Sovereign debt crisis and differential bond market dependencies in the eurozone : A dynamic copula approach

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Abstract

We examine the dependency between the European government bond markets around the recent sovereign debt crisis. A dynamic copula approach is used to model the time-varying dependence structure of those government bond markets, evaluate the nature and strength of their dependencies over time, and gauge the transmission of the crisis shocks. Our results can be summarized as follows: *i*) the eurozone sovereign bond markets under consideration have a significant dependence with the Greek and the EMU benchmark sovereign bond markets; *ii*) the Dynamic BB7 copula function best describes the dependence structure between these sovereign bond markets and provides evidence of asymmetric tail dependence; iii) the conditional probability of crisis transmission from Greece to other eurozone countries is higher than the other way around; and iv) Greece is the most vulnerable country when the eurozone entered into the sovereign debt crisis.

Keywords: Eurozone, sovereign debt crisis, government bonds, dynamic copulas, time-varying dependence.
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1. Introduction

The eurozone debt crisis started in the sovereign credit sectors of the weak economies of Greece, Portugal, Ireland, Italy and Spain following the 2007/2008 global financial crisis that started in the United States and then spread globally (De Santis, 2012; Baur, 2012; Bekiros, 2013). These debt-sensitive economies had managed for some time to borrow huge amounts of money at attractive rates, which was facilitated by being remembers of the eurozone. They hoped to bridge the gap between their economies and those of the economic powers Germany and France. However, most of the borrowed money did not go into building strong economic infrastructure, and later the borrowing countries have had trouble paying back their borrowed loans. Some of the debt money went to overleveraged financial institutions as the financial turmoil has spilled over into the banking sectors, contributing to bank runs and market seizures. This has forced national governments to guarantee those sectors, adding new debt to existing sovereign debt and heaping more debt upon those governments.[1] Consequently, investors have demanded higher yields in order to hold the sovereign debts of those countries. Therefore, higher interest rates on the sovereign debt of those heavily indebted countries have exacerbated the crisis (Dell'Ariccia et al., 2012).

To the extent that the eurozone economies are quite heterogeneous in terms of industrial structure, fiscal practices, economic performance and that some of them are highly uncompetitive and shackled by a "too strong" common currency, the eurozone crisis has provided an ideal environment for researchers to examine the reasons behind and the implications of the recent sovereign debt crisis in this region. The research has dealt with issues related to contagion between stock, government bond and sovereign CDS markets for low and high risk countries in the European Monetary Union (EMU) and eurozone countries.

[1] For example, in May 2010, the European Union and IMF provided €110 billion ($140 billion) in bailout loans to Greece to help its government pay its creditors. It soon became apparent that this amount would not be enough, so a second €130 billion bailout was agreed on later. In return for all these loans, the European Union and IMF insisted that Greece had to embark on a major austerity drive involving drastic spending cuts, tax increases, and labor market and pension reforms.

Several authors have examined the dynamics of the European sovereign bond markets before and with the occurrence of the eurozone financial crisis (e.g., Abad et al., 2010; Coronado et al., 2012). For instance, Abad et al. (2010) use a CAPM-based model of Bekaert and Harvey (1995) to compare the differences in the relative importance of two sources of systemic risk (the world vs. the eurozone factors) on government bond returns of two groups comprising countries in the EU-15. Their results show that euro markets are less vulnerable to the influence of the world risk factors, but more vulnerable to the EMU risk factors. The markets of the countries that decided to stay out of the Monetary Union exhibit a higher degree of vulnerability to external risk factors. Coronado et al. (2012) examine the lead-lag relationships between the sovereign Credit Default Swaps (CDS) and stock market for eight European countries over the period 2007-2010. They show a leading role for the stock markets over the sovereign CDS markets during the whole period, as the latter leads the former when the turbulent year 2010 is isolated from the rest of the stock markets, translating the credit risk to the private companies which holds the CDSs.[2]

During the eurozone debt crisis, existing works on the sovereign bond markets focus more on the influence of global financial conditions (e.g., Lane, 2012; Allen and Ngai, 2012; Haider, 2012), and the contagion issue and the extreme dependence between these markets and the sovereign CDS markets (e.g., Metiu, 2012; Fong and Wong, 2012; Arghyrou and Kontonikas, 2012; Beirne and Fratzscher, 2013; Philippas and Siriopoulos, 2013).[3] These studies uncover not only the main causes of the ongoing debt crisis but also the existence of several forms of contagion effects. Lane (2012) attributes the origin and propagation of the

[2] Norden and Weber (2009) also find a leading role of stock markets over the corporate CDS and bond markets during the period 2000-2002.

[3] Maltritz (2012) examines the determinants of sovereign bond yield spreads for the EMU and find evidence to suggest that fiscal and global financial conditions influence the sovereign spreads. In a related study, Bernoth and Erdogan (2012) show that macroeconomic fundamentals determine the sovereign differentials before 2006, while after that year there is a shift in investors' risk aversion which contributed to altering in risk pricing. Afonso et al. (2012) conduct an event study to analyze the reaction of government yield spreads before and after announcements from rating agencies and find significant responses of sovereign bond yield spreads to changes in rating notations and outlook, particularly if the announcements are negative.

eurozone sovereign debt crisis to the flawed original design of the euro. The author further argues that the “on the fly” management responses to the incremental multicounty crisis are destabilizing factors, and that the crisis provides an opportunity to implement reforms to improve resilience to future shocks. Allen and Ngai (2012) contend that attempts to contain the sovereign deficits and debts through the Stability and Growth Pack failed, and that the austerity programs have induced downward spirals in growth. Metiu (2012) tests for the contagion of credit events in euro area sovereign bond markets and finds evidence of significant contagion effects among long-term bond yield premia over the period from January 2008 to February 2012. Fong and Wong (2012) use the CoVaR methodology to study the tail risk relationships among European sovereign markets and show that some countries like Greece and Portugal are the most vulnerable during the ongoing debt crisis. Arghyrou and Kontonikas (2012) investigate the contagion during the EMU sovereign-debt crisis, and find evidence of contagion particularly among EMU periphery countries. The contagion was mainly originating from Greece in the early EMU debt crisis, but it actually involves multiple sources of contagion. Consistently, Beirne and Fratzscher (2013) examine the drivers of sovereign risk for 31 advanced and emerging economies during the European sovereign debt crisis, and document the presence of fundamental contagion (i.e., a sharp rise in the sensitivity of financial markets to fundamentals) and herding contagion (i.e., sharp, simultaneous increases in sovereign yields across countries) for some groups of countries including the eurozone ones. The contagion evidence for the EMU countries is also found in Philippas and Siriopoulos (2013) who use both regime-switching and time-varying copula models to examine this issue. For those authors, the macroeconomic imbalances for some countries and the sovereign’s risk perception and the arbitrage appetites of international bond portfolios for others are the main drivers of this contagion effect.

Some other studies focus on the dynamics of the sovereign CDS markets in order to infer the sovereign credit risk in the eurozone countries. They mainly find that: i) the liquidity of the sovereign CDS markets has a substantial time-varying impact on the sovereign bond credit spreads, in particular for several countries including Greece, Ireland and Portugal (Calice et al., 2013); ii) the CDS markets of Spain and Ireland have the biggest impact on the European CDS market, whereas the CDS market of the United Kingdom does not cause a big distress in the eurozone and Greece has a lower capacity to trigger a contagion (Kalbaska and Gątkowski, 2012); and iii) the higher the distress level, the larger the influence of the sovereign CDS market on the government bond markets (Delatte et al., 2012).

Out study extends the existing literature by attempting to identify the time-varying dependence structure of ten sovereign bond markets in the eurozone. It also questions the extent of crisis transmission between Greece and other eurozone markets around the Greek and European debt crisis. We are particularly motivated by the fact that the appetite and perception of debt risk are likely to change under the stress conditions of the crisis. While most of the published research on the eurozone debt crisis deal with this crisis before it completed its full course, our study concentrates on the full years of the crisis and also covers the 2007/2008 global financial crisis.

More precisely, our contributions are threefold. The first is to use a dynamic copula approach to model the time-varying dependence structure of the government bonds of ten major eurozone countries with respect to the Greek sovereign government bond market and the 10-year EMU benchmark government bond index. The ten countries include Austria, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, and Spain. Studies have found that euro markets are less vulnerable to the influence of the world risk factors but more so to EMU risk factors (Abad et al., 2010).

Second, our data-driven dynamic copula approach, which typically relies on the combination of the several copula and the Dynamic Conditional Correlation (DCC) model of Engle (2002), allows us to examine the strength and nature of the dependence among the eurozone sovereign bond markets through time. It also permits one to discern how the pricing of sovereign risk changes over the years of the eurozone debt crisis and to capture the possible asymmetric dependence in the tails of the distributions. To date, several recent studies have adopted the same modeling approach to macroeconomic and financial data, but they only consider the elliptical copulas such as the Gaussian and Student-*t* copulas), which ignores asymmetry and tail dependence (e.g., Wen et al., 2012; Berger, 2013). Our study thus extends this modeling framework to Archimedean copulas which account for these stylized facts.

Finally, we contribute to the related literature (e.g., Amisano and Tristani, 2011 and references therein) by investigating how the financial shocks which are related to the European sovereign debt crisis occurring in 2010 are transmitted to those eurozone countries. In particular, we explore the extent of crisis transmission between Greece and other eurozone markets around the Greek and eurozone debt crisis by examining the probability that a sovereign bond market experiences a crash event given that an extreme loss has already occurred in another market like the Greek market. We consider the Value-at-Risk (VaR) at the 99%, 99.5% and 99.9% confidence levels, which is a common tool to assess the markets' systemic risk as a measure of an extreme loss. Based on the empirical results of our dynamic copula approach, we also evaluate the probability of crisis transmission from Greece to other eurozone markets in extreme situations by making use of the extreme value theory.

The findings of our study thus provide valuable information to policymakers, regulators and investors about vulnerable countries during the ongoing debt crisis and crisis transmission directions within the eurozone. They should be of interest to various market participants since the presence of strong asymmetric dependence and contagion effects during bad times may generate tremendous portfolio losses and economic inefficiency.

The remainder of this article is organized as follows. Section 2 introduces the dynamic copula approach which we use to model the dependence structure among the eurozone government bond markets. Section 3 describes the data and their stochastic properties. Section 4 reports and discusses the obtained results. Section 5 concludes the paper.

2. Empirical method

This section successively presents the dynamic copula approach, marginal models, and estimation issues.

3.1 Dynamic copula models

Copulas are functions that link multivariate distributions to univariate uniform marginal distributions which are defined in the interval [0,1]. The most important characteristic of a copula is its ability to gauge the dependence structure (both average dependence and extreme dependence) between variables. The theory of copulas dates back to Sklar (1959)'s theorem based on which the joint distribution of two continuous random variables *X* and *Y*, $F_{XY}(x, y)$, with marginal functions $F_X(x)$ and $F_Y(y)$, is modeled by a copula function *C* such that:

$$F_{XY}(x, y) = C\big(F_X(x), F_Y(y)\big)\ for\ all\ x, y \in R \tag{1}$$

where *X* and *Y* represent any two government bond returns in our study. According to Eq. (1), if $F_X(x)$ and $F_Y(y)$ are continuous, *C* is uniquely determined on $RanF_X \times RanF_Y$. On the other hand, if *C* is a copula and F_X and F_Y are cumulative distribution functions of two random variables under consideration, $F_{XY}(x, y)$ is thus the joint function with margins F_X and F_Y.[4] This feature implies that copulas can be used to connect margins to a multivariate distri-

[4] More details about copulas and their fundamental properties can be found in Joe (1997) and Nelsen (1999).

bution function which, in turn, can be decomposed into its univariate marginal distributions. Consequently, a copula is suitable for modeling the conditional dependence structure of variables independently from their margins, thus providing greater flexibility than the parametric multivariate distributions.

Another important feature of copulas is the possibility of estimating the upper and lower tail dependence between variables X and Y, which is invariant under strictly increasing transformation of X and Y. Here the upper and lower tail dependence coefficients refer to the probability that both variables are jointly in the right and left tails of their distributions, where the tails are defined by a certain upper and lower thresholds. They are defined as follows:

$$\lambda_U = \lim_{t \to 1} Pr[X \geq F_X^{-1}(t) | Y \geq F_Y^{-1}(t)] \tag{2}$$

$$\lambda_L = \lim_{t \to 0} Pr[X \leq F_X^{-1}(t) | Y \leq F_Y^{-1}(t)] \tag{3}$$

where F_X^{-1} and F_Y^{-1} are the quantiles of the marginal distributions. λ_U and λ_L are bounded between 0 and 1. Any two random variables exhibit upper and lower tail dependence if $\lambda_U > 0$ and $\lambda_L > 0$. They display asymmetric tail dependence if λ_U is not equal to λ_L.

To model the conditional dependence structure between government bond returns in eurozone countries, we make use of four types of bivariate copulas including Gumbel , SJC , BB1 and BB7 which belongs to the Archimedean copula family. These asymmetric copula with higher probability concentrated in both tails of the return distributions are also found to be suitable for modeling the dependence of financial time series.

The Gumbel copula is given by

$$C(u, v; \delta) = exp\left(-\left[(-lnu)^{\delta} + (-lnv)^{\delta}\right]^{1/\delta}\right) \tag{4}$$

where u and v are the uniform marginal distributions of the random variables under consideration, X and Y, and $\delta \in [1, \infty)$ measures the degree of dependence between u and v, with higher values implying greater dependence. The coefficient of the upper tail dependence is

$\lambda_U = 2 - 2^{1/\delta}$, while the coefficient of the lower tail dependence is $\lambda_U = 0$. There is independence between the variables when $\delta = 1$. Perfect dependence occurs when $\delta \to +\infty$.

BB1 copula (Joe,1997) has the following functional form :

$$C_{bb1}(u_1,u_2,\kappa,\gamma) = (1+[\left(u_1^{-\kappa}-1\right)^{\gamma}+\left(u_2^{-\kappa}-1\right)^{\gamma}]^{1/\gamma})^{-1/\kappa}, \kappa \in (0,\infty), \gamma \in (1,\infty) \quad (5)$$

The BB1 copula has upper and lower tails given by $\lambda_u = 2-2^{1/\gamma}$ $and \lambda_l = 2^{-1/\kappa\gamma}$

The BB7 copula has the following functional form:

$$C_{bb7}(u_1,u_2,\kappa,\gamma) = 1-\left(1-(\left(1-(1-u_1)^{\kappa}\right)^{-\gamma}+[1-(1-u_2)^{\kappa}]^{-\gamma}-1)^{-1/\gamma}\right)^{-1/\kappa}, \quad \kappa \in (1,\infty), \gamma \in (0,\infty) \quad (6)$$

similarly it has both tails given by $\lambda_u = 2-2^{1/\kappa}$ $and \lambda_l = 2^{-1/\gamma}$ while its dependence dynamics are the same to those of the BB1.

The SJC copula defined by Patton (2006) takes the following form:

$$C_{SJC}(u_1,u_2 / \lambda_U, \lambda_L) = 0.5.(C_{JC}(u_1,u_2 / \lambda_U, \lambda_L) + C_{JC}(1-u_1,1-u_2 / \lambda_U, \lambda_L) + u_1 + u_2 - 1) \quad (7)$$

where C_{JC} is the Joe-clayton copula defined above with $\kappa = 1/\log_2(2-\lambda_u), \gamma = -1/\log_2(\lambda_l)$ and $\lambda u, \lambda_L \in (0,1)$

It is now common that dependence between financial time series changes through time. Past studies such as Patton (2004, 2006) and Jondeau and Rockinger (2006) have mainly developed time-varying copulas by letting the copula parameter follow an autoregressive or a GARCH-type specification. We also model the time-varying dependence, but base it on a dynamic equation similar to the dynamic conditional correlation (DCC) specification of Engle (2002) as given in Eqs. (8) -(10).

$$R_t = diag\left\{Q_t^{-(\frac{1}{2})}\right\} Q_t diag\left\{Q_t^{-(\frac{1}{2})}\right\} \quad (8)$$

$$Q_t = (1-\alpha-\beta)\bar{Q}_t + \alpha\hat{\varepsilon}_{t-1}\hat{\varepsilon}'_{t-1} + \beta Q_{t-1} \quad (9)$$

$$\rho_t = (Q_t^*)^{-1} Q_t (Q_t^*)^{-1} \quad (10)$$

where R_t is the (2×2) symmetric matrix of dynamic conditional correlations. Q_t and $\bar{Q}$ are the (2×2) symmetric positively-defined matrices of the conditional and unconditional variance-covariance of the returns' standardized residuals from the marginal models, $E(\hat{\varepsilon}_{t-1}\hat{\varepsilon}'_{t-1})$. The parameters α and β which measure the persistence and strength of the past correlation are the unknowns to be estimated, satisfying the conditions: $\alpha > 0$, $\beta > 0$ and $\alpha + \beta \leq 1$. These specifications guarantee the positivity of R_t. Notes that Q_t^* is a (2×2) matrix with zeros as off-diagonal elements and the square root of the matrix Q elements as diagonal elements. The coefficients ρ_t are thus the off-diagonal element of the matrix R_t and corresponds to the dynamic conditional correlation between two random variables under consideration, which is confined in the range $[-1,1]$.

We can then deduce Kendall's tau (τ) from ρ_t as in Eq. (11) and elaborate the relationship between Kendall's tau and the Gumbel, SJC, BB1 and BB7 copula dependence parameter (δ), (κ, γ) as in Eq. (12) such as[5]

$$\tau_t = 2\arcsin(\rho_t)\,/\pi \tag{11}$$

$$\tau_t = 4\int_{[0,1]^2} C(u, v; \delta, \kappa, \gamma)\, dC(u, v; \delta, \kappa, \gamma) - 1 \tag{12}$$

It is worth noting that the computation of the copula dependence parameter from Kendall's tau has become standard in the previous literature as the latter captures the nonlinearity in the dependence structure, which is ignored by the linear correlation coefficients. Overall, the four time-varying copulas modeling as described above (DCC Gumbel copula, DCC-SCJ, DCC-BB1 and DCC-BB7) are highly efficient and flexible for capturing not only the changing dependence structure, but also the potential of asymmetric tail dependence. While several studies have recently adopted the same approach to macroeconomic and financial data, they only consider the elliptical copulas (i.e., the Gaussian and Student copulas), which ignores asymmetry and tail dependence (e.g., Wen et al., 2012; Berger, 2013; Sriboonchitta, 2013). Our results show that ignoring these stylized features in modeling the dependence of sovereign bond returns leads to erroneous dependence assessment.

3.2 Models for marginal distributions

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[5] See, for example, Heinen and Valdesogo (2008) for more details.

In order to estimate the Dynamic copulas copula in Eq. (4) (5) (6) and (7), the univariate marginal distributions of the variables are essential. Since return series frequently exhibit leptokurtic behavior, serial correlation, time-varying volatility and asymmetric volatility responses to positive and negative shocks, we use an ARMA process to model the conditional mean of the return series with a threshold generalized autoregressive conditional heteroscedasticity (TGARCH) process (Glosten et al., 1993; Zakoian, 1994).

More precisely, the marginal model for return series takes the following form:

$$r_t = \phi_0 + \sum_{j=1}^{p} \phi_j r_{t-j} + \varepsilon_t - \sum_{i=1}^{q} \theta_i \varepsilon_{t-j} \tag{13}$$

where p and q are nonnegative integers. ϕ and θ are the autoregressive and moving-average parameters, respectively.

The residuals ε_t of the conditional mean equation is assumed to follow a Student-*t* distribution with υ degrees of freedom, with the conditional variance σ_t^2 evolving over time according to Eq. (14):

$$\sigma_t^2 = \omega + \sum_{j=1}^{s} \varphi_j \sigma_{t-j}^2 + \sum_{i=1}^{m} \epsilon_j \varepsilon_{t-i}^2 + \sum_{j=1}^{m} \gamma_j \varepsilon_{t-j} I_{t-j} \tag{14}$$

where ω is a constant, σ_{t-j}^2 the lagged conditional variance (the GARCH component), and ε_{t-j} the return innovation (the ARCH component). I_{t-j} takes the value of 1 if $\varepsilon_{t-j} < 0$ and zeros otherwise. The parameter γ captures the leverage effects and if it is positive, the negative shock has greater impact on the conditional variance than a positive shock of the same magnitude. The optimal lag lengths (p, q, m, and s) are selected on the basis of the Akaike information criterion (AIC).

3.3 Copula estimations

As we are only interested on the bivariate relationships between the same detailed signal for different pairs of financial market indexes, the marginal distribution for each detail is modeled via a non parametric approach. In other words, to avoid model misspecifications by assuming a parametric form for the marginal distributions, we consider empirical cumulative distribution functions (ecdf) for all details. In a second moment, using maximum likelihood estimation, we obtain the copula parameters estimates. This method is called CML - *Canonical Maximum Likelihood*[6]. It comes from the idea of approximating an unknown parametric distribution function through empirical distribution functions defined as

$$\hat{F}_n(\cdot) = \frac{1}{T}\sum_{t=1}^{T} 1_{[X_{nt} \le \cdot]} \text{ for } n = 1, \ldots, N,$$

where $1_{[X_{nt} \le \cdot]}$ is an indicator function. In a general form, the CML method is performed in two steps:

1) transform each detailed signal *j* for each index return *i* into uniform variables using ecdf, i.e., $\hat{u}^i_{jt} = \hat{F}_j(d^i_{jt})$;
2) estimate the copula parameter vector via maximum likelihood using the transformed marginals obtained in the previous step. Thus, obtain

$$\hat{\lambda}^{CML} = \underset{\lambda}{\operatorname{argmax}} \sum_{t=1}^{T} \ln c(\hat{u}_{it}{}^{j}, \hat{u}_{it}{}^{m}; \lambda\ (S_t)),\quad j \ne m \tag{16}$$

where c is the copula density

3.4 Goodness-of-fit tests

The evaluation of goodness-of-fit for the marginal models is crucial to the construction of the copula models. If the marginal distributions are misspecified, their probability integral transform $\hat{u}_t = F_X(x_t, \hat{\alpha}_x)$ and $\hat{v}_t = F_Y(y_t, \hat{\alpha}_y)$ will not be *i.i.d* uniform [0,1], which leads to the misspecification of the copula.

For this purpose, we first evaluate the *i.i.d.* assumption by examining the serial correlation of $(\hat{u}_t - \bar{u})^k$ and $(\hat{\upsilon}_t - \bar{\upsilon})^k$ of both variables at *h* lags and for *k* = 1, 2, 3, 4. Second, we test the null hypothesis that $\hat{u}_t$ and $\hat{v}_t$ are uniform [0,1] using the well-known Kolmogorov–Smirnov, Cramer–von Mises and Anderson–Darling tests, all of which compare the empirical distribution and the specified theoretical distribution function.

[6]This is just the pseudo-likelihood estimator of Genest et al (1995).

Two goodness of fitting tests are used in this paper (Introduced by Genest et al.(2006,2011) to evaluate the copula fitting. These latter are based on the empirical copula, Pickand dependence function as well as Cramer-Von mises distances .In doing so, the test statistics are given by

$$S_n = \int \{C_n(u,v) - C_\theta(u,v)\}^2 dC_n(u,v)$$

And $$M_n = \int_0^1 n \left|A_n(t) - A_{\theta_n}(t)\right|^2 dt \qquad (17)$$

The first statistic S_n measures how close the fitted copula $C_{\theta_n}$is to the empirical copula C_n while the second test M_n reflects the distance between a non parametric rank-based estimator of the pickands dependence function $A_n$and a parametric estimation A_{θ_n}. Large values of the computed tests lead to reject the null hypothesis that the estimated copula belongs to an empirical copula family i.e. the considered will not be the best candidate for the data)

4. Data and empirical results

4.1 Data

We consider the daily yields for the 10-year government bonds of ten EU countries that belong to the eurozone, namely: Austria, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal and Spain. The data for all countries correspond to the Thomson Reuters' government bond indices and are the end-of-day 10-year government bond yields as calculated by Datastream. We also consider the 10-year EMU benchmark government bond index as the overarching impact factor related to those government bonds. This index represents the fixed rate government debt in the EMU and has been used in previous studies to compute the government bond markets' relative risk, compared to stock markets as well as the time-varying credit risk premium in the government bond market (e.g., Abad et al., 2011).

All data are expressed in euros and are extracted from Datastream database. The sample spans the period from September 15, 2008 to October 26, 2012. It thus enables to capture the two distinct phases in the linkages between government bond returns in the eurozone. The first phase corresponds to the most severe episode or the heart of the global financial crisis (from September 15, 2008 to December 31, 2009) and the second coincides with the duration of the European sovereign debt crisis that occurred in the wake of the global financial crisis (from January 1, 2010 to October 26, 2012).

[Please insert Table 1 about here]

The government bond returns are compounded continuously and computed as the difference in the logarithm between two successive index prices. Table 1 summarizes the statistical properties of these daily return series. As can be seen, the government bond returns are positive for all countries, except Ireland and Spain where bond returns are negative reflecting the unusual impact of the sovereign crisis on those countries. The bond return distributions are leptokurtic and positively skewed, except for Australia and Portugal in light of their corresponding excess kurtosis and skewness coefficients. The non-normality is clearly confirmed by the Jarque-Bera test. The Engle (1982) test for conditional heteroscedasticity indicates the rejection of the null hypothesis of no ARCH effects. Taken together, the evidence of asymmetry, leptokurtic behavior and ARCH effects justifies our choice of the TGARCH model to filter the raw returns before they can be used in copula dependence modeling.

4.2 Estimation results of the marginal distributions

Table 2 reports the results of the best specification of the TGARCH model for the government bond returns in our sample countries. For all the cases, the TGARCH(1,1) is the best suited model for the sample data. The estimation results suggest that the TGARCH is flexible enough to capture the stylized facts of conditional volatility of government bond returns. Indeed, the estimated coefficients of this model are highly significant and there is no remaining autocorrelation in both the residuals and the squared residuals, except in Germany where the residuals exhibit serial correlation at the 5% level.

[Please insert Table 2 about here]

It should also be noted that the conditional volatility of the government bond returns is very persistent as the sum of the estimated ARCH and GARCH coefficients is close to unity. Moreover, the volatility leverage effect is significantly present in four eurozone countries (Spain, Ireland, Italy and EMU) out of the eleven series (as indicated by the coefficients γ. Finally, the degrees of freedom (v) which range from 4 to 11 imply that the data are still substantially non-normal. This finding thus suggests the suitability of the copula approach in modeling the potential of nonlinear and extreme dependence among the government bond returns.

4.3 Goodness-of-fit tests and choice of copula functions

Copula models perform better if the marginal distributions are correctly specified or , independently and identically distributed (*i.i.d*). To check this condition, we first transform the estimated residuals of the best-suited marginal model, TGARCH(1,1), into univariate variables using their empirical cumulative distribution functions and then use three of the most well-known goodness-of-fit tests (GoF) to examine the *i.i.d* assumption. These GoF tests include the Kolmogorov-Smirnov (KS) test, the Cramer-von Mises (CvM) test, and the Anderson-Darling (AD) test. We consider the null hypothesis that the empirical marginal distributions of the univariate variables are uniform [0,1] by comparing them to the theoretical distributions. The results which are reported in Table 3 indicate that the hypothesis of a uniform distribution cannot be rejected for all the residual series at the 1% level. We also perform the Ljung-Box test for autocorrelation in the estimated residuals (filtered returns) and the obtained results reject the presence of serial correlations in all cases.[7] Taken together, our GoF tests show that the estimated residuals from the selected marginal model are not mis-specified. Therefore, the empirical copula models can be employed to adequately capture the dependency between the sovereign bond returns.

[Please insert Tables 3-4 about here]

we compare the performance of the DCC Archimedean copulas with that of the DCC Gaussian and the DCC Student-*t* copulas. The log likelihood criterion selects the DCC BB7 copula as the best-suited model (Table 4). Similar results are obtained when we use the two fitting tests that are based on the empirical copula, Pickand dependence function as well as Cramer-Von mises distances. This empirical evidence thus suggests that presence of dependence structure for the euro zone sovereign bond markets with each of the EMU benchmark and the Greek sovereign bond markets.

4.4 Conditional dynamic correlations

The analysis of time-varying comovement among sovereign debt markets in the euro-zone is of particular interest as it allows one to investigate the strength of their dependence over time, and to link this dependence to major economic and financial events. Our investigation is based on the estimates of the dynamic conditional correlations (DCCs) given in Eq. (8).

[Please insert Figures 1-2 about here]

Figure 1 shows how the DCCs between the Greek and European sovereign bond markets evolve over time. Their dependence paths exhibit substantial fluctuations with both negative and positive values. Beside several important negative peaks, the DCCs are generally positive and higher during the most severe period of the European debt crisis (i.e., between the late 2009 and mid-2010) than the period onwards. This increase in the DCCs could poten-

[7] These results are not reported here for space limitation, but can be made entirely available upon request to the corresponding author.

tially be associated with contagion effects. Since 2011, the DCCs' values decrease substantially for both parameters oscillating almost between -0.2 and 0.2 values, which reflect the fact that other eurozone countries have implemented policy and technical measures to prevent the harmful and contagious effects of the Greek debt crisis, cutting herding mentality. These measures include, among others, the austerity policy, the public expense cuts, the structural economic reforms, and the recapitalization of domestic banks with exposures to the Greek debt securities.

Figure 2 depicts the evolution of the DCCs of the sample sovereign bond markets with the European benchmark (left panel) and Greek (right panel) markets. The right panel graphs show that the comovement patterns with the European sovereign bond benchmark market are generally different across the sample eurozone countries. Two main similarities can be noted. First, the comovement level is relatively high between September 2008 and mid-2010 and then a decreasing tendency is observed for most countries. This period covers the Great Recession and later the beginning of economic recovery in the United States. It also includes the beginning of the eurozone debt crisis. The exceptions are the sovereign bond markets in Austria, Finland, France and the Netherlands, whose dependence with the EMU benchmark still remains high until late 2011 and before a breakdown of comovement occurred. Note however that Finland, which has one of the highest growth rates in the eurozone, still continues to have a high degree of comovement with the EMU benchmark market. Second, for most countries in our sample, the decreasing tendency in their comovement with the EMU benchmark experiences between 2010 and 2011, but starts to rise since the end of 2012. In particular, four countries, which are the highly indebted Ireland, Italy, Portugal, and Spain, have relatively similar patterns of comovement with the EMU benchmark as their economies share many economic and public debt characteristics in common. Together with Greece, they are identified as the five most at-risk economies during the European sovereign debt crisis.

The right panel of Figure 2 indicates that the time-paths of the DCCs between the Greek and other eurozone sovereign bond markets are similar. They can be divided into two dynamic phases. The first phase, which is related to the most severe period of the global financial and European debt crises (September 2008 to April 2010), is characterized by a high comovement level. The second period from mid-2010 until the end of our estimation period (October 2012) is characterized by a close-to-zero or even negative comovement, except for the Greece-Spain pair where the comovement reached some high values during the first haft of 2011 and for the Greece-Portugal pair where the comovement sharply rose in early 2012. Those countries are well known for their high sovereign credit risk premium.

4.5 Dependence structure of the eurozone sovereign bond markets

We now examine the conditional dependence between each national eurozone sovereign bond market and the EMU sovereign bond benchmark. Table 5 reports the estimation results of the dynamic BB7 copula parameters. Recall that the conditional dependence parameter of the BB7 copula is computed through the estimation of the parameters of the dynamic conditional correlation (DCC) processes for the pairs of the markets under consideration (e.g., France and EMU benchmark). A close look at the DCC's estimated α and β coefficients, which respectively measure the strength of the past correlation and its persistence, shows that these coefficients are in general highly significant. The high values of the β coefficients as compared to those of the α coefficients suggest that the DCC processes depend much more on the past conditional correlation and do not change much with respect to correlation shocks which are caused by changing markets conditions. Taken together, the high significance of the DCC processes attests that the dependence structure is time-varying, and thus a constant copula model is not adequate for modeling the dependence between these sovereign bond markets. Additionally, the stationarity condition for the DCC BB7 copula is guaranteed as the sum (α + β) is close to, but less, than unity. This evidence suggests a high degree of dependence persistence through time.

[Please insert Table 5 about here]

The value and significance level of the estimated coefficients κ, γ are of greater interest in our study as they reflect the degree to which the sovereign bond returns in a particular country is dependent with that those of the EMU benchmark sovereign bond market. The higher this copula dependence parameter, the stronger is the dependence level. We see that both copula dependence parameters are positive and significant for all pairs of the markets under consideration. They vary across the pairs of the markets and ranges from1.022 (NDR-EMU) to 1.269(GER-EMU) for the first parameter while the second one ranges between 0.551 (GRE-EMU) and 0.818 (GER-EMU) .There are two blocks of the markets that have relatively high and similar levels of dependence with the EMU benchmark index. The first block includes France, Finland, Italy, and Germany with a relatively high degree of dependence. The second one covers Ireland, the Netherlands, Portugal and Spain with a relatively lower degree of dependence which is mostly dominated by high debtors.

These findings thus suggest that the sovereign bond markets in the eurozone have a certain level of integration which typically depends on the relative size of debt, the economic importance and political influence of the particular country in question. There is finally evidence of asymmetric tail dependence between each sovereign bond market and the EMU benchmark market since both tail dependence coefficients are positive and significant at the 1% level, the lower tail estimates are more pronounced than the upper tail values providing evidence on the fact that the pair wised bond markets are likely to crash together. The highest upper tail dependence with the EMU benchmark is found for Germany, followed by Finland. Germany is different from most of the eurozone members since it is the strongest and largest economy in Europe and has responsibilities towards highly indebted fellow countries. The

European economic integration has also benefited Germany more than other members in the eurozone since it increased its global competitiveness at the expense of other eurozone countries. This country had been protected by its triple A rating and still has stable outlook buffeted by strong exports to China, Australia and Southeast Asian countries. Moreover, the EMU benchmark suffers from aggregation bias.

[Please insert Table 6 about here]

We also investigate the dependence structure of sovereign bond returns between each eurozone country and Greece. Greece is chosen as the central part because it had been at the roots of the eurozone sovereign-debt crisis during 2009-2012, which was triggered by the advent of the recent global financial crisis and the Great Recession of 2008-2009.[8] The estimation reported in Table 6 shows evidence of significant and positive dependence on average for all pairs of the countries. Sovereign bond markets in the peripheral countries (Spain, Portugal and Italy) have the highest degree of dependence with changes in the Greek sovereign bond market, while the average dependence is the least for Germany with reference to the first dependence parmater. Similar results are provided by the second parameter when France have show the highest dependence level .

It is worth noting that the dependence structure is time-varying and persistent regardless of the pairs considered, in view of the high significance of the DCCs' α and β parameters. Moreover, we see that the estimates in Table 6 are in general lower/higher than those in Table 5, specifically to the country, suggesting that Greece's integration with the whole eurozone system is still weak. The economic failure of Greece will probably not cause much trouble to

[8] Indeed, the fears and signs of a sovereign debt crisis in the euro-zone happened following the investors' concerns about the Greece's ability to meet its debt obligations which is due to its highly elevated sovereign debt levels, structural weaknesses, and high structural deficits. This loss of confidence has caused the sharp rise in Greece's borrowing cost, as reflected by the huge widening of its sovereign bond yield spreads, compared to those of other countries in the eurozone. Following the downgrade of the Greek government debt to the junk bond status in April 2010, Greece's access to international capital markets was practically blocked. For this reason, the European Union and the International Monetary Fund (IMF) asked Greece to implement austerity measures and structural reforms in order to obtain the €110 billion bailout loan.

the some eurozone countries. Finally, there is also evidence of asymmetric tail dependence since both tail coefficients are highly significant. The French sovereign debt market has the highest right tail dependence with the Greek market, this latter is also more pronounced that the left tail value. It is worth noting that Austria and Portugal have very close tail amplitudes while the lowest tail dependence is found between Germany and Greece. The aforementioned countries have not great probability of booming nor crashing together. Even though German and French lenders are the biggest foreign holders of Greek government bonds, the German market is less exposed to changes in the quality of the Greek public debt owing to Germany's resilient and strong economic fundamentals.

4.5 Crisis transmission analysis

4.5.1 VaR-based approach

The DCCs and copula-based dependence results in Subsections 4.3 and 4.4, respectively, show that the sovereign bond markets in the eurozone countries have a certain degree of integration and substantial dependence with both the EMU and Greek debt markets. These results are expected given the increased economic, financial and fiscal integration among the EU countries over the last two decades. These links however create fears of devastating consequences of contagion but with varying degrees if a crisis occurs in a particular country, such as the one that struck Greece's economy due to its high public debt level. The increase in the dynamic conditional correlations during the European debt crisis indeed provides some sign of contagious effects. To further address this issue, we attempt to evaluate the potential of contagion between Greece and other eurozone countries, with Greece being the crisis country of reference. To do so, we consider the value-at-risk (VaR) as a measure of market risk and compute the probability that one market falls below its VaR at the probability level p_2 or p_3, given that another market falls below its VaR at levels p_1. The levels p_1, p_2 and p_3 stand for the probability that the VaR is exceeded. We set the condition $p_1 > p_2 > p_3$ in order to detect the direction of crisis transmission.

Recall that VaR for a loss random variable X with the distribution function F_x at the probability level p_j (j = 1, 2, 3) is defined by

$$VaR_{p_j}(X) = F^{-1}(p_j) \tag{13}$$

where $F^{-1}(p_j) = inf(t \in \Re: F_x(t) \geq p_j)$ denotes the inverse function of F_x. In our study, we set p_1=0.01, p_2=0.005 and p_3 = 0.001 which correspond to the 99%, 99.5% and 99.9% confidence levels, respectively.

Let A_j and B_j denote the event $\left[X < VaR_{p_j}(X)\right]$ and $\left[Y < VaR_{p_j}(Y)\right]$, where X and Y represents the loss functions (e.g., sovereign bond returns) of two countries under consideration. The contagion from country X to country Y and the contagion from country Y to country X are thus measured by the conditional probabilities $P(B_j/A_i)$ and $P(A_j/B_i)$, respectively. We set $i<j$ so that contagion only exists if the country affected by the crisis realizes higher losses than the original crisis country. For example, we compute the probability that the sovereign bond market Y falls below its VaR at 0.005 level given that the sovereign bond market X falls below its VaR at the 0.01 level. If $P(B_j/A_i)$ and $P(A_j/B_i)$ are not equal, there is asymmetric crisis transmission.

[Please insert Table 7 about here]

Table 7 reports the estimated probabilities of crisis transmission between Greece and the other eurozone countries. Several intriguing findings can be noted. First, the probability of crisis transmission from the Greek sovereign bond market to other eurozone markets is higher than the probability in the other way around, i.e., $P(B_2/A_1) < P(A_2/B_1)$ and $P(B_3/A_2) < P(A_3/B_2)$ for most cases. This finding suggests that the direction of crisis contamination goes from Greece to the other European countries. In particular, the debt-laden countries Italy and Spain are the two countries that receive the most crisis shock from the Greek sovereign debt market. Moreover, Ireland and Portugal are the other countries that are also exposed significantly to the crisis shock in Greece. With the onset of the European sovereign debt crisis, these PIIGS countries are identified as the five most at-risk European economies owing to their high levels of public debt and their economic fragility. This empirical evidence is also supported by the neighbourhood crisis effect, suggesting a high probability of crisis transmission among the neighbouring countries since the latter often have macroeconomic similarities (Haile and Pozo, 2008). The French sovereign bond market is also severely affected by the Greek crisis since French banks hold a significant amount of the Greek debt.

Second, the German sovereign bond market is found to be the least exposed to the crisis transmission effects. This result corroborates our previous analysis in the sense that the solid economic structure, the largeness of the economy and strong economic performance makes Germany the least affected by the Greek crisis.

Third, Finland and Austria are apparently protected against the crisis propagation in view of the low conditional probabilities. This decoupling effect can potentially be explained by these countries' less integration with the eurozone. Finland and Austria are among the highest GDP per capita and the lowest debt-to-GDP ratio members of the eurozone. In fact, Austria had been considered the best economy in the eur-ozone. On the other hand, Finland's economy is dominated by services but it is also competitive in manufacturing and its revenues are bigger than its debt.[9] It was the only country with a triple-A rating and stable outlook after Moody's downgraded the credited risk ratings for Germany and Luxembourg. Finland also insists on collateral in exchange for aid. These characteristics have led some to believe that Finland, rather than Greece, might be the first country to quit the single currency.

Finally, when looking at the conditional probabilities of crisis transmission between the Greek and the EMU benchmark markets, the results provide evidence to confirm the fact

[9] See "How Finland keeps its head above eurozone crisis".
http://www.theguardian.com/business/2012/jul/24/finland-triple-aaa-rating-moodys-eurozone

that the Greek sovereign bond market significantly transmitted the crisis shock to the whole eurozone countries with a probability of 0.257. By contrast, the Greek market was the most vulnerable when the eurozone entered into the crisis period, as the probabilities that the Greek market falls below its VaR at the 0.005 and 0.001 levels (or the 99.9% and 99.9% confidence levels), given that the EMU market falls below its VaR at the 0.01 and 0.005 level (or 99% and 99.5% confidence levels) are the highest and equal to 0.336 and 0.288, respectively.

4.5.2 Crisis transmission based on the extreme value theory (EVT)

To further investigate the sovereign debt crisis transmission across the eurozone countries, we rely on the advantages of the extreme value theory. The main motivation behind this methodological choice is that it allows one to address the crisis transmission issue during turmoil conditions, which manifests itself in the presence of tail dependence we identified previously. For this purpose, the peak-over-threshold (POT) approach is used to identify the extreme values for pairs of sovereign bond markets based on specific threshold values. We select these threshold values (upper and lower thresholds) by using a non-parametric approach, namely, the Hill estimator, which is directly applied to the sovereign bond returns series estimated from the TGARCH-Dynamic-BB7 copula model, $\{\hat{R}_t\}_{t=1}^{T}$. To do so, we first sort these return bond series from the lowest to the highest (i.e., $\hat{R}_1 \leq \hat{R}_2 \leq \cdots \leq \hat{R}_T$) and then estimate the Hill estimator with respect to a positive integer *k* such as

$$H(k) = \frac{1}{k}\sum_{i=1}^{k}\left[ln\left(\hat{R}_{T-i+2}\right) - ln\left(\hat{R}_{T-k}\right)\right] \quad (14)$$

Eq. (14) shows that the Hill estimator depends on *k*. Following Tsay (2010), the correct value of *k* is obtained by plotting the Hill estimator against different values of *k* and choosing the most appropriate value of *k* as the one for which the Hill estimator is stable.[10]

[10] The results for the upper and lower threshold values are not reported here for space limitation purpose, but can be made entirely available upon request to the corresponding author.

To the extent that the Hill estimator helps to identify the upper and lower threshold values in the right and left tails of the sorted return series, returns can be classified into three categories: extremely positive returns, non-extreme returns, and extremely negative returns. Given this classification, we are able to compute the matrix of conditional probabilities of dependence between two particular markets at time *t* as follows

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{bmatrix} \tag{15}$$

where $p_{ij} = Prob(I_t^A = i | I_{t-1}^B = j)$ for $(i, j = 1, 2{,}3)$ is the probability that the market A is in the state *i* given that the market B is in the state *j*, with 1, 2, and 3 being respectively the categories of extremely positive returns, non-extreme returns, and extremely negative returns. I_t^A and I_t^B are the indicator sequences of two sovereign bond return series under consideration. Accordingly, p_{12} measures, for example, the probability that the first market is booming given that the second market crashes. Considering the market A, the conditional probabilities of dependence with the market B, p_{ij}, can be estimated by maximizing the following log-likelihood function under conditional dependence (see, Reboredo and Rivera-Castro, 2014):

$$l(P; I_1^A, I_2^A, \dots, I_T^A) = \sum_{i=1, j=1}^{3} p_{ij}^{n_{ij}} \tag{16}$$

where n_{ij} represents the number of observations of I_t^B with value *i* followed by observations of I_t^A with value *j*. The estimated parameters $\hat{p}_{ij}$ are indeed given by the following ratios:

$$\hat{p}_{ij} = \frac{n_{ij}}{n_{i1} + n_{i2} + n_{i3}} \tag{17}$$

Since we are interested in the issue of crisis transmission around the Greek sovereign debt crisis, we compute the conditional probabilities of dependence between the Greek sovereign bond market and each of the other eurozone sovereign bond markets in the sample. The obtained results are reported in Table 8. Among the conditional probabilities, $\hat{p}_{11}$, $\hat{p}_{13}$, $\hat{p}_{31}$, and $\hat{p}_{33}$ are the most important. While $\hat{p}_{11}$ and $\hat{p}_{33}$ represent the co-boom and co-crash probabilities, $\hat{p}_{13}$ and $\hat{p}_{31}$ refer to the probabilities that two markets under consideration move in the opposite direction.

[Please insert Table 8 about here]

A close look at the $\hat{p}_{33}$ estimates shows that sovereign bond markets in the PIIS (Portugal, Ireland, Italy, and Spain) countries have the highest co-crash conditional probabilities with the Greek market. In particular, given the public debt crisis in Greece, Spain is the most vulnerable country with a probability of experiencing a co-crash of 80.3%, followed by Italy (72.8%) and Portugal (59.4%). The sovereign bond market in France is also at-risk as it has the highest probability of a co-crash after the PIIS countries. The probability of a joint crash with Greece is the lowest for Germany as this country has a strong economy. Moreover, Germany has the highest probabilities of moving in the opposite direction of the Greek sovereign bond market (42.8% when the Greek market is bearish, and 49.1% when the Greek market is bullish). With respect to the $\hat{p}_{11}$ estimates, we see that the eurozone sovereign bond markets have low probabilities of experiencing a co-boom with the Greek market, except for Portugal with a probability of 45.4%. It is finally worth noting that all eurozone sovereign bond markets we consider have a relatively short lived duration in staying at normal (stable) market regime during the study period, because the conditional probabilities of dependence in the center of the return distributions, $\hat{p}_{22}$, are generally low.

Overall, the above-mentioned results corroborate the findings provided in Table 7. They confirm the vulnerability of the sovereign bond markets in the PIIGS countries, the high risk of crisis for the one in France and the resilience of those in Austria and Germany.

5. Conclusion

The sovereign debt crisis that seriously plagued the countries of the eurozone region since early 2009 has created tremendous fears and loss of confidence for the whole community of policymakers and international investors. This crisis has also led to important crisis spillovers among the vulnerable countries in the eurozone, owing to their high levels of public debt, macroeconomic imbalances and slow growth following the 2007/2008 U.S. subprime crisis and the beginning of the unprecedented 2008-2009 global financial crisis. Increased market interdependence, deeper fiscal policy integration (e.g., budget and debt convergence rules) since the introduction of the euro, as well as the cross holdings of assets, are thus among the main driving factors of shock transmission in case of widespread panics and financial turbulences.

In this article, we use a dynamic copula-based approach to model the time-varying dependence structure of the eurozone sovereign bond markets around the European debt crisis that occurred in early 2009. Our empirical methodology offers the possibility to detect the changing patterns of dependence over time and the existence of potential asymmetry in this dependence structure. We also assess the strength and direction of the crisis transmission by computing the conditional probability that a market experiences large losses when another market entered into a crisis phase (i.e., realizing a large loss). An analysis of crisis transmission based on the results of the empirical DCC-Gumbel copula model and the extreme value theory is also provided.

Examining the 10-year government bond indices of ten EU countries over the period September 15, 2008 to October 26, 2012, we find evidence of significant and positive dependence between each of the sample sovereign debt markets and each of the Greek and the EMU sovereign bond markets. This dependence is found to vary through time and exhibit obvious asymmetry with positive dependence in boom markets (i.e., upper tail dependence). Moreover, the transmission of crisis from Greece to other eurozone countries is also found to be more probable than from other eurozone countries to Greece. This evidence is expected as Greece's difficult fiscal and economic fundamentals during the European debt crisis came to the center of international fear and anxiety. In particular, Greece is found to be the most vulnerable country once the eurozone entered into the sovereign debt crisis. The existence of crisis transmission from Greece to the PIIS countries (Portugal, Ireland, Italy, and Spain) is also confirmed when our empirical model is combined with the extreme value theory. Finally, our results attest to the suitability and superiority of the dynamic Gumbel copula over the dynamic Gaussian and Student-*t* copulas in modeling the dependence structure between the eurozone sovereign bond markets.

Taken together, our findings are useful for policymakers to understand the extent of dependence structure within the eurozone sovereign debt markets, which is needed to plan and implement appropriate measures to reduce the contagious effects of potential future crises. Investors also may use these results to adjust their portfolio allocation weights. The seriousness of a financial crisis-triggered contagion calls on monetary authorities to consider employing non-standard monetary policy measures over the course of the crisis to curb the contagion.

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Table 1. Summary statistics of daily government bond returns

	Mean (%)	Std. Dev. (%)	Skewness	Kurtosis	JB	ARCH(20)
Austria	0.0208	0.0122	-0.1418	2.6427	302.80^{+}	122.85^{+}
Finland	0.0208	0.0119	0.0661	1.0418	46.96^{+}	40.79^{+}
France	0.0182	0.0124	0.0403	2.7161	316.50^{+}	74.35^{+}
Germany	0.0212	0.0129	0.0859	1.2145	64.17^{+}	60.84^{+}
Greece	0.1318	0.0717	0.7270	45.3463	8.86E+04^{+}	83.00^{+}
Ireland	-254E-06	0.0273	0.4455	13.9566	8412^{+}	128.52^{+}
Italy	740E-05	0.0202	1.1863	14.6770	9509^{+}	117.00^{+}
Netherlands	0.0216	0.0119	0.0348	1.0822	50.09^{+}	54.15^{+}
Portugal	0.0191	0.0374	-0.4479	23.0922	2.30E+04^{+}	160.54^{+}
Spain	-337E-05	0.0205	1.37913	12.2349	6767^{+}	191.07^{+}
EMU Benchmark	0.0210	0.0129	0.0859	1.2106	63.77^{+}	61.11^{+}

Notes: This table provides the summary statistics of government bond returns for 10 eurozone countries under consideration, as well as those of the EMU government bond benchmark index. JB and ARCH refer to the empirical statistics of the Jarque-Bera test for normality and the Engle (1982) test for conditional heteroscedasticity applied to 20 lags of the residuals, respectively. $^{+}$ indicates the rejection of the null hypotheses of normality and no ARCH effects at the 1% level.

Table 2: Estimation results of the TGARCH models for marginal distributions

	SPA	POR	GRE	FRA	IRE	AUS	ITA	GER	FIN	NLD	EMU
Mean Equation											
ϕ_0	2e-005	8e-005	9e-005*	0.0001*	8e-005*	0.000*	5e-005	0.000*	8e-005*	0.000*	0.000*
	(0.494)	(1.503)	(1.864)	(1.939)	(1.624)	(2.29)	(0.277)	(2.412)	(1.627)	(2.41)	(2.184)
Variance Equation											
ω	0.003*	0.001*	0.002*	0.017*	0.003*	0.001*	0.001*	0.003*	0.001*	0.003*	0.001*
	(8.247)	(9.351)	(9.250)	(8.601)	(18.151)	(7.802)	(10.015)	(30.501)	(6.350)	(31.105)	(6.901)
α	0.298*	0.064*	0.064*	0.086*	0.298*	0.081*	0.058*	0.096*	0.097*	0.296*	0.023*
	(1.315)	(84.812)	(51.372)	(103.081)	(3.061)	(93.06)	(93.654)	(2.867)	(149.587)	(2.672)	(146.252)
β	0.170	0.902*	0.828*	0.927*	0.654*	0.927*	0.933*	0.904*	0.892*	0.703*	0.951*
	(0.782)	(32.806)	(15.712)	(99.353)	(1.915)	(94.520)	(72.765)	(1.896)	(115.325)	(1.847)	(118.489)
γ	2.460*	0.767	0.373	-0.130	2.965*	0.106	2.302*	0.457	-0.202	0.6118	-0.391*
	(3.086)	(1.547)	(1.454)	(-0.617)	(3.079)	(0.414)	(1.913)	(0.834)	(-1.067)	(0.962)	(-2.412)
ν	4.571*	4.267*	4.275*	8.360*	3.568*	8.510*	7.633*	6.619*	11.005*	7.258*	10.692*
	(26.224)	(48.354)	(48.157)	(42.354)	(50.971)	(15.023)	(43.107)	(51.349)	(12.509)	(18.390)	(41.189)
Log-lik	15065.1	14753.3	14220	15470	14813.2	15636.2	15484.1	15346.5	15701.3	15483.7	15464.4
Q(12)	15.90	18.38	14.31	16.26	14.44	19.78	11.59	23.42	10.84	11.20	18.27
	[0.23]	[0.23]	[0.81]	[0.17]	[0.53]	[0.08]	[0.55]	[0.05]	[0.54]	[0.32]	[0.10]
$Q^2(12)$	10.64	25.4	14.57	17.04	27.74	8.07	22.53	17.06	10.95	19.45	9.09
	[0.51]	[0.36]	[0.27]	[0.14]	[0.71]	[0.77]	[0.13]	[0.23]	[0.53]	[0.99]	[0.69]

Notes: SPA, POR, GRE, FRA, IRE, AUS, ITA, GER, FIN, NLD, and EMU denote the government bond return series for Spain, Portugal, Greece, France, Ireland, Austria, Italy, Germany, Finland, the Netherlands, and the EMU benchmark. The numbers in parentheses and brackets are the t-statistics and the p-values, respectively. $Q(12)$ and $Q^2(12)$ refer to the Ljung-Box tests for the autocorrelation of the residuals and the squared residuals with 12 lags, respectively. The asterisk * indicates significance at the 5% level.

Table 3. Goodness-of-fit (GoF) tests for marginal models

	SPA	POR	GRE	FRA	IRE	AUS	ITA	GER	FIN	NLD	EMU
K-S	0.881	0.802	0.772	0.831	0.682	0.502	0.973	0.833	0.662	0.694	0.833
CvM	0.692	0.364	0.985	0.561	0.826	0.874	0.785	0.861	0.886	0.785	0.963
A-d	0.755	0.917	0.872	0.994	0.971	0.813	0.773	0.591	0.713	0.877	0.891
First moment	0.819	0.828	0.523	0.714	0.823	0.808	0.723	0.754	0.908	0.923	0.714
Second moment	0.833	0.795	0.883	0.917	0.883	0.795	0.883	0.917	0.795	0.883	0.617
Third moment	0.992	0.470	0.790	0.995	0.890	0.570	0.994	0.695	0.570	0.790	0.695
Fourth moment	0.772	0.768	0.878	0.706	0.878	0.765	0.878	0.506	0.665	0.878	0.746

Notes: This table reports the p-values of the three GoF tests including the Kolmogorov-Smirnov (KS) test, the Cramer-von Mises (CvM) test, and the Anderson-Darling (AD) test, applied to the transformed residuals of the best-suited marginal model. These tests examine the null hypothesis of the *i.i.d.* distributions. SPA, POR, GRE, FRA, IRE, AUS, ITA, GER, FIN, NLD, and EMU denote Spain, Portugal, Greece, France, Ireland, Austria, Italy, Germany, Finland, the Netherlands and European Monetary Union, respectively.

Table 4. Choice of appropriate copula functions

Panel A: Dependence with the EMU benchmark

	SPA-EMU	POR-EMU	FRA-EMU	IRE-EMU	ITA-EMU	AUS-EMU	GER-EMU	FIN-EMU	NLD-EMU	GRE-EMU
Dynamic Student-t copula	-173.36	-205.75	-263.69	-222.52	-249.63	-309.66	-195.37	-187.23	-224.38	-263.66
S_n	0.13	0.12	0.13	0.09	0.25	1.16	0.56	0.13	0.08	0.22
	(0.001)	(0.005)	(0.052)	(0.014)	(0.152)	(0.245)	(0.147)	(0.003)	(0.125)	(0.102)
M_n	1.02	1.14	0.25	0.47	0.66	0.78	0.38	0.47	0.29	0.13
	(0.005)	(0.009)	(0.422)	(0.122)	(0.116)	(0.007)	(0.004)	(0.022)	(0.004)	(0.001)
Dynamic Gaussian copula	-171.56	-206.93	-245.42	-219.89	-248.63	-304.15	-214.65	-192.74	-166.47	-178.36
S_n	0.25	0.16	0.22	0.14	0.07	0.15	1.07	0.26	0.09	0.34
	(0.005)	(0.004)	(0.17)	(0.002)	(0.001)	(0.005)	(0.003)	(0.001)	(0.001)	(0.001)
M_n	0.63	0.47	0.55	1.14	0.97	1.05	0.58	0.88	0.42	0.16
	(0.142)	(0.023)	(0.015)	(0.042)	(0.163)	(0.002)	(0.007)	(0.029)	(0.421)	(0.355)
Dynamic Gumbel	-207.83	-243.62	-288.56	-242.53	-251.02	-315.75	-223.29	-197.58	-227.61	-296.22

copula										
S_n	0.07 (0.002)	0.17 (0.015)	0.06 (0.019)	0.04 (0.005)	0.17 (0.009)	0.23 (0.142)	0.09 (0.042)	0.04 (0.199)	0.26 (0.432)	0.10 (0.006)
M_n	0.25 (0.231)	0.33 (0.128)	0.19 (0.004)	0.29 (0.001)	0.41 (0.102)	0.67 (0.115)	0.33 (0.364)	0.30 (0.123)	0.17 (0.007)	0.22 (0.187)
Dynamic SJC copula	-250.41	-303.55	-401.12	-322.17	-299.66	-360.01	-366.77	-205.44	-303.53	-316.22
S_n	0.04 (0.001)	0.22 (0.112)	0.11 (0.004)	0.08 (0.007)	0.14 (0.223)	0.29 (0.455)	0.02 (0.006)	0.05 (0.026)	0.18 (0.099)	0.12 (0.113)
M_n	0.22 (0.145)	0.31 (0.005)	0.66 (0.012)	0.52 (0.932)	1.33 (0.141)	0.44 (0.228)	0.12 (0.112)	0.14 (0.744)	0.05 (0.156)	0.36 (0.645)
Dynamic BB1 copula	-255.09	-317.14	-415.33	-356.12	-409.85	-404.51	-314.47	-301.77	-307.06	-361.99
S_n	0.17 (0.008)	0.33 (0.016)	0.63 (0.025)	0.22 (0.296)	0.14 (0.312)	0.08 (0.422)	0.04 (0.004)	0.04 (0.009)	0.18 (0.255)	0.63 (0.122)
M_n	0.42 (0.002)	0.55 (0.019)	0.74 (0.025)	1.66 (0.044)	0.23 (0.067)	0.45 (0.012)	0.98 (0.252)	0.63 (0.122)	0.44 (0.152)	0.89 (0.003)
Dynamic BB7 copula	**-280.05**	**-322.19**	**-431.22**	**-377.42**	**-412.88**	**-418.62**	**-400.55**	**-307.36**	**-345.33**	**-378.63**
S_n	**0.02 (0.001)**	**0.07 (0.012)**	**0.05 (0.025)**	**0.04 (0.004)**	**0.04 (0.022)**	**0.17 (0.003)**	**0.01 (0.001)**	**0.03 (0.006)**	**0.07 (0.049)**	**0.05 (0.016)**
M_n	**0.17 (0.025)**	**0.04 (0.032)**	**0.19 (0.099)**	**0.20 (0.124)**	**0.33 (0.062)**	**0.03 (0.002)**	**0.11 (0.006)**	**0.02 (0.014)**	**0.06 (0.014)**	**0.12 (0.042)**
Panel B: Dependence with Greece										
	SPA-GRE	POR-GRE	FRA-GRE	IRE-GRE	ITA-GRE	AUS-GRE	GER-GRE	FIN-GRE	NLD-GRE	
Dynamic Student-t copula	-233.50	-264.99	-207.34	-253.66	-242.70	-271.35	-212.61	-283.99	-266.84	
S_n	0.25 (0.051)	0.17 (0.129)	0.09 (0.001)	0.28 (0.012)	0.16 (0.332)	0.66 (0.175)	0.05 (0.366)	0.15 (0.128)	0.39 (0.152)	
M_n	1.03 (0.556)	0.93 (0.153)	0.77 (0.663)	0.45 (0.229)	1.25 (0.331)	0.42 (0.066)	0.33 (0.011)	0.96 (0.154)	0.22 (0.622)	
Dynamic Gaussian copula	-230.81	-258.55	-208.61	-266.34	-239.22	-245.62	-230.48	-278.64	-259.33	
S_n	0.19 (0.051)	0.33 (0.034)	0.19 (0.195)	0.14 (0.336)	0.24 (0.522)	0.65 (0.169)	0.36 (0.054)	0.57 (0.033)	0.51 (0.127)	
M_n	0.24 (0.016)	1.44 (0.002)	1.37 (0.004)	1.05 (0.144)	0.44 (0.255)	1.24 (0.301)	1.55 (0.001)	0.78 (0.052)	0.89 (0.042)	
Dynamic Gumbel copula	-236.36	-278.07	-266.93	-294.42	-244.79	-285.05	-259.64	-297.08	-272.08	
S_n	0.22 (0.006)	0.26 (0.010)	0.14 (0.005)	0.19 (0.009)	0.11 (0.013)	0.13 (0.045)	0.08 (0.069)	0.06 (0.002)	0.25 (0.006)	
M_n	0.88 (0.002)	0.55 (0.005)	0.42 (0.004)	0.33 (0.099)	0.62 (0.128)	0.28 (0.244)	0.47 (0.071)	0.36 (0.149)	0.62 (0.186)	
Dynamic SJC copula	-303.55	-298.05	-345.22	-317.66	-278.28	-290.63	-262.99	-313.82	-401.55	
S_n	0.17 (0.022)	0.26 (0.245)	0.39 (0.123)	0.14 (0.341)	0.33 (0.234)	0.12 (0.142)	0.24 (0.052)	0.22 (0.166)	0.45 (0.217)	
M_n	0.29 (0.136)	0.42 (0.006)	0.51 (0.221)	1.02 (0.328)	0.77 (0.140)	0.35 (0.045)	0.60 (0.038)	0.42 (0.047)	0.63 (0.074)	
Dynamic BB1 copula	-314.04	-352.11	-352.09	-360.22	-287.44	-294.78	-264.22	-315.22	-399.36	
S_n	0.08 (0.127)	0.17 (0.104)	0.09 (0.075)	0.11 (0.055)	0.15 (0.152)	0.23 (0.143)	0.19 (0.005)	0.07 (0.192)	0.15 (0.229)	
M_n	0.36 (0.113)	0.29 (0.055)	0.44 (0.062)	0.62 (0.412)	0.22 (0.334)	0.50 (0.122)	0.17 (0.098)	0.14 (0.111)	0.25 (0.067)	
Dynamic BB7 copula	**-316.50**	**-368.78**	**-359.77**	**-360.73**	**-292.41**	**-298.15**	**-270.36**	**-318.00**	**-405.66**	
S_n	**0.05 (0.002)**	**0.07 (0.051)**	**0.03 (0.003)**	**0.01 (0.064)**	**0.06 (0.019)**	**0.14 (0.039)**	**0.04 (0.005)**	**0.06 (0.015)**	**0.05 (0.004)**	
M_n	**0.17 (0.005)**	**0.22 (0.009)**	**0.09 (0.027)**	**0.16 (0.001)**	**0.19 (0.008)**	**0.13 (0.011)**	**0.23 (0.009)**	**0.14 (0.062)**	**0.16 (0.005)**	

Notes: This table reports the values of the log likelihood functions of different copula models. The best model is the one which has the highest absolute log likelihood values. SPA, POR, GRE, FRA, IRE, AUS, ITA, GER, FIN, NLD, and EMU denote Spain, Portugal, Greece, France, Ireland, Austria, Italy, Germany, Finland, the Netherlands and European Monetary Union, respectively.

Table 5: Estimated parameters of the dynamic BB7 copula for pairs of each country's and EMU sovereign bond returns

	SPA-EMU	POR-EMU	FRA-EMU	IRE-EMU	ITA-EMU	AUS-EMU	GER-EMU	FIN-EMU	NLD-EMU	GRE-EMU
γ	0.681	0.654	0.726	0.544	0.779	0.662	0.818	0.745	0.661	0.551
	(0.024)	(0.132)	(0.227)	(0.120)	(0.068)	(0.037)	(0.021)	(0.044)	(0.090)	(0.113)
α	0.022	0.049	0.018	0.072	0.036	0.119	0.052	0.035	0.062	0.059
	(0.006)	(0.024)	(0.001)	(0.018)	(0.001)	(0.009)	(0.011)	(0.013)	(0.023)	(0.008)
β	0.875	0.951	0.963	0.938	0.888	0.794	0.922	0.881	0.914	0.951
	(0.075)	(0.041)	(0.123)	(0.149)	(0.237)	(0.056)	(0.103)	(0.074)	(0.152)	(0.211)
κ	1.054	1.028	1.142	1.061	1.163	1.079	1.269	1.190	1.022	1.047
	(0.052)	(0.104)	(0.199)	(0.211)	(0.062)	(0.071)	(0.151)	(0.189)	(0.106)	(0.321)
α	0.051	0.082	0.074	0.0441	0.063	0.098	0.021	0.011	0.033	0.015
	(0.002)	(0.012)	(0.051)	(0.017)	(0.025)	(0.014)	(0.016)	(0.007)	(0.012)	(0.006)
β	0.901	0.877	0.917	0.785	0.899	0.821	0.645	0.697	0.966	0.792
	(0.275)	(0.142)	(0.321)	(0.122)	(0.078)	(0.119)	(0.173)	(0.114)	(0.421)	(0.133)
λ_U	0.070	0.037	0.165	0.078	0.185	0.099	0.273	0.210	0.030	0.061
	(0.012)	(0.016)	(0.003)	(0.023)	(0.023)	(0.004)	(0.053)	(0.074)	(0.005)	0.011
λ_L	0.361	0.347	0.385	0.280	0.411	0.351	0.429	0.394	0.350	0.284
	(0.123)	(0.196)	(0.074)	(0.045)	(0.170)	(0.089)	(0.084)	(0.127)	(0.071)	(0.064)
LogLik.										

Notes: This table reports the parameters of the dynamic conditional correlation processes (α, β) as well as the estimated average dependence parameters (κ γ) and the upper tail dependence coefficient (λ_U) as well as the lower tail coefficient (λ_L) of the dynamic BB7 copula model. The standard errors are in parentheses. SPA, POR, GRE, FRA, IRE, AUS, ITA, GER, FIN, NLD, and EMU denote Spain, Portugal, Greece, France, Ireland, Austria, Italy, Germany, Finland, the Netherlands and European Monetary Union, respectively. * And *** denote significance at the 10% and 1% levels, respectively.

Table 6: Estimated parameters of the dynamic BB7 copula for pairs of each country's and Greek sovereign bond returns

	SPA-GRE	POR-GRE	FRA-GRE	IRE-GRE	ITA-GRE	AUS-GRE	GER-GRE	FIN-GRE	NLD-GRE
γ	0.882	0.794	0.655	0.632	0.914	0.594	0.324	0.668	0.812
	(0.125)	(0.014)	(0.152)	(0.421)	(0.123)	(0.048)	(0.122)	(0.089)	(0.054)
α	0.025	0.032	0.041	0.012	0.019	0.063	0.054	0.037	0.016
	(0.001)	(0.011)	(0.006)	(0.005)	(0.003)	(0.024)	(0.017)	(0.012)	(0.004)
β	0.964	0.954	0.901	0.895	0.971	0.928	0.762	0.907	0.667
	(0.226)	(0.189)	(0.162)	(0.134)	(0.196)	(0.079)	(0.152)	(0.227)	(0.125)
κ	1.34	1.456	1.556	1.098	1.179	1.300	1.022	1.054	1.155
	(0.424)	(0.121)	(0.149)	(0.223)	(0.118)	(0.201)	(0.194)	(0.166)	(0.038)
α	0.094	0.052	0.011	0.036	0.012	0.026	0.058	0.042	0.035
	(0.034)	(0.002)	(0.004)	(0.005)	(0.007)	(0.012)	(0.034)	(0.013)	(0.017)
β	0.781	0.902	0.691	0.702	0.756	0.963	0.633	0.866	0.781
	(0.176)	(0.321)	(0.349)	(0.162)	(0.092)	(0.180)	(0.150)	(0.126)	(0.143)
λ_U	0.323	0.390	0.439	0.120	0.200	0.296	0.030	0.070	0.178
	(0.064)	(0.008)	(0.154)	(0.034)	(0.122)	(0.063)	(0.001)	(0.001)	(0.003)
λ_L	0.456	0.418	0.347	0.334	0.468	0.311	0.118	0.354	0.426
	(0.137)	(0.066)	(0.089)	(0.017)	(0.057)	(0.013)	(0.068)	(0.191)	(0.142)
LogLik.									

Notes: This table reports the parameters of the dynamic conditional correlation processes (α, β) as well as the estimated average dependence parameters (κ γ) and the upper tail dependence coefficient (λ_U) as well as the lower tail coefficient (λ_L) of the dynamic BB7 copula model. The standard errors are in parentheses. SPA, POR, GRE, FRA, IRE, AUS, ITA, GER, FIN, NLD, and EMU refer to Spain, Portugal, Greece, France, Ireland, Austria, Italy, Germany, Finland, the Netherlands and European Monetary Union. * and *** denote significance at the 10% and 1% levels, respectively.

Table 7: Conditional probabilities of contagion risk with Greece as the crisis country

	Crisis transmission from other euro-zone countries to Greece		Crisis transmission from Greece to other eurozone countries	
	$P(B_2/A_1)$	$P(B_3/A_2)$	$P(A_2/B_1)$	$P(A_3/B_2)$
Austria - Greece	0.140	0.170	0.159	0.451
Finland - Greece	0.223	0.345	0.314	0.375
France - Greece	0.459	0.643	0.469	0.664
Germany - Greece	0.312	0.392	0.385	0.411
Ireland - Greece	0.246	0.301	0.279	0.361
Italy - Greece	0.771	0.756	0.576	**0.798**
Netherlands - Greece	0.262	0.295	0.305	0.316
Portugal - Greece	0.456	0.420	0.501	0.523
Spain - Greece	0.712	0.661	0.724	0.689
EMU - Greece	**0.786**	**0.689**	**0.664**	0.694

Notes: This table reports the conditional probability that one market falls below its VaR at the p_2 or p_3 levels given that another market falls below its VaR at level p_1. The probability levels p_1, p_2 and p_3 are equal to 0.01, 0.005 and 0.001, respectively. *B* and *A* denotes the shock events in Greece and other eurozone countries, respectively. The bold numbers indicate the highest probability of crisis transmission among all estimated probabilities with Greece or other eurozone countries as the crisis country.

Table 8. Conditional probabilities of dependence based on extreme value theory

	$\hat{p}_{11}$	$\hat{p}_{12}$	$\hat{p}_{13}$	$\hat{p}_{21}$	$\hat{p}_{22}$	$\hat{p}_{23}$	$\hat{p}_{31}$	$\hat{p}_{32}$	$\hat{p}_{33}$	Loglik
Austria - Greece	0.249	0.243	0.256	0.184	0.075	0.096	0.157	0.160	0.347	652.228
Finland - Greece	0.185	0.198	0.164	0.162	0.159	0.152	0.122	0.084	0.328	674.253
France - Greece	0.124	0.078	0.023	0.089	0.132	0.178	0.231	0.012	0.413	541.880
Germany - Greece	0.196	0.211	0.428	0.114	0.041	0.052	0.491	0.276	0.216	556.339
Ireland- Greece	0.174	0.054	0.295	0.241	0.062	0.096	0.144	0.275	**0.446**	517.662
Italy - Greece	0.283	0.204	0.074	0.221	0.003	0.023	0.107	0.066	**0.728**	644.321
Netherlands - Greece	0.320	0.095	0.136	0.197	0.046	0.206	0.237	0.028	0.359	572.412
Portugal - Greece	0.454	0.142	0.099	0.276	0.162	0.103	0.119	0.243	**0.594**	609.558
Spain - Greece	0.345	0.118	0.276	0.142	0.221	0.188	0.126	0.264	**0.803**	412.639
EMU - Greece	0.378	0.087	0.357	0.190	0.104	0.215	0.291	0.045	0.396	505.411

Notes: The table shows the conditional probability matrix estimates for Eq. (15). Loglik denotes the value of the log-likelihood function in Eq. (16). p_{ij} $(i, j = 1,2,3)$ is the probability that the first market (e.g., Spain) is in the state *i* given that the second market (e.g., Greece) is in the state *j*, with 1, 2, and 3 being respectively the states of extremely positive returns, non-extreme returns, and extremely negative returns.

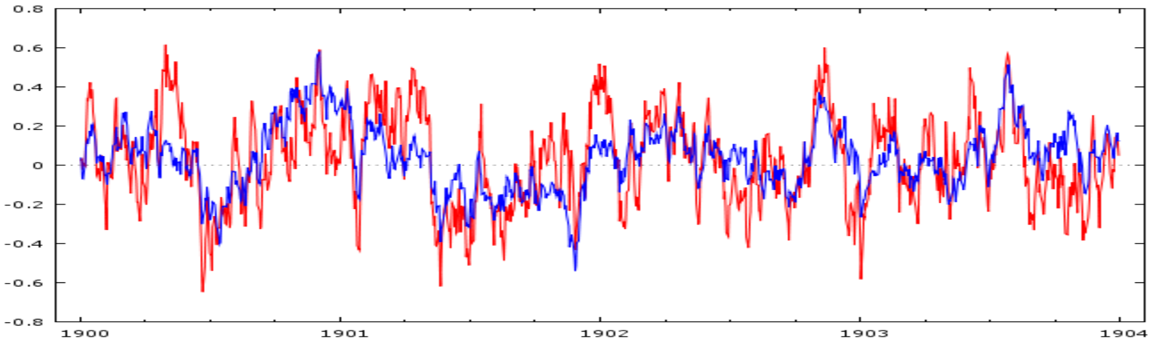
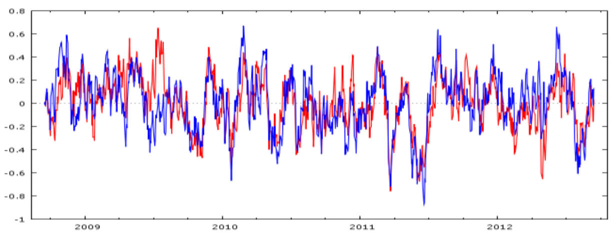
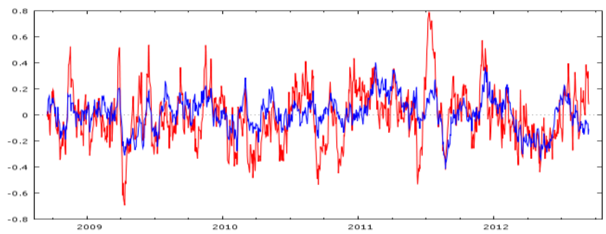


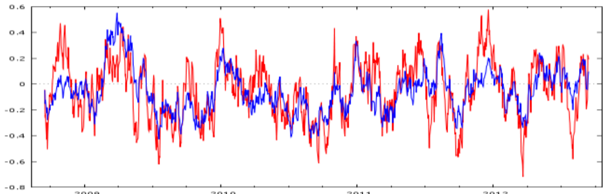
Figure 1. Time-varying comovement between the EMU benchmark and Greek of sovereign bond returns

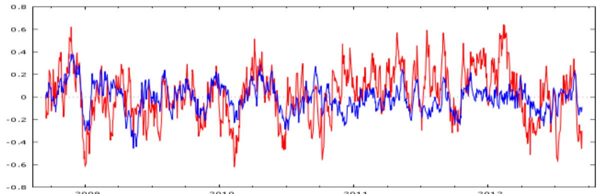




Euro Benchmark - Austria

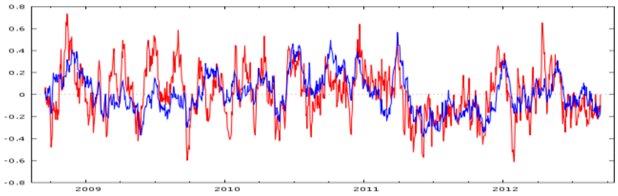
Greece - Austria

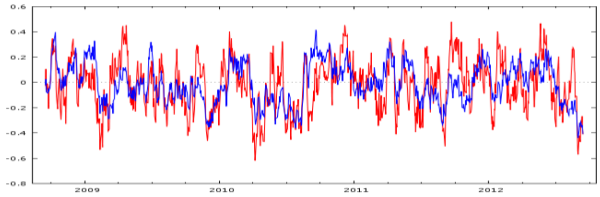




EMU benchmark - France

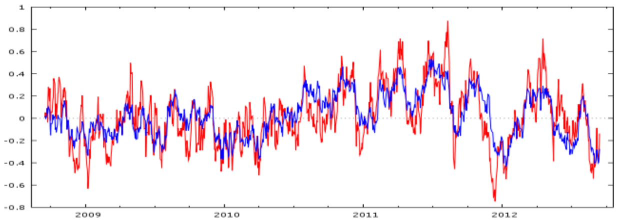
Greece - France

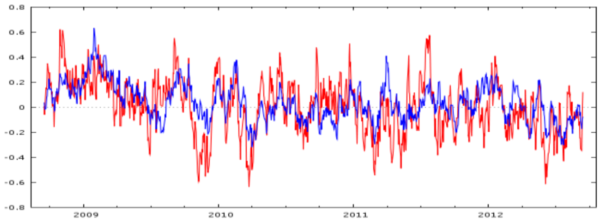




EMU benchmark - Finland

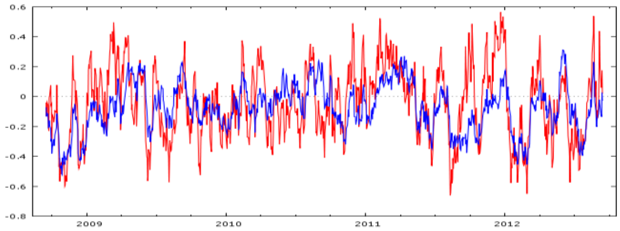
Greece - Finland

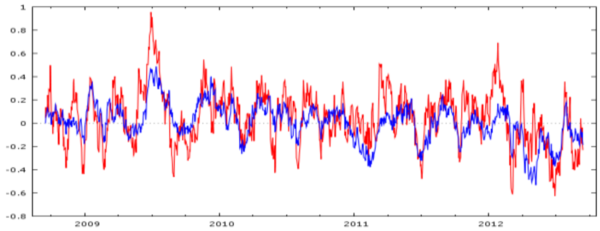




EMU benchmark - Germany

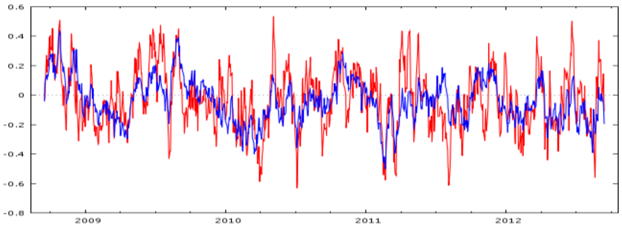
Greece - Germany

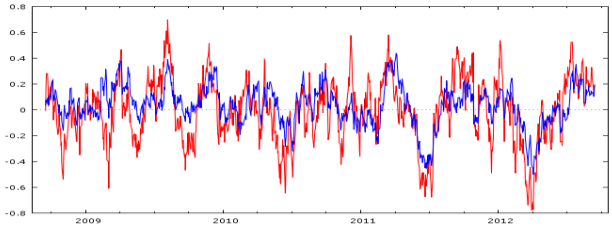




EMU benchmark - Ireland

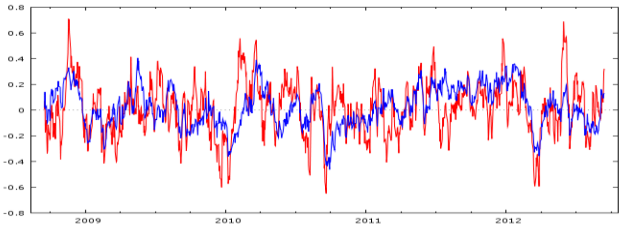
Greece - Ireland

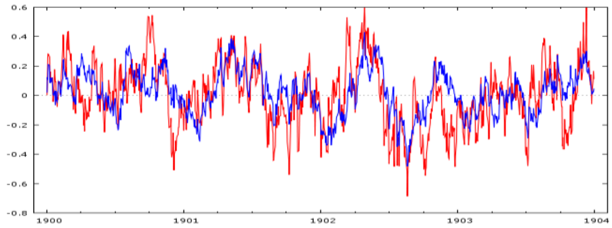




EMU benchmark - Italy

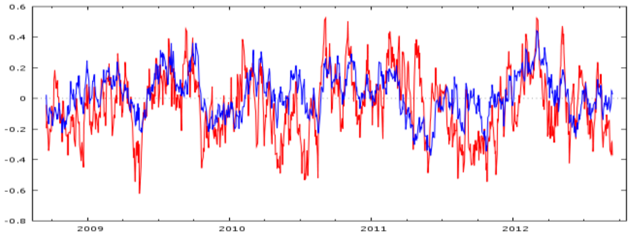
Greece - Italy

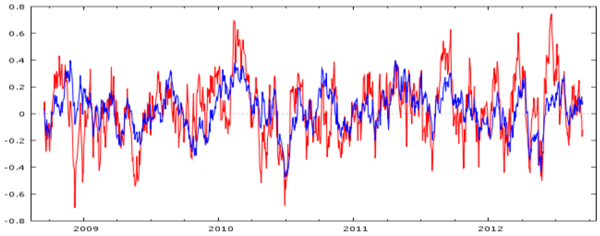




EMU benchmark - Netherlands

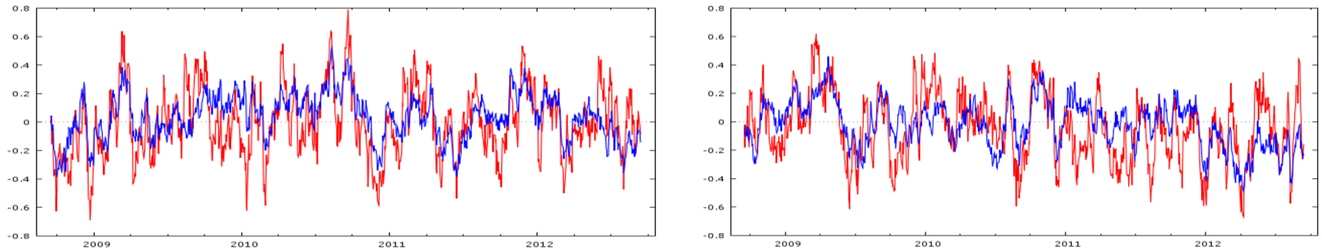
Greece - Netherlands





EMU benchmark - Spain

Greece - Spain



EMU benchmark - Portugal

Greece - Portugal

Figure 2. Time-varying comovement with the EMU benchmark and Greek sovereign bond markets