece, (3) the rise in borrowing costs for Spain and Italy, and (4) the announcement of Mario Draghi, ECB president, of the commitment to “preserve the euro”.

Figure 2: Return Volatility and Sovereign Bond Yields, 2007-2013

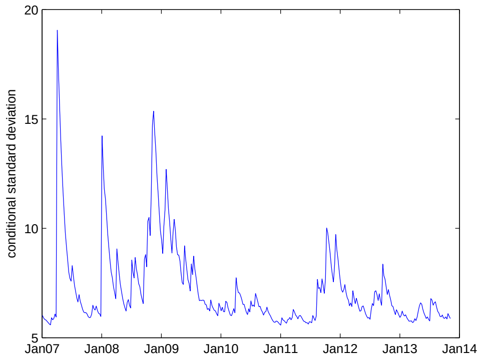
(a) BNP Paribas return volatility



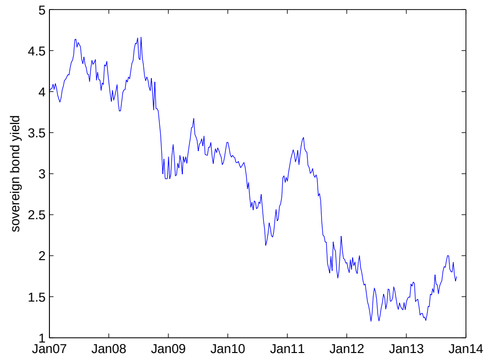
(b) French sovereign bond yields



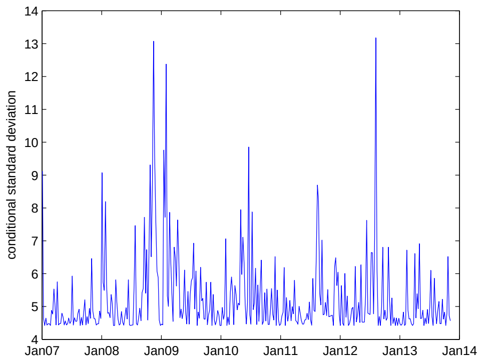
(c) Deutsche Bank return volatility



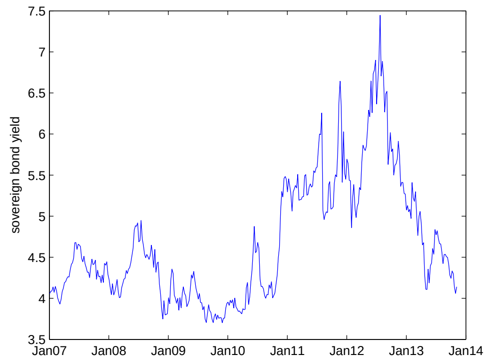
(d) German sovereign bond yields



(e) Santander return volatility



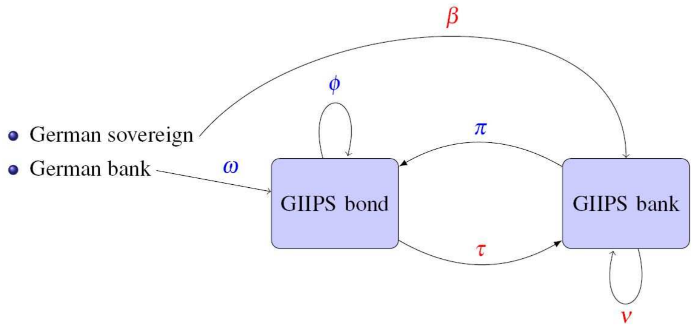
(f) Spanish sovereign bond yields



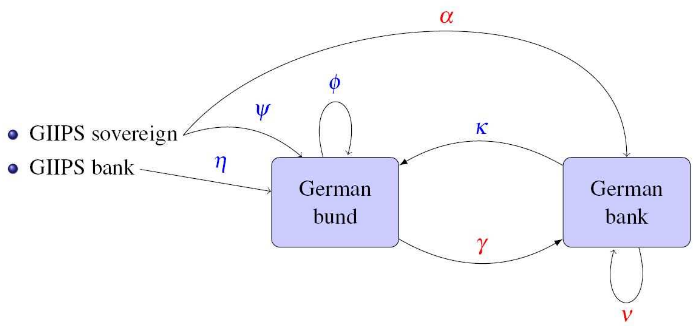
Note: Sample period: January 3, 2007 - November 6, 2013. This illustrates how banks respond to movements in the sovereign debt market. Asset return volatilities, which are at the left panel, were computed through obtaining the predicted conditional standard deviations from a Gaussian GARCH(1,1) estimation. Sovereign bond yields were obtained from Datastream.

Figure 3: Distributional linkages between bond and bank returns

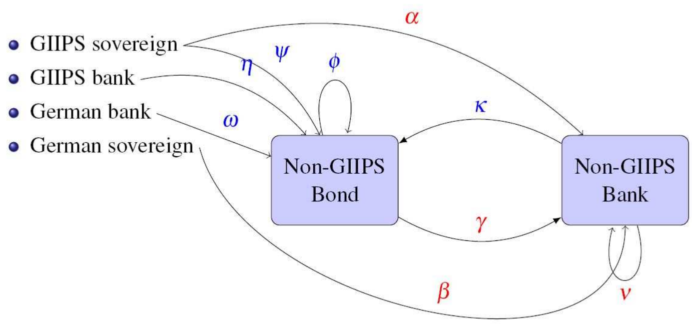
(a) GIIPS banks and sovereigns



(b) German banks and sovereigns



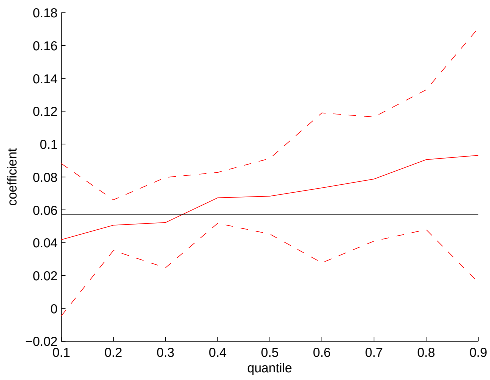
(c) Non-GIIPS, non-German banks and sovereigns



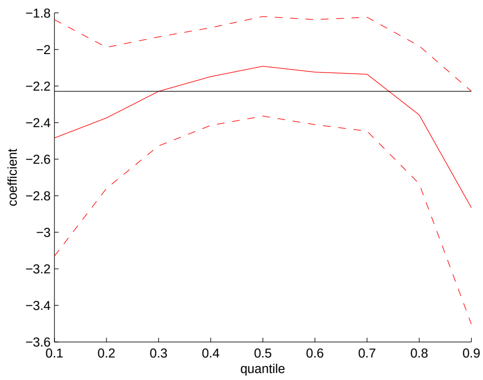
Note: This figure illustrates the linkages between bond and bank returns that are of interest, which we use to parameterise the quantile functions estimated in sections 3, 4 and 5. Each subfigure illustrates the linkages relevant to the group of banks and sovereigns labelled below it. The red parameters correspond to those of the bank equation (1) blue parameters correspond to the parameters of the bond equation (2).

Figure 4: OLS and QR coefficients of the bank equation in the baseline model

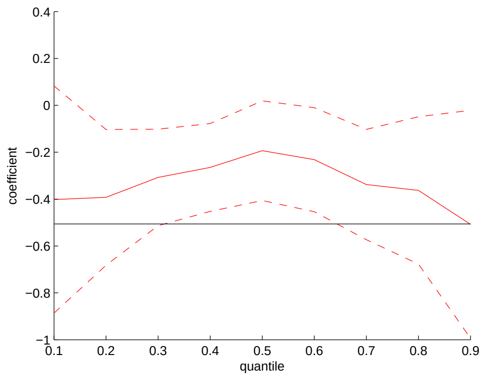
(a) GIIPS bond on non-GIIPS bank



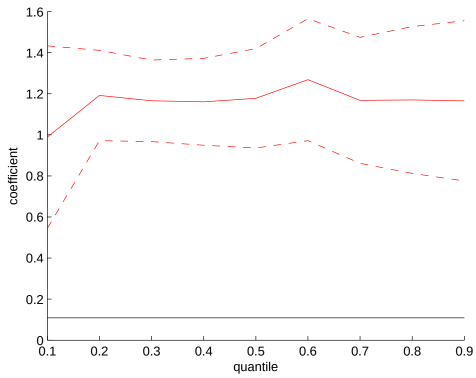
(b) German bond on non-German bank



(c) Own bond effect for non-GIIPS countries



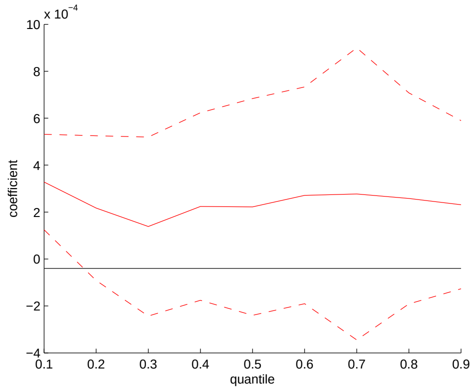
(d) Own bond effect for GIIPS countries



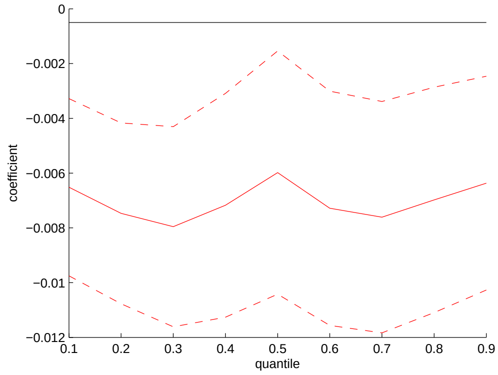
Note: This illustrates the graphs of the OLS and the quantile regression (QR) coefficients of the baseline model equation (3). The x-axis corresponds to the quantile level, while the y-axis corresponds to the coefficient value. The black line corresponds to the OLS coefficient, while the red line corresponds to the quantile regression coefficients. The dashed red lines correspond to the quantile regression 90 % confidence bands.

Figure 5: OLS and QR coefficients of the bond equation in the baseline model

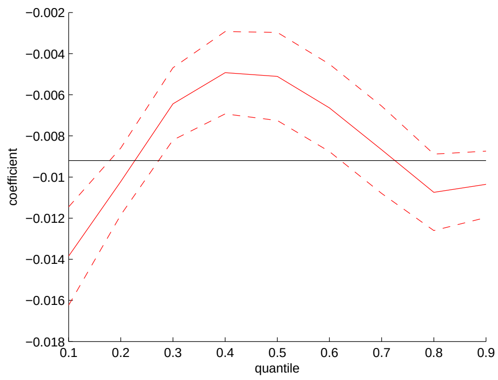
(a) GIIPS bank on non-GIIPS bond



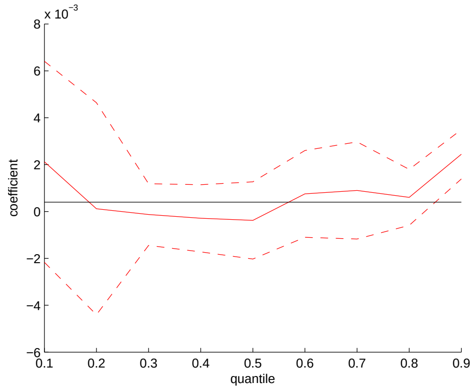
(b) German bank on non-German bond



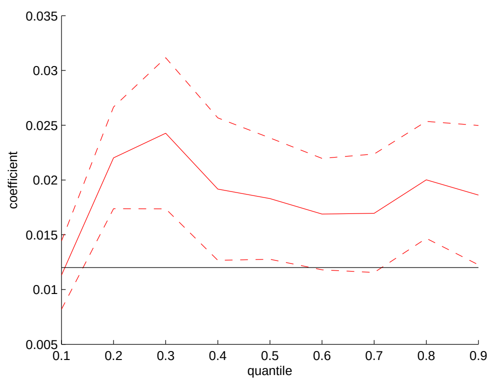
(c) Own bank effect for non-GIIPS countries



(d) Own bank effect for GIIPS countries



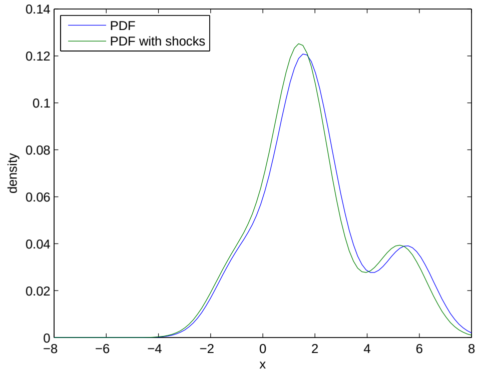
(e) GIIPS bond on non-GIIPS bond



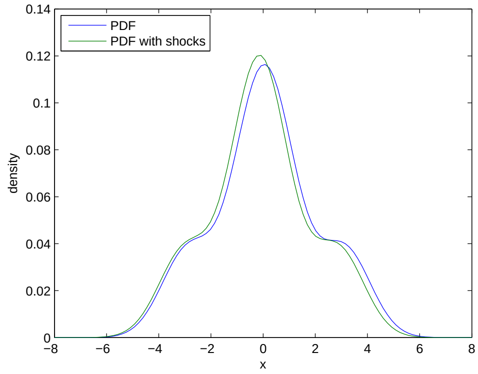
Note: This illustrates the graphs of the OLS and the quantile regression (QR) coefficients of the baseline model equation (4). The x-axis corresponds to the quantile level, while the y-axis corresponds to the coefficient value. The black line corresponds to the OLS coefficient, while the thick red line corresponds to the quantile regression coefficients. The dashed red lines correspond to the quantile regression 90 % confidence bands.

Figure 6: Sensitivity analysis of conditional densities, BNP Paribas

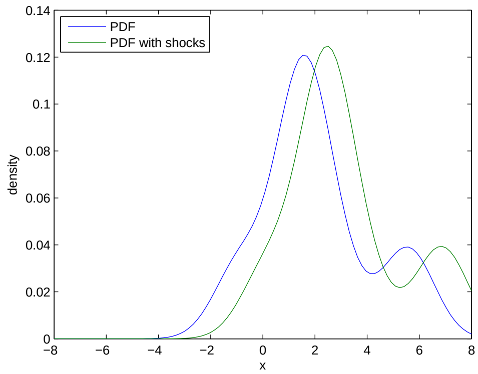
(a) GIIPS bond shock, June 2007



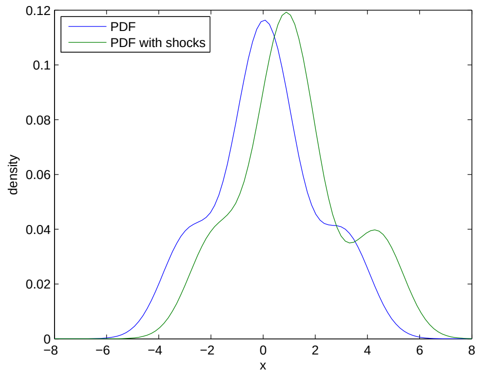
(b) GIIPS bond shock, December 2009



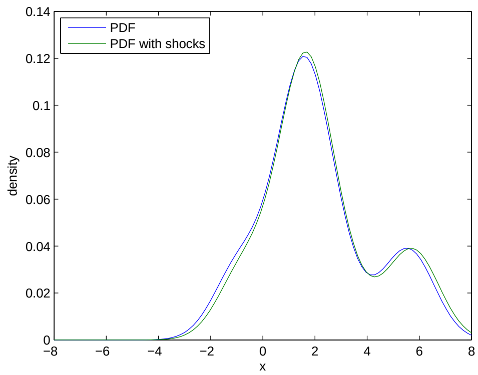
(c) German bond shock, June 2007



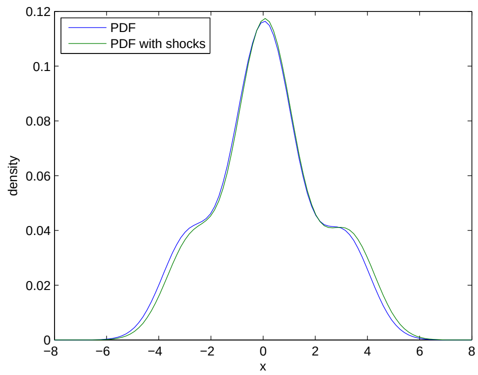
(d) German bond shock, December 2009



(e) French bond shock, June 2007



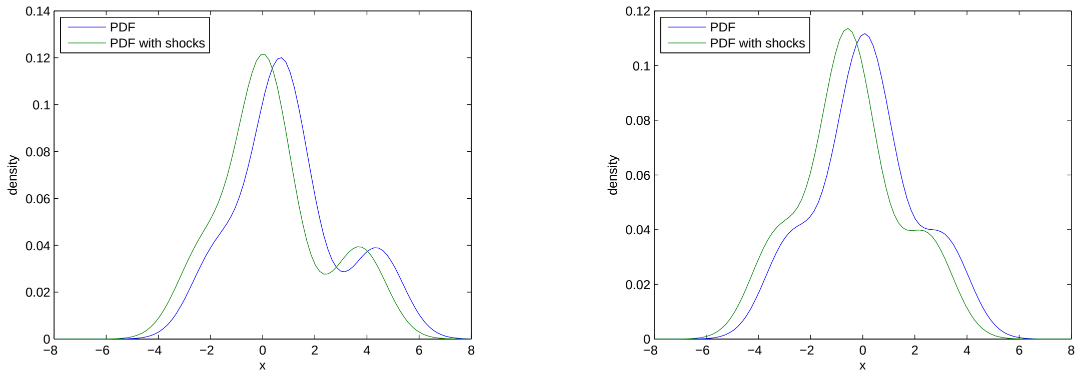
(f) French bond shock, December 2009



Note: This illustrates the conditional return density of BNP Paribas computed through the kernel interpolation methodology at two different chosen dates, and the impact on the density if there is a shock on the the corresponding sovereign bond (or bonds) in the title that makes the returns lower by the standard deviation of that bond (or in the case of the GIIPS bonds, the weighted standard deviation) in the sample. The dates chosen were a pre-crisis date (June 2007) and a crisis date (December 2009). The blue line corresponds to the original conditional density, while the green line corresponds to the conditional density with shocks.

Figure 7: Sensitivity analysis of conditional densities, Banco Santander

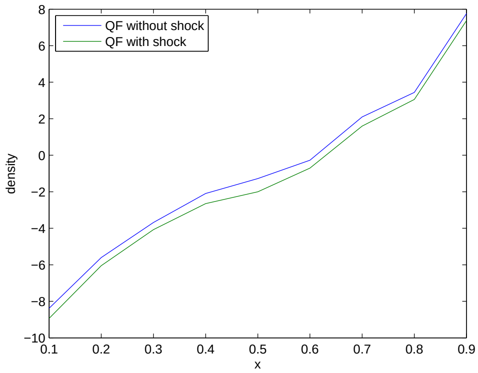
(a) Spanish bond shock, June 2007 (b) Spanish bond shock, December 2009



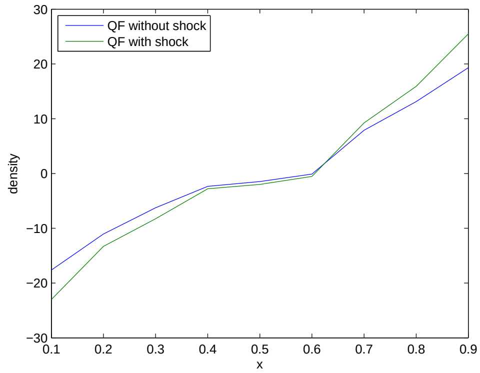
Note: This illustrates the conditional return density of Banco Santander computed through the kernel interpolation methodology at two different chosen dates, and the impact on the density if there is a shock on the the corresponding sovereign bond in the title that makes the returns lower by the standard deviation of that bond in the sample. The dates chosen were a pre-crisis date (June 2007) and a crisis date (December 2009). The blue line corresponds to the original conditional density, while the green line corresponds to the conditional density with shocks.

Figure 8: Sensitivity of conditional quantile functions over time to a permanent shock

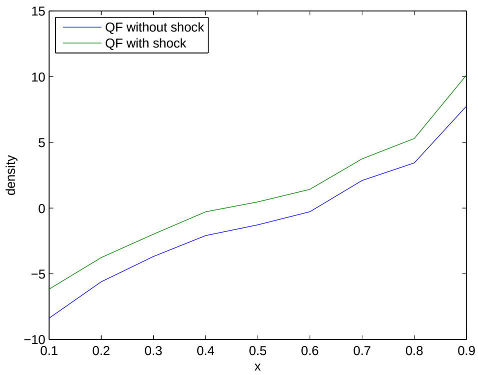
(a) 1 month ahead, GIIPS bond shock



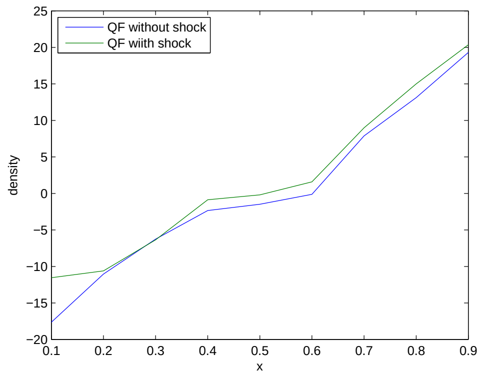
(b) 1 year ahead, GIIPS bond shock



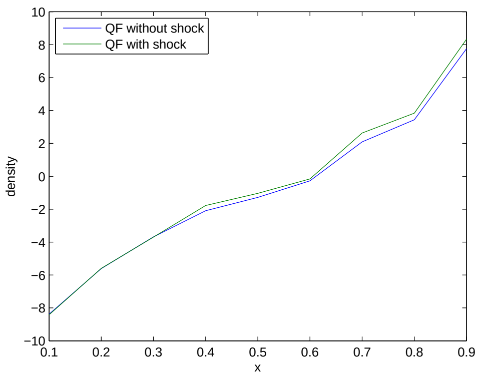
(c) 1 month ahead, German bund shock



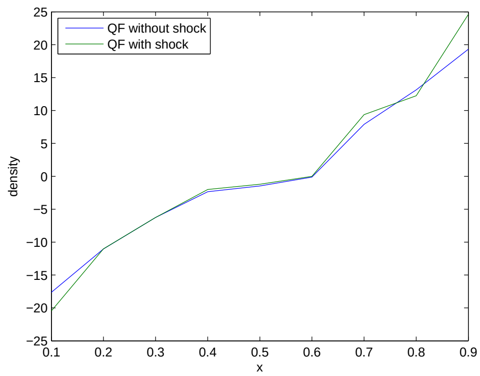
(d) 1 year ahead, German bund shock



(e) 1 month ahead, French bond shock



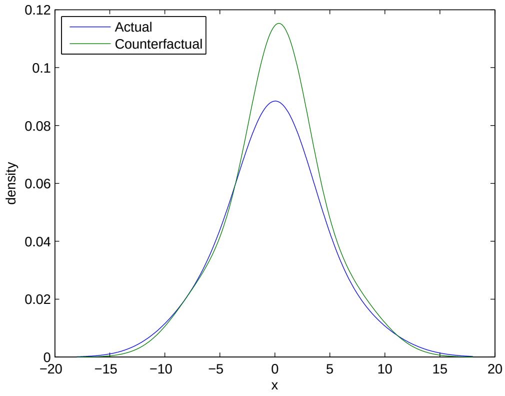
(f) 1 year ahead, French bond shock



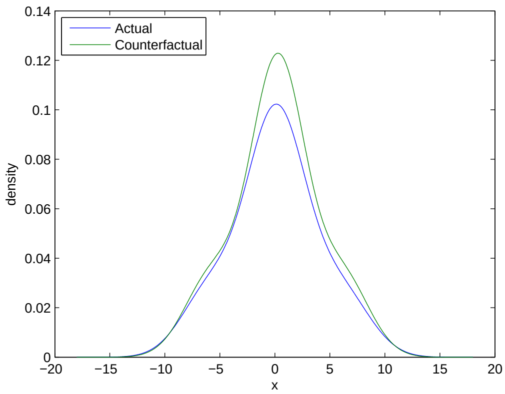
Note: These illustrate the evolution over time of the conditional quantile functions with and without a shock for BNP Paribas, where the shock being studied is a permanent shock on the sovereign bond (or bonds) of interest. The blue line corresponds to the conditional quantile function without a shock, while the green line corresponds to the conditional quantile function with a shock. The x-axis corresponds to the quantile level, while the y-axis corresponds to the quantile function value.

Figure 9: Actual and Counterfactual Densities of Bank Asset Returns

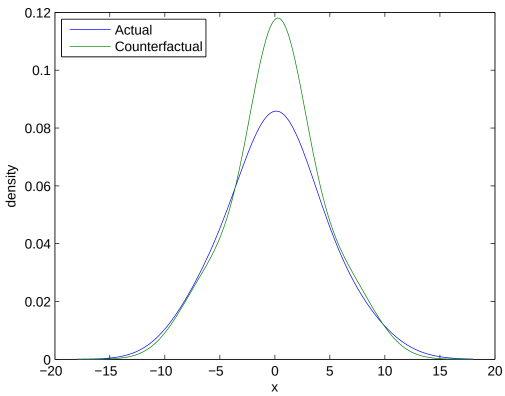
(a) BNP Paribas



(b) Deutsche Bank



(c) Banco Santander



Note: This illustrates the actual and counterfactual densities for the following banks: BNP Paribas, Deutsche Bank, and Banco Santander in the situation that there was no sovereign debt crisis; that is, the marginal distribution of sovereign bond returns is assumed to be the pre-crisis period marginal distribution. The blue line corresponds to the actual kernel density, while the green line corresponds to the counterfactual kernel density. The date chosen was for the analysis was December 2009.