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Sovereign bond market dependencies and crisis transmission around the eurozone debt crisis: 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 and positive 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: sovereign debt crisis, government bonds, dynamic copulas, stochastic dependence.
JEL Classifications: C58, E44, G12, H63

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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 U.S. banking sector and then spread globally to private and public sectors (Bekiros, 2014; Sarafrazi et al., 2014; Kräussl et al., 2016). These debt-sensitive economies had managed for some time to borrow huge amounts of money at attractive rates, which was facilitated by being members of the eurozone. They hoped within the eurozone 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] Investors have thus demanded higher yields in order to hold the sovereign debts of those countries.

The eurozone crisis has provided an ideal environment for researchers to examine its roots and implications on the economies of the European Monetary Union (EMU) countries, to the extent that the latter 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. In this context, accurately measuring the stochastic dependence and capturing the shock transmission mechanisms during crisis periods are among the main challenges (Grundke and Simone Polle, 2012; Ye et al., 2012; Creal and Tsay, 2015; Jayech, 2016).

To date, a major strand of research has examined the dynamics and determinants of the European sovereign bond markets before and with the occurrence of the eurozone financial crisis (e.g., Abad et al., 2010; Maltritz, 2012; Bernoth and Erdogan, 2012; Dewachter et al., 2015). 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 influ-

[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.

ence of the world's risk factors, but more vulnerable to the EMU's 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. 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. Dewachter et al. (2015) quantify the fundamental component of eurozone sovereign bond yield spreads using a multi-market, no-arbitrage affine term structure model with a unique pricing kernel and show that it is dominantly driven by economic fundamentals.

The second strand of research focused 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 during the eurozone debt crisis (e.g., Fong and Wong, 2012; Arghyrou and Kontonikas, 2012; Beirne and Fratzscher, 2013; Philippas and Siriopoulos, 2013; Pragidis et al., 2015). These studies uncover not only the main causes of the ongoing debt crisis but also the existence of several forms of contagion effects, and flight to quality. Lane (2012) attributes the origin and propagation of the 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 multi-country 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 economic growth. 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. The contagion evidence for the EMU countries is also found in Philippas and Siriopoulos (2013) who document, from regime-switching and time-varying copula models, macroeconomic imbalances, strong perception of the severity of sovereign risk and the high appetites for arbitrage by international bond portfolio managers as the main drivers of this contagion effect.[2]

[2] There are also some studies focusing 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 countries including

Our study extends the existing literature by attempting to identify the time-varying dependence structure of sovereign bond markets in the Eurozone as well as the associated crisis transmission mechanisms between them. We are particularly motivated by the changing appetite and perception of debt risk under the stress conditions of the 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 sovereign bonds of ten major eurozone countries (Austria, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, and Spain) with respect to the Greek government bond market and the 10-year EMU benchmark government bond index. This approach is methodologically more effective and realistic than the vine copula method (Zhang, 2014) because the latter is based on static pairwise copulas which are unable to capture the changing dependence structure around turmoil periods.

Second, our data-driven dynamic copula approach, which typically relies on the combination of several copula families and the Dynamic Conditional Correlation (DCC) process 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). We thus extend 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 direction of crisis transmission between Greece and other eurozone markets around the Greek and eurozone debt crises by examining the conditional 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 market risk as a measure of an extreme loss. Based on the obtained empirical results of our dynamic

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 while 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).

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 which countries are vulnerable during the ongoing debt crisis and directions of crisis transmission 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 empirical results. Section 4 concludes the paper.

2. Methodology

Copulas are functions that link univariate uniform marginal, which are defined in the interval [0,1], to their multivariate distributions. The most important characteristic of a copula is its ability to gauge the dependence structure (both average dependence and extreme dependence) between random variables. In this paper, our dynamic copula models (also referred to as DCC-copulas in the related literature) allow the copula's dependence parameters to vary through time according to the dynamic conditional correlation process as in Engle (2002). In what follows, we successively presents the marginal models, the dynamic copula approach, and estimation issues.

2.1 Marginal models

When modeling conditional dependence between random variables through copulas, it is essential to estimate, in the first stage, their univariate marginal distributions. To the extent that return series frequently exhibit leptokurtic behavior, serial correlation, time-varying volatility and asymmetric volatility responses to positive and negative shocks, we combine an ARMA process and the Glosten-Jagannathan-Runkle generalized autoregressive conditional heteroscedasticity (GJR-GARCH) process as in Glosten et al. (1993) to model the conditional mean and variance of the sovereign government bond returns. The marginal model thus takes the following form:

$$r_t = \emptyset_0 + \sum_{j=1}^{p} \emptyset_j r_{t-j} + \varepsilon_t - \sum_{i=1}^{q} \theta_i \varepsilon_{t-j} \quad (1)$$

where p and q are nonnegative lag length integers, while $\emptyset$ 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 such as:

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

where ω is a constant, σ_{t-j}^2 is the lagged conditional variance (the GARCH component), and ε_{t-j} is 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, then a 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).

2.2 Dynamic copula models

The theory of copulas dates back to Sklar (1959)'s theorem which states that 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:

$$F_{XY}(x, y) = C\big(F_X(x), F_Y(y)\big) \; for \; all \; x, y \in R \quad (3)$$

where X and Y represent any two government bond returns in our study. According to Eq. (3), if $F_X(x)$ and $F_Y(y)$ are continuous, C is uniquely determined on the range of F_X and F_Y, i.e., $RanF_X \times RanF_Y$ or the unit square $[0,1]^2$. 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.[3] This feature implies that copulas can be used to connect margins to a multivariate distribution function which, in turn, can be decomposed into its univariate marginal distributions. Consequently, a copula is suitable for modeling the dependence structure of variables independently from their margins, which thus provides greater flexibility than the parametric multivariate distributions.

Another important feature of copulas is the possibility of estimating the asymptotic tail dependence between variables X and Y, which is invariant under strictly increasing transformation of X and Y. Here the upper and lower asymptotic tail dependence coefficients refer to the conditional probability that one variable is in the right/left tail given that the other variable

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

is already in the right/left tail, where the right and left tails are defined by extreme quantiles of the marginal distributions. They are defined as follows:

$$\lambda_U = \lim_{t\to 1} Pr[X \geq F_X^{-1}(t) | Y \geq F_Y^{-1}(t)] \quad (4)$$

$$\lambda_L = \lim_{t\to 0} Pr[X \leq F_X^{-1}(t) | Y \leq F_Y^{-1}(t)] \quad (5)$$

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 asymptotic tail dependence if $\lambda_U > 0$ and $\lambda_L > 0$. They display asymmetric asymptotic tail dependence if λ_U is not equal to λ_L. A zero value of these coefficients indicates that the tail dependence gradually vanishes in the limit for the most extreme values.

To model the dependence structure between government bond returns in eurozone countries, we mainly make use of four types of bivariate copulas including the Gumbel, the Symmetrized Joe-Clayton (SJC), the BB1, and the BB7 copulas. These copulas, which belong to the Archimedean copula family, are popular in economics and finance applications because they allow one to model various dependence features (e.g., average dependence, tail dependence, asymmetric tail dependence). While the symmetric Gaussian and Student-t copulas are not explicitly considered in this paper, we also estimate them at the empirical stage in order to provide a comparison with the selected copulas.[4]

The Gumbel copula is given by

$$C(u, v; \delta) = exp\left(-\left[(-lnu)^\delta + (-lnv)^\delta\right]^{1/\delta}\right) \quad (6)$$

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 $\delta \to +\infty$.

We also use the BB1 copula (Joe, 1997) which allows for capturing both lower and upper tail dependence. This copula has the following functional form:

$$C_{bb1}(u, v, \kappa, \gamma) = \left(1 + [(u^{-\kappa} - 1)^\gamma + (v^{-\kappa} - 1)^\gamma]^{1/\gamma}\right)^{-1/\kappa}, \kappa \in (0, \infty), \kappa \in (1, \infty) \quad (7)$$

[4] Interested authors can refer to Berger (2013), among others, for a formal presentation of the static and dynamic elliptical copulas (Gaussian and Student-t) as well as their estimation approach.

The upper and lower tail dependence parameters of the BB1 copula are respectively given by $\lambda_U = 2 - 2^{1/\gamma}$ and $\lambda_L = 2^{-1/\kappa\gamma}$.

The BB7 copula (Joe, 1997) is referred to as the Joe-Clayton copula and is given by

$$C_{bb7}(u, v, \kappa, \gamma) = 1 - \left\{1 - [(1 - \tilde{u}^{\kappa})^{-\gamma} + (1 - \tilde{v}^{\kappa})^{-\gamma} - 1]^{\frac{-1}{\gamma}}\right\}^{-\frac{1}{\kappa}}, \kappa \in (1, \infty), \gamma \in (1, \infty) \quad (8)$$

where $\tilde{u} = (1 - u)$ and $\tilde{v} = (1 - v)$. The BB7 copula's upper and lower tail dependence parameters are given by $\lambda_U = 2 - 2^{1/\kappa}$ and $\lambda_L = 2^{-1/\gamma}$.

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

$$C_{SJC}(u, v|\lambda_U, \lambda_L) = 0.5\{C_{JC}(u, v|\lambda_U, \lambda_L) + C_{JC}(\bar{u}, \bar{v}|\lambda_U, \lambda_L) + u + v - 1\} \quad (9)$$

where C_{JC} is the BB7 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 worth noting 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. In this paper, we also model time-varying dependence, but base it on the dynamic conditional correlation (DCC) specification of Engle (2002) as given in Eqs. (10)-(12) below. This approach begins with modeling the conditional correlation between two particular sovereign bond return series, and then infers the (copula) nonlinear dependence via the relationship between Kendall's tau and the copula dependence parameter. Formally, we have

$$R_t = diag\left\{Q_t^{-(\frac{1}{2})}\right\} Q_t diag\left\{Q_t^{-(\frac{1}{2})}\right\} \quad (10)$$

$$Q_t = (1 - \alpha - \beta)\bar{Q}_t + \alpha\hat{\varepsilon}_{t-1}\hat{\varepsilon}'_{t-1} + \beta Q_{t-1} \quad (11)$$

$$\rho_t = (Q_t^*)^{-1} Q_t (Q_t^*)^{-1} \quad (12)$$

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 that ought to be estimated, satisfying the conditions: $\alpha > 0$, $\beta > 0$ and $\alpha + \beta \leq 1$. These specifications guarantee the positivity of R_t. Note that Q_t^* is a (2×2) matrix with zeros as the off-diagonal elements and the square root of the matrix Q elements as the diagonal el-

ements. The coefficients ρ_t are thus the off-diagonal elements of the matrix R_t and correspond to the dynamic conditional correlations between two random variables under consideration, which is confined in the range $[-1,1]$.

Following Heinen and Valdesogo (2008), we infer the time-varying dependence parameters of our copula models from their relationship with the Kendall's tau (τ) as it is given by Eq. (13), where the Kendall's tau is linked to the dynamic correlation ρ_t as in Eq. (14).

$$\tau_t = 4 \int_{[0,1]^2} C(u, v; \delta, \kappa, \gamma) dC(u, v; \delta, \kappa, \gamma) - 1 \tag{13}$$

$$\tau_t = 2 \arcsin(\rho_t) / \pi \tag{14}$$

Note that the computation of the copula dependence parameter from the Kendall's tau has become standard in the existing literature as this parameter captures the nonlinearity in the dependence structure, which is ignored by the linear correlation coefficients. Overall, the four time-varying copula models we consider (DCC-Gumbel, DCC-SJC, 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 ignore asymmetry and tail dependence (e.g., Wen et al., 2012; Berger, 2013). Our results show that ignoring these stylized features in modeling the dependence of sovereign bond returns leads to erroneous dependence assessment.

2.3 Copula estimation

In order to estimate our dynamic copula models, we first estimate the marginal models, i.e., ARMA-GJR-GARCH, by maximum likelihood and then use the Canonical Maximum Likelihood (CML) to estimate the copula parameters given the estimated coefficients in the marginal models (Cherubini et al., 2004; Aloui et al., 2013). Within the semiparametric approach of the CML, we proceed, in the first step, to a nonparametric estimation of the marginals, F_X and F_Y, via the empirical cumulative distribution functions (ECDFs) of the respective standardized residuals that we obtain from the marginal models in Eq. (1). The ECDFs are defined as:

$$\hat{F}_X(x) = \frac{1}{n} \sum_{i=1}^{n} 1\{X_i < x\} \text{ and } \hat{F}_Y(y) = \frac{1}{n} \sum_{i=1}^{n} 1\{X_i < y\} \tag{15}$$

In the second step, the standardized residuals of the marginal models are transformed into uniform variates $(\hat{u}, \hat{v})$ using their ECDFs, and the unknown parameters $\hat{\theta}_2$ of the copula models are estimated by maximizing the copula log-likelihood function such as[5]

$$\hat{\theta}_{2_{CML}} = \arg\max_{\delta} \sum_{i=1}^{T} lnC\left(\hat{F}_X(x_i), \hat{F}_Y(y_i); \theta_2(\propto, \beta); \hat{\theta}_1\right) \quad (16)$$

where C is the copula density function, the dynamics of θ_2 is driven by the parameters of the DCC process $(\propto, \beta)$, and $\hat{\theta}_1$ is related to the estimated coefficients of the marginal we obtained in the first step. Genest et al. (1995) show that under suitable regularity conditions, the estimator $\hat{\theta}_{2_{CML}}$ is consistent, asymptotically normal and fully efficient.

2.4 Goodness-of-fit tests

The evaluation of goodness-of-fit (GoF) for the marginal models is crucial for 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* (independently and identically distributed) 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 $(\hat{v}_t - \bar{v})^k$ 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.

As to the evaluation of the copula fitting, we use two GoF tests introduced by Genest et al. (2006, 2011). These tests are based on the empirical copula, Pickands dependence function and Cramer-von Mises distances. The test statistics are given by

$$S_n = \int \{C_n(u,v) - C_\theta(u,v)\}^2 dC_n(u,v) \text{ and } M_n = \int_0^1 n \left|A_n(t) - A_{\theta_n}(t)\right|^2 dt \quad (17)$$

The first statistic S_n measures this distance between the fitted copula $C_{\theta_n}$and the empirical copula C_n, while the second test statistic M_n refers to the distance between a nonparametric rank-based estimator of the Pickands dependence function A_n and a parametric estimation A_{θ_n}. The null hypothesis that the estimated copula describes the empirical data well is rejected for large values of the computed statistics, which implies that the considered copula is not a suitable form for the data.

[5] As noted by Wang et al. (2013), the transformation of the standardized residuals via their ECDFs always results in uniform variates asymptotically, regardless of the specification of marginal models. This feature of the CML approach is thus of particular interest for copula estimations because we do not need to make any assumptions about the distributions of the marginal (Giacomini et al., 2009).

3. Data

We consider the daily price data 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. We also include 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 European government bond markets' relative risk, compared to the 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 bond 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 Austria 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 GJR-GARCH model to filter the raw returns before they can be used in copula dependence modeling.

4. Empirical results

4.1 Estimation results of the marginal distributions

Table 2 reports the results of the best specifications of the GJR-GARCH model for the government bond returns in our sample countries. For all of the cases, the GJR-GARCH(1,1) is the best-suited model for the sample data. The results suggest that the GJR-GARCH 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 three eurozone countries as well as the EMU (Spain, Ireland, Italy and EMU) out of the eleven series (as indicated by the coefficient γ). Finally, the degrees of freedom (v) which range from 4 to 11 imply that the data are still substantially non-normal. This finding suggests the suitability of the copula approach in modeling the potential of nonlinear and extreme dependence among the government bond returns.

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

Copula models perform better if the marginal distributions are correctly specified. To check this condition, we first transform the estimated residuals of the best-suited marginal model 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 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.[6] Taken together, our

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

GoF tests show that the estimated residuals from the selected marginal model are not misspecified. 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]

Table 4 compares the performance of the different dynamic copula models when they are used to assess the dependence between each of the euro zone sovereign bond markets with either the EMU benchmark or the Greek sovereign bond market. The log likelihood criterion selects the DCC-BB7 copula as the best-suited model for all pairs of sovereign bond markets. The two GoF tests based on the Pickands dependence function and the Cramer-von Mises distances provide similar results as the distance between the estimated and the empirical copulas are minimal.

4.3 Dynamic conditional correlations

The analysis of time-varying comovement among sovereign debt markets in the eurozone 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. We present, in Figures 1-2, the estimated dynamic conditional correlations (DCCs) from the best-suited copula model (DCC-BB7).

[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. The DCCs are generally positive and higher during the period preceding the European debt crisis (i.e., between 2008 and the first half of 2009). This increase in the DCCs could potentially be associated with contagion effects and financial stress from the global financial crisis. Since then, the DCC values decrease substantially and are mainly negative, which seems to 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 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 EMU benchmark (left panel) and with the Greek markets(right panel). The left panel graphs show that the comovement patterns with the EMU 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 for most countries in our sample, and then a decreasing tendency is observed for most countries, particularly since the end of 2012. This beginning of this period covers the Great Recession and later the beginning of economic recovery in the United States. The latter part 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. Second, the four countries (Ireland, Italy, Portugal, and Spain), which are the highly indebted, have relatively similar patterns of comovement with the EMU benchmark as their economies have 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 relatively 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 the second half of 2011. Those countries are well known for their high sovereign credit risk premium.

4.4 Dependence structure of the eurozone sovereign bond markets

We now turn to the analysis of the dependence structure which is assessed through the DCCs for the pairs of the markets under consideration. Table 5 reports the estimation results of the DCC-BB7 copula model for the conditional dependence between individual sovereign bond markets and the EMU benchmark. A close look at the estimated α and β coefficients of the DCC processes, which respectively measure the strength of the past correlation and its persistence, shows that these coefficients are highly significant at the 5% and 1% levels. The relatively 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 together with their time-paths presented in Figures 1-2 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 ($\alpha + \beta$) 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 (γ and κ) 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 is, the stronger is the dependence level. We see that both dependence parameters of the BB7 copula are positive and significant for all pairs of the markets under consideration. The parameter γ ranges from 0.551 (Greece-EMU) to 0.818 (Germany-EMU), while the parameter κ varies from 1.022 (Netherlands-EMU) to 1.269 (Germany-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. It includes mostly the economic powerhouses of the eurozone, and the exception is Finland but this country experienced relatively very high economic growth and its per capita output is equal to that of other economies in this block. The second one covers Ireland, the Netherlands, Portugal and Spain which are mostly dominated by high debtors. This block is however characterized with a relatively lower degree of dependence. The exception in this group is the Netherlands but this country was also hit hard by the sharp downturn in world trade in 2008 and 2009 since it has more open economy than many of the countries in the eurozone.

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 dependence (λ_L) is much more pronounced than the upper tail dependence (λ_U), providing evidence of the fact that the paired bond markets are likely to crash together during turbulence periods. Germany has the highest upper tail dependence with the

EMU benchmark. This country 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 also 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. This country 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 onset of the recent global financial crisis and the Great Recession of 2008-2009.[7] The estimation reported in Table 6 provides evidence of significant, positive and asymmetric dependence on average for all Greece-centered pairs of the eurozone countries. The dependence structure is also time-varying and persistent, in view of the high significance of the DCCs' α and β parameters.

During the bearish market periods, sovereign bond markets in four countries (Spain, Portugal, Italy, and Netherlands) have the highest degree of dependence with changes in the Greek sovereign bond market, while this dependence is the least for Germany. In bullish market conditions, the French and German sovereign bond markets exhibit the highest and least dependence with the Greek one, respectively. 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

[7] Indeed, the fears and signs of a sovereign debt crisis in the eurozone 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 results of the DCCs and copula-based dependence in Subsections 4.3 and 4.4, respectively, show that 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 a 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

$$VaR_{p_j}(X) = F^{-1}(p_j) \tag{18}$$

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 respectively correspond to the 99%, 99.5% and 99.9% confidence levels, and estimate the VaR in Eq. (18) based on the empirical quantiles of the distribution of sovereign bond returns.

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 represent the loss functions (i.e., sovereign bond returns in our study) 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, where i represents the original crisis country. 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 member countries, whereby *B* and *A* denotes the shock events in Greece and other eurozone countries, respectively. 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 $P(B_3/A_2) < P(A_3/B_2)$, although the difference is not always substantial. 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 southern European 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. The German sovereign bond market is found to be the less exposed to the crisis transmission effects than the French one. This result corroborates our previous analysis in the sense that solid economic structure and strong economic performance make Germany more resilient to the Greek crisis.

Second, Austria, Finland and Netherlands are apparently protected against the crisis propagation in view of the low conditional probabilities. For Austria and Finland, this decoupling effect can potentially be explained by these countries' less integration with the eurozone. These three countries are also 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 eurozone. 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.[8] 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. As for the Netherlands' national debt, its 65.2 percent

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

of gross domestic product is considerably below that of France (85.8 percent) and even Germany (82.1) as of April 2012, according to the European statistics agency (Eurostat).

Finally, the results provide evidence to confirm the fact that the Greek sovereign bond market significantly transmitted the crisis shock to the whole eurozone countries with probabilities of 0.664 and 0.694 with respect to risk levels considered. 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 conditionally on the fall of the EMU market below its VaR at the 0.01 and 0.005 levels are the highest. These probabilities equal to 0.786 and 0.689, 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 particularly allows one to address the crisis transmission issue during turmoil conditions, which manifests itself in the presence of tail dependence we identified previously. Compared to the analysis in the Subsection 4.5.1, we use the fitted returns from the DCC-copula model, instead of the realized returns, in order to take the dependence between the pairwise bond returns into account. By doing so, the conditional probability of crisis transmission between two sovereign bond markets is evaluated given their dependence characteristics that are captured by our copula models.

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 estimated from the GJR-GARCH-DCC-BB7 copula model, $\{\hat{R}_t\}_{t=1}^{T}$. In practice, we first sort these bond return 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

$$H(k) = \frac{1}{k}\sum_{i=1}^{k}\left[ln\left(\hat{R}_{T-i+2}\right) - ln\left(\hat{R}_{T-k}\right)\right] \quad (19)$$

Eq. (19) 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.[9]

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

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{bmatrix} \tag{20}$$

where $p_{ij} = Prob(I_t^A = i | I_{t-1}^B = j)$ for $(i, j = 1, 2, 3)$ is the probability that market A is in state *i* given that market B is in 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 market A, the conditional probabilities of dependence with market B, p_{ij}, can be estimated by maximizing the following log-likelihood function under conditional dependence (see, Reboredo and Rivera-Castro, 2014):

$$l(P; I_1^A, I_2^A, \dots, I_T^A) = \sum_{i=1,j=1}^{3} p_{ij}^{n_{ij}} \tag{21}$$

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:

$$\hat{p}_{ij} = \frac{n_{ij}}{n_{i1} + n_{i2} + n_{i3}} \tag{22}$$

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.

[9] 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.

[Please insert Table 8 about here]

A closer 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 the strongest economy in the eurozone. 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.

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 relatively higher resilience of those in Austria, Finland, Germany, and Netherlands.

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 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 the case of widespread panics and financial turbulences.

This article used 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. An analysis of crisis transmission based on the results of the best-suited empirical DCC-BB7 copula model and the extreme value theory is also provided.

Examining the 10-year government bond indices of ten EU countries, 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 exhibits 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 BB7 copula over the other Archimedean, Gaussian, and Student-*t* copulas in modeling the dependence structure between the eurozone sovereign bond markets.

Overall, our results are helpful for policymakers to understand the dependence structure within the eurozone sovereign debt markets, which is needed in order 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 (e.g., quantitative easing and forward guidance, and non-commercial monetary policy which combines actions from the central banks, SEC and the legislatures) 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 GJR-GARCH 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										
Log-likelihood	-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
M_n	1.02	1.14	0.25	0.47	0.66	0.78	0.38	0.47	0.29	0.13
Dynamic Gaussian copula										
Log-likelihood	-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
M_n	0.63	0.47	0.55	1.14	0.9	1.05	0.58	0.88	0.42	0.16
Dynamic Gumbel copula										
Log-likelihood	-207.83	-243.62	-288.56	-242.53	-251.02	-315.75	-223.29	-197.58	-227.61	-296.22
S_n	0.07	0.17	0.06	0.04	0.17	0.23	0.09	0.04	0.26	0.10
M_n	0.25	0.33	0.19	0.29	0.41	0.67	0.33	0.30	0.17	0.22
Dynamic SJC copula										
Log-likelihood	-250.41	-303.55	-401.12	-322.17	-299.66	-360.01	-366.77	-205.44	-303.53	-316.22
S_n	0.04	0.22	0.11	0.08	0.14	0.29	0.02	0.05	0.18	0.12
M_n	0.22	0.31	0.66	0.52	1.33	0.44	0.12	0.14	0.05	0.36
Dynamic BB1 copula										
Log-likelihood	-255.09	-317.14	-415.33	-356.12	-409.85	-404.51	-314.47	-301.77	-307.06	-361.99
S_n	0.17	0.33	0.63	0.22	0.14	0.08	0.04	0.04	0.18	0.63
M_n	0.42	0.55	0.74	1.66	0.23	0.45	0.98	0.63	0.44	0.89
Dynamic BB7 copula										
Log-likelihood	**-280.05**	**-322.19**	**-431.22**	**-377.42**	**-412.88**	**-418.62**	**-400.55**	**-307.36**	**-345.33**	**-378.63**
S_n	**0.02**	**0.07**	**0.05**	**0.04**	**0.04**	**0.17**	**0.01**	**0.03**	**0.07**	**0.05**
M_n	**0.17**	**0.04**	**0.19**	**0.20**	**0.33**	**0.03**	**0.11**	**0.02**	**0.06**	**0.12**

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									
Log-likelihood	-233.50	-264.99	-207.34	-253.66	-242.70	-271.35	-212.61	-283.99	-266.84
S_n	0.25	0.17	0.09	0.28	0.16	0.66	0.05	0.15	0.39
M_n	1.03	0.93	0.77	0.45	1.25	0.42	0.33	0.96	0.22
Dynamic Gaussian copula									
Log-likelihood	-230.81	-258.55	-208.61	-266.34	-239.22	-245.62	-230.48	-278.64	-259.33
S_n	0.19	0.33	0.19	0.14	0.24	0.65	0.36	0.57	0.51
M_n	0.24	1.44	1.37	1.05	0.44	1.24	1.55	0.78	0.89
Dynamic Gumbel copula									
Log-likelihood	-236.36	-278.07	-266.93	-294.42	-244.79	-285.05	-259.64	-297.08	-272.08
S_n	0.22	0.26	0.14	0.19	0.11	0.13	0.08	0.06	0.25
M_n	0.88	0.55	0.42	0.33	0.62	0.28	0.47	0.36	0.62
Dynamic SJC copula									
Log-likelihood	-303.55	-298.05	-345.22	-317.66	-278.28	-290.63	-262.99	-313.82	-401.55
S_n	0.17	0.26	0.39	0.14	0.33	0.12	0.24	0.22	0.45
M_n	0.29	0.42	0.51	1.02	0.77	0.35	0.60	0.42	0.63
Dynamic BB1 copula									
Log-likelihood	-314.04	-352.11	-352.09	-360.22	-287.44	-294.78	-264.22	-315.22	-399.36
S_n	0.08	0.17	0.09	0.11	0.15	0.23	0.19	0.07	0.15
M_n	0.36	0.29	0.44	0.62	0.22	0.50	0.17	0.14	0.25
Dynamic BB7 copula									
Log-likelihood	**-316.50**	**-368.78**	**-359.77**	**-360.73**	**-292.41**	**-298.15**	**-270.36**	**-318.00**	**-405.66**
S_n	**0.05**	**0.07**	**0.03**	**0.01**	**0.06**	**0.14**	**0.04**	**0.06**	**0.05**
M_n	**0.17**	**0.22**	**0.09**	**0.16**	**0.19**	**0.13**	**0.23**	**0.14**	**0.16**

Notes: This table reports the values of the log likelihood functions of different copula models as well as the statistics of the two goodness-of-fit tests. Bold numbers indicate the best-suited models (i.e., the ones with the highest absolute values of the log likelihood functions and the lowest distances between the estimated copula and the empirical one). 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 DCC-BB7 copula for the dependence with EMU benchmark market

	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)

Notes: This table reports the parameters of the dynamic conditional correlation processes (α, β), the estimated average dependence parameters (γ, κ) and the upper and lower tail dependence coefficients (λ_U, λ_L). 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 5% and 1% levels, respectively.

Table 6: Estimated parameters of the DCC-BB7 copula for the dependence with the Greek market

	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)

Notes: This table reports the parameters of the dynamic conditional correlation processes (α, β), the estimated average dependence parameters (γ, κ) and the upper and lower tail dependence coefficients (λ_U, λ_L). 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 5% 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	0.443	0.469	0.464
Germany - Greece	0.312	0.392	0.385	0.411
Ireland - Greece	0.246	0.301	0.279	0.461
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., Germany) 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. Dynamic dependence between the EMU benchmark and Greek of sovereign bond returns

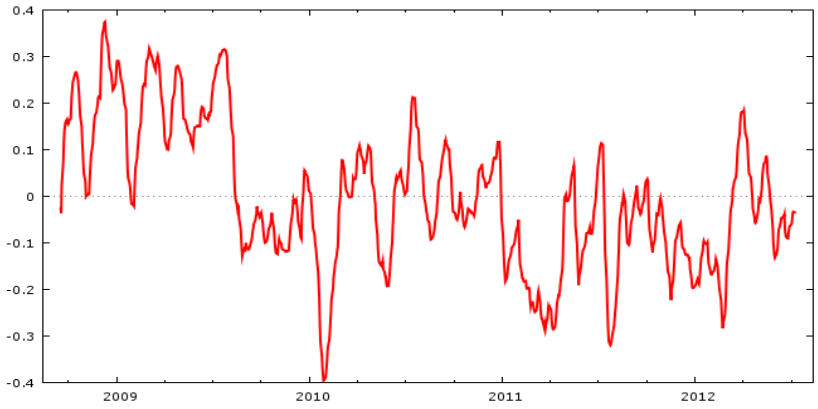


Figure 2. Dynamic dependence with the EMU benchmark and with Greek sovereign bond markets

