Comparing CDS spreads of EU sovereigns in the progress of the Global Financial Crisis and the Eurozone Debt Crisis

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Abstract

This paper investigates how differently have the Credit Default Swap (CDS) spreads of EMU core, EMU periphery, and Non-EMU economies evolved in the progress of the Global Financial Crisis (GFC) and the Eurozone Debt Crisis (EDC). To analyze the structural changes in the weekly movements of the CDS spreads during the crises, we employ GARCH-copula models.

We nearly don't find structural changes in the conditional means after controlling for the common determinants of the sovereign CDS spreads, autocorrelations, and heteroscedasticities. In terms of conditional volatility, however, the EMU periphery group shows significantly larger increment than the others after the EDC period whereas the three groups exhibit similar structural increases in the volatilities after the GFC. As a result of the dependence analysis using time-varying copulas, we find (EMU core, EMU core) and (Non-EMU, Non-EMU) pairs generally experience structural increase in both the Gaussian and the tail dependences during the two crisis periods. However, (EMU periphery, EMU periphery) overall exhibits no or structural decrease in dependence during both the GFC and the EDC period. Lastly, the asymmetry in dependence is skewed to the lower tail for the GFC period whereas not for the EDC period, in general.

JEL classifications: C51; G20; G32

Keywords: Copula; Eurozone Debt Crisis; European Monetary Union; Global Financial Crisis

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1 Introduction

This paper empirically investigates how have European Union (EU) sovereign CDS spreads evolved during the Global Financial Crisis (GFC) and the Eurozone Debt Crisis (EDC) in terms of their conditional means, conditional volatilities, and dependences. We especially focus on the difference among the EU sovereign CDS markets' reactions to the crises across types of EU countries - 6 EMU core, 5 EMU peripheral (*GIIPS*), and 3 Non-EMU economies. Figure 1 presents the weekly series of 14 EU sovereign CDS spreads of 5-year maturity for the period from 16 May 2007 to 29 March 2017. It clearly shows that the CDS spreads are stable prior to September 2008 and fluctuate tremendously for all countries after that.

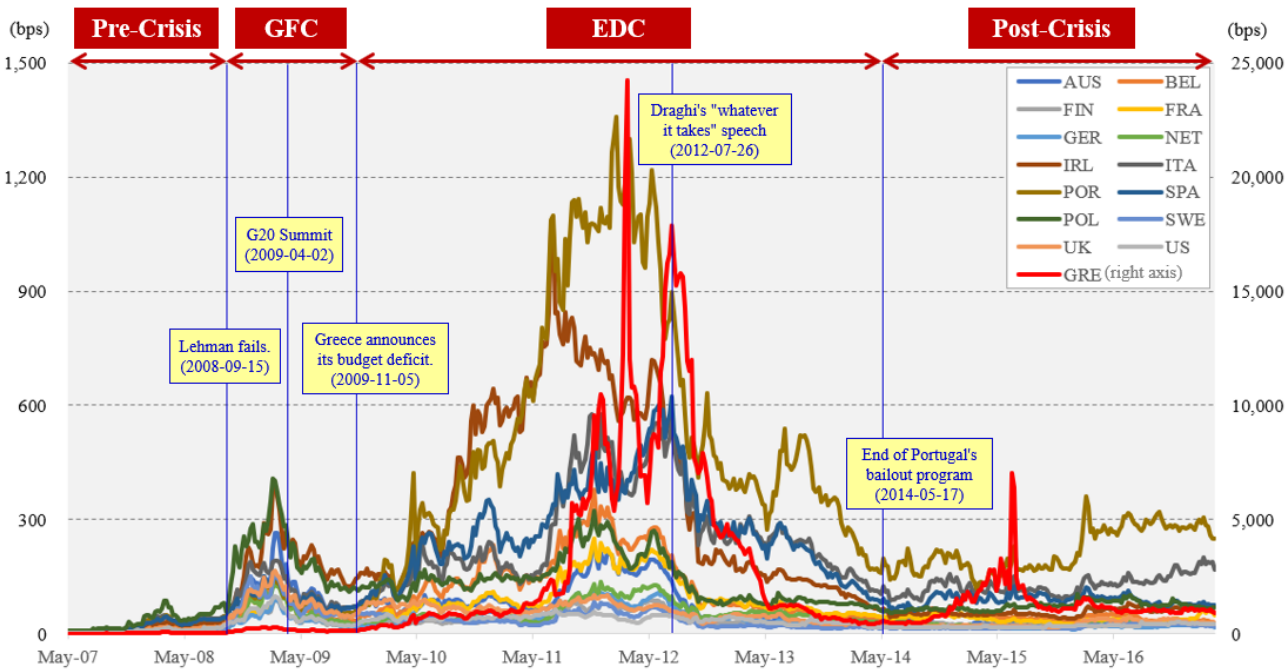

Figure 1: Weekly series of sovereign CDS spreads of 5-year maturity for 14 EU economies - Austria (AUD), Belgium (BEL), Finland (FIN), France (FRA), Germany (GER), Netherlands (NET), Greece (GRE), Ireland (IRL), Italy (ITA), Portugal (POR), Spain (SPA), Poland (POL), Sweden (SWE), and the United Kingdom (UK) - from 16 May 2007 to 29 March 2017. The right axis represents the CDS spread for Greece (GRE).

To explain the movements of the CDS spreads, we consider common factors including market liquidity of each CDS market, global sovereign credit risk, euro regional variables, and dummy variables for crisis regimes. In addition, we control for the stylized facts such as autocorrelation and heteroscedasticity in the marginal process by using a GARCH model and apply various types of copulas to the standardized residuals for time-varying dependence. In this paper, we interpret the CDS spread as a market perceived risk of sovereign default.

We nearly don't observe structural increases in the conditional mean of the filtered CDS spread changes during the crisis periods in general after controlling for the common determinants. However, we find structural increases in the idiosyncratic volatilities. The three groups exhibit similar structural increments during the GFC period. On the other hands, during the EDC period, the EMU periphery group shows the highest increment relative to the Pre-crisis period. Regarding dependence, (EMU core, EMU core) and (Non-EMU, Non-EMU) pairs generally experience structural increase in both the Gaussian and the tail dependence during the two crisis periods compared to the Pre-crisis period. However, (EMU peripheral, EMU peripheral) overall exhibits no or structural decrease in dependence during both the GFC and the EDC period. Lastly, the asymmetry in dependence is skewed to the lower tail for the GFC period overall, **whereas no for the EDC period**.

The rest of this paper proceeds as follows. In Section 2, we review some basic backgrounds for this study. In Section 3, we discuss our econometric model. Section 4 presents the data and Section 5 discusses the empirical results. Lastly, Section 4.6 concludes.

2 Backgrounds

This section gives a simple sketch about the European Union. Also, the progress of the crises from the GFC to the EDC is briefly reviewed and we will split the sample period into 4 sub-periods based on the progress.

2.1 European Union

The European Union (EU) is a political and economic union of countries (or states) in Europe. Figure 2 illustrates European countries' economic cooperation relationship.[1] Europe consists of total 48 countries (or states) and currently 28 of them are members of the EU. In addition, 19 of the total 28 members of the EU belong to European Monetary Union (EMU), so called "Eurozone".

[1]On 29 March 2017, the UK provided the EU with formal notification under Article 50 of the Treaty on European Union of its intention to leave the European Union and Euratom (EU (2018)).

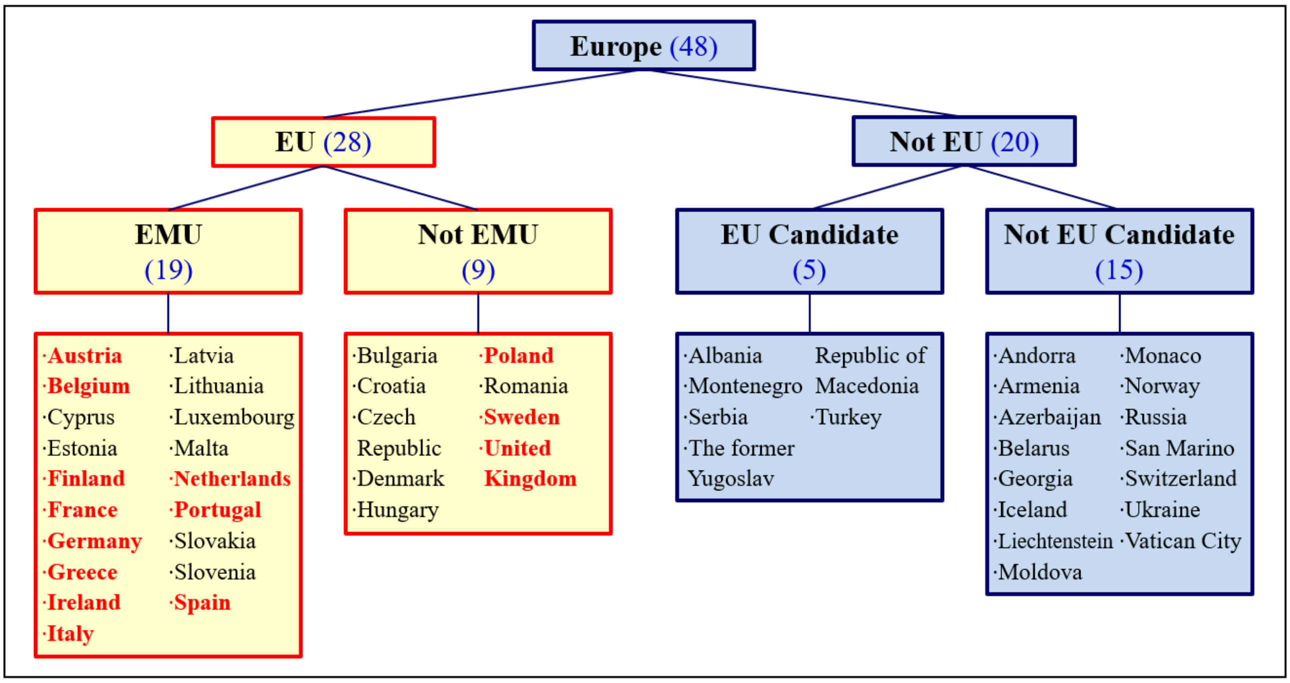

Figure 2: European countries' economic cooperation relationship. The red colored bold members are the sample countries to be analyzed. The figures in parentheses are the number of countries in each categories.

Figure 3 shows time-series of the EU members' aggregate annual real GDP in billion euros and contributions by individual members for the time period from 1995 to 2017. As of 2017, the aggregate GDP in EU is 15,373,553 billion euros and the main contributors are GER (21.1%), the UK (15.2%), FRA (14.9%), ITA (11.2%) and SPA (7.6%). The aggregation of the main contributors amounts to more than 70% and the other members' individual contributions are less than 5%. The shaded region stands for the periods of the GFC and the EDC.

2.2 The GFC and The EDC

Figure 4 shows a time line of main events in the progress of the GFC and the EDC. There are several signaling events in Euro area about the upcoming huge crises. On 09 August 2007, BNP Paribas halts redemptions on their three investment funds. About one month later on 14 September 2007, the Bank of England is authorized to provide liquidity support to Northern Rock who has been experiencing a bank run. These events indicate that the EDC mainly originate from the financial sector in Europe.

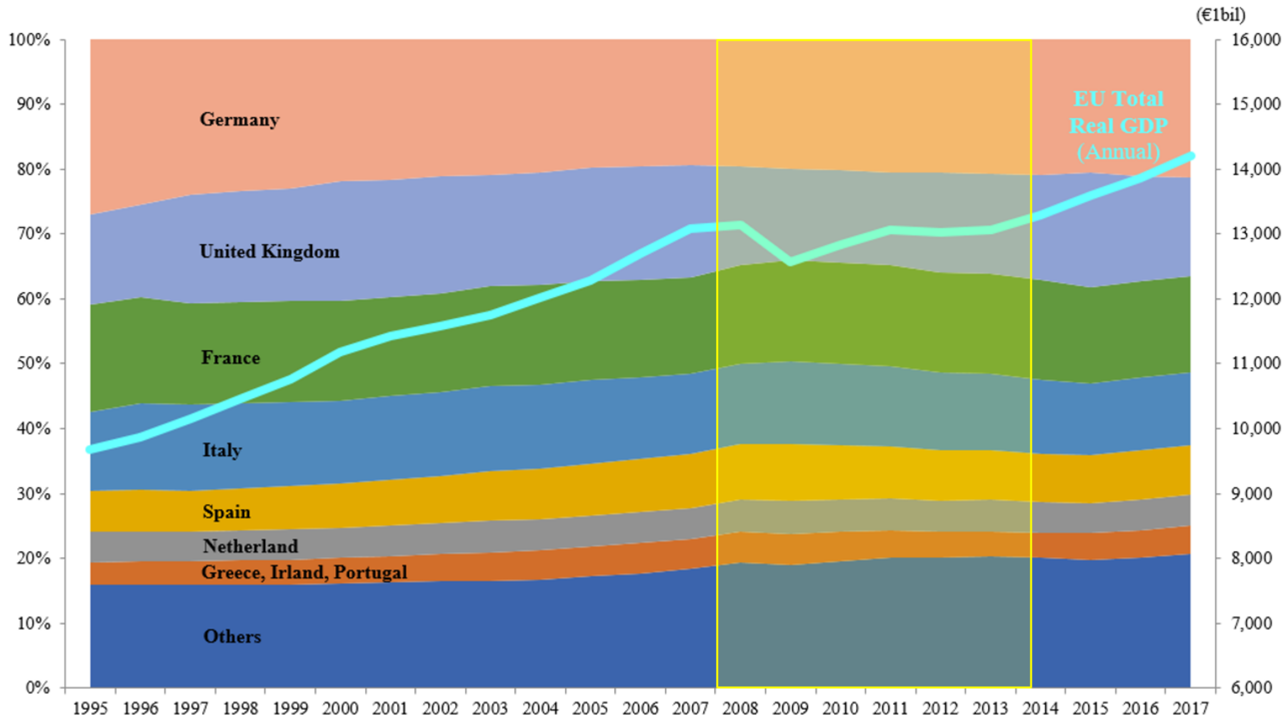

Figure 3: The EU members' aggregate annual real GDP (in billion euros) and contributions by individual members for the time period from 1995 to 2017. The right axis stands for the total GDP in EU and the left axis represents individual member's contribution. (Data source: Eurostat's website)

Figure 4: Timeline of the Global Financial Crisis (GFC) and the Eurozone Debt Crisis (EDC). (Source: Financial crisis timeline provided by the Federal Reserve Bank of St. Louis the Guardian)

2.3 Defining Sub-periods

Our sample spans from 16 May 2007 to 29 March 2017 and overlaps the periods of the GFC and the EDC. As shown in Figure 1, economic events such as the default of Lehman Brothers and Greek government's announcement of its public deficit address structural changes in the time series of the CDS spreads. The structural breaks should be considered for an empirical analysis. For example, Gorea and Radev (2014) divide their sample period (Jan 2007 - Aug 2011) of daily data into three sub-periods splitted by Lehman Brother's bankruptcy and the Greek government's announcement based on their estimates of the joint default probabilities extracted from the CDS spreads of sovereigns in Europe. Amstad et al. (2016) define the GFC period as Sep 2008 - April 2009 in their sample period (Jan 2004 - April 2009) of monthly data based on several statistical tests with 28 sovereign CDS spreads, including 10 EU countries, and define the "old normal" and the "new normal" as before and after the GFC periods, respectively.[2]

Furthermore, it is evident that the EDC has greater impacts than the GFC on European economies from Figure 1. The focus of this paper is to investigate how conditional mean, volatility, and pairwise dependence of EU sovereign spreads have evolved in the progress of the GFC and the EDC. For this purpose, we divide the full sample period into four sub-periods - the Pre-crisis (sub-period 0), the GFC (sub-period 1), the EDC (sub-period 2), and the Post-crisis (sub-period 3) periods - based on three important economic events related to the GFC and the EDC. The three cut-off dates are:

- Date 1 (the beginning of the GFC period): 15 September 2008 when Lehman Brothers files for bankruptcy
- Date 2 (the beginning of the EDC period): 05 November 2009 when the new Greek government announces that the public deficit would top 10% of GDP
- Date 3 (the beginning of the Post-crisis period): 17 May 2014 when the bailout program to Portugal has ended[3]

[2]Actually, they define only the start date of the GFC based on the results of Bai-Perron, Quandt-Andrews and Chow tests. They select the end date of the GFC period based on the graph of the CDS spreads.

[3]The only remaining sovereigns of bailout are Greece and Cyprus.

3 Model

In this section, we describe the econometric models employed by this paper. We first describe the marginal regression model for CDS spread with AR(m)-EGARCH(p,q) error. Then we discuss explanatory variables included in the conditional mean and variance equations. Lastly, we explain copula employed for modeling the pairwise dependence between movements of the CDS spreads..

3.1 Marginal Model: AR(m)-EGARCH(p,q)

Let y_t^i be the change of economy i's CDS spread between week $t-1$ and week t, i.e. $y_t^i = CDS_t^i - CDS_{t-1}^i$ for $i =$\{AUD, BEL, FIN, FRA, GER, NET, GRE, IRL, ITA, POR, SPA, POL, SWE, UK\}. We consider the following AR(m)-EGARCH(p,q) model in order to describe the marginal processes of the CDS spread changes. For each i, we suppose that

$$\begin{aligned} y_t^i &= \beta_0^i + \beta_{BA}^i BA_t^i + \sum_{k=1}^{G} \beta_k^i x_{k,t}^g + \sum_{k=1}^{3} \gamma_k^i I_{k,t} + \varepsilon_t^i \\ \varepsilon_t^i &= \nu_t^i - \varphi_1^i \varepsilon_{t-1}^i - \cdots - \varphi_m^i \varepsilon_{t-m}^i \\ \nu_t^i &= \sigma_t^i \eta_t^i \\ \ln(\sigma_t^i)^2 &= a_0^i + \sum_{s=1}^{p} an_s^i g(\eta_{t-s}^i) + \sum_{s=1}^{q} b_s^i \ln(\sigma_{t-s}^i)^2 + \sum_{k=1}^{3} c_k^i I_{k,t}, \end{aligned} \tag{1}$$

where $g(\eta_t^i) = \theta\eta_t^i + |\eta_t^i| - \sqrt{\frac{\pi}{2}}$. BA_t^i represents market liquidity of sovereign CDS market i and $x_{k,t}^g$'s are common factors influencing sovereign risks of all the EU economies. $I_{k,t}$'s are binary indicators of crisis regimes which will be discussed in Section 3.2.3. The standardized filtered residual η_t^i is assumed be *i.i.d.* standard normally distributed.[4]

We select AR(4)-EGARCH(1,1) model. $m = 4$ in the conditional autocorrelation equation means the reflection of past information during the recent month and $p = q = 1$ in the conditional variance equation is the benchmark choice of using a GARCH type model.

3.2 Explanatory Variables

To control for common components of the EU sovereign CDS spreads, we include global and Euro-regional variables in the conditional mean regression in (1). We consider the common risk factors

[4]The EGARCH process for conditional volatility is common in sovereign CDS and bond yield literature using copula. Recent examples are Fabozzi et al. (2016) which consider EGARCH(1,1) with Gaussian marginal and copula as one of their candidate models to analyze weekly Eurozone sovereign CDS spreads and Silvapulle et al. (2016) that apply EGARCH(1,1)-X model with innovations of unknown distributions to obtain "other effects" free daily sovereign yield spreads (relative to Germany) together with copula for financial contagion analysis.

only since the inclusion of economy-specific variables can harm inferences from the dependence analysis in Section 5.2 where we aim to analyze dependence between the CDS spreads after controlling for aggregate market conditions and uncertainty. In addition, Longstaff et al. (2011) report that global variables play more important roles than country-specific variables in explaining sovereign CDS spreads. Therefore, the inclusion of common factors only in the conditional mean in Equation (1) is reasonable. Indicator variables for each sub-periods are also included both in the conditional mean and variance equations to incorporate structural breaks observed from Figure 1.[5]

3.2.1 Market Illiquidity (BA_t^i)

Notwithstanding our goal in this section is to specify common variables affecting changes of EU sovereign spreads in Equation (1) correctly, we consider this economy-specific factor as a regressor since we want to interpret the CDS spread as a measure of market perceived sovereign default risk. As pointed out by De Santis and Stein (2016), CDS spreads are not immune to liquidity risk, which is not a credit risk, as well as aggregate market uncertainty. Furthermore, Bongaerts et al. (2011) show that part of the CDS spread reflects liquidity effects and find strong evidence of an expected liquidity premium earned by the credit protection seller, although it is the case of the US corporate and financial CDS market. We use the bid-ask spread of a CDS premium as a proxy of the market illiquidity to disentangle pure credit risk component similar to De Santis (2014) and De Santis and Stein (2016).[6] An increase in this variable will increase the corresponding CDS spread.

3.2.2 Common Factors ($x_{k,t}^g$)

Global sovereign credit risk Longstaff et al. (2011) show that the 1st principal component accounts for 64% of the variation in CDS premiums of 26 countries. Amstad et al. (2016) also find that the 1st principal component explains 51% and 64% of the movements in 28 sovereign CDS spreads before and after the GFC, respectively. These findings suggest that the EU sovereign CDS markets are closely related to the sovereign CDS markets outside the Europe. For example, all the CDS spreads of EU sovereigns are definitely affected by US sovereign CDS market during the GFC period. To

[5]If our goal is to identify financial contagion such as wake-up call or pure contagion between EU sovereign CDS markets, it is more correct to include economy-specific variables such as local stock market return in the marginal process. For more discussion about this issue, please refer Pesaran and Pick (2007) and Ludwig (2014).

[6]Inclusion of a market illiquidity variable is common in sovereign bond yield literature. For example, Bernoth and Erdogan (2012), Giordano et al. (2013), Ludwig (2014), Paniagua et al. (2017), and many others. However, it is rare in studies on sovereign CDS spreads.

represent this relation, we consider US sovereign CDS spread as a proxy of the global sovereign credit risk outside Europe in the conditional mean equation. An increase in this variable will increase EU sovereign CDS spreads.

Overall corporate credit condition in EU Since credit conditions of non-government sectors are closely related to sovereign CDS spreads (Giordano et al. (2013), Longstaff et al. (2011), and Ludwig (2014)), we include iTraxx Europe index as investor's consensus on overall credit risk of EU corporates in our model. iTraxx Europe index is composed of 125 most actively traded CDS on European investment grade companies and covers various sectors including financial.[7] Ang and Longstaff (2013) and Fabozzi et al. (2016) use iTraxx Europe index as a regressor to explain Eurozone sovereign CDS spreads. Alter and Beyer (2014) include this index as a variable to control for common trends in the sovereign and the banking CDS spreads. Amstad et al. (2016) employ this index to figure out determinants of the 1st principal component of the CDS spreads for 28 sovereigns. Overall higher default probabilities of corporates could be seen by investors as a signal of transferring corporate default risks to the public sector, leading increased market perceived probability of sovereign defaults. Thus, the higher iTraxx Europe index becomes, the higher the EU sovereign CDS spreads will be.

Outlook of the overall state of the economy in Europe Stock markets are generally seen as a good representation and prediction of the overall state of the economy (Chiarella et al. (2015)). We employ Eurostoxx50 index as a proxy of overall economic outlook in Europe since it consists of 50 largest companies in 11 Eurozone countries and serves as a market based proxy for the outlook of an entire euro economy.[8] Higher stock market returns indicate positive economy outlooks by investors leading to a sovereign's better ability to repayment. An increase in this variable will decrease the EU sovereign CDS spread.

Value of EUR currency One of the most notable impact of the EDC on global financial markets is that investors no longer treat Eurozone as a group of homogeneous economies although they share one currency, EUR. Thus, we include weekly appreciation of EUR against USD as a common component

[7] We do not consider european financial sector's credit condition, usually proxied by iTraxx Financials Senior or iTraxx Financial Sub index, separately since 30 entities of the 125 companies comprising iTraxx Europe are from financial sector.

[8] We do not include volatility index which is usually considered as a general risk aversion in financial markets. We originally have tried both Eurostoxx50 and VSTOXX, however, they showed multicollinearity problem due to their very high correlation. In addition, Eurostoxx50 showed better explanatory power. Ang and Longstaff (2013) find that stock market returns are significantly related to the systemic component of Eurozone sovereign CDS spreads, whereas volatility index is not.

of EU sovereign CDS spread movements in our model. Wong and Fong (2011) use EUR appreciation against USD as a regressor to calculate CoVaR with sovereign CDS spreads, where most of them are European sovereigns. The increase in EUR/USD currency rate (i.e., appreciation of EUR) will decrease the CDS spreads on EU sovereigns.

Funding illiquidity in the EUR interbank funding market Since the crisis in Europe has partially begun from the banking sector as a result of banks' debts taken over by governments, the EUR funding illiquidity could affect sovereign CDS premiums. We use the spread between 3-month EURIBOR and EONIA rate to reflect the funding liquidity risk since the region of our interest is Europe. The EURIBOR-EONIA spread in EUR funding market is the counterpart to the LIBOR-OIS spread, which is a general measure of funding illiquidity in the interbank USD funding market. Gorea and Radev (2014) employ the EURIBOR-EONIA spread as a regional control variable to explain CDS-implied joint default probability between Eurozone sovereigns. Alter and Beyer (2014) consider this variable to control for common trends in the sovereign and the banking CDS spreads. Lack of money in the interbank market both weakens possibility of refund and increases financing costs of sovereigns. Therefore, higher level of this spread will lead EU sovereign CDS spreads to higher.

3.2.3 Crisis Regime Indicator ($I_{k,t}$)

As illustrated in Figure 1, there obviously exists structural breaks in the time-series of CDS spreads to be analyzed since our sample period overlaps the periods of the GFC and the EDC. We define indicator functions for crisis regimes as following corresponding to each sub-periods in Section 2.3:

- Pre-crisis Indicator: $I_{0,t}$ (or $I_{Pre,t}$) $= 1$ if $t <$ 2008-09-15 (Lehman's failure), 0 otherwise.
- GFC Indicator: $I_{1,t}$ (or $I_{GFC,t}$) $= 1$ if 2008-09-15 $\leq t <$ 2009-11-05 (Greece's deficit announcement), 0 otherwise.
- EDC Indicator: $I_{2,t}$ (or $I_{EDC,t}$) $= 1$ if 2009-11-05 $\leq t <$ 2014-05-17 (End of Portugal's bailout), 0 otherwise.
- Post-crisis Indicator: $I_{3,t}$ (or $I_{Post,t}$) $= 1$ if $t \geq$ 2014-05-17, 0 otherwise.

These indicators serve as dummy variables in Equation (1) for the inference about structural changes in conditional mean, variance and dependence of the CDS spread movements in the progress of crisis regimes. Note that the coefficient of $I_{k,t}$ for economy i ($\gamma_{k,t}^i$) means the structural change in the weekly movements of sovereign i's CDS spread for sub-period k relative sub-period 0 (the Pre-crisis period).

3.3 Dependence Model: Copula

Copula is a function which joins a multivariate distribution function to its one-dimensional marginal distributions. Consider a two-dimensional continuous random variable (X, Y) whose marginal distributions are $u = F_X$ and $v = F_Y$. Let $F_{X,Y}$ be the joint distribution of (X, Y). According to Sklar's theorem (Sklar (1959)), there exists a probability distribution function $C : [0, 1]^2 \to [0, 1]$ satisfying

$$F_{X,Y}(x, y) = C(u, v). \tag{2}$$

Here, the function C is called *copula.* Differentiating both sides of Equation (2) with respect to x and y yields

$$f_{X,Y}(x, y) = c(u, v) f_X(x) f_Y(y), \tag{3}$$

where $c(u, v) = \dfrac{\partial^2 C(u, v)}{\partial u \partial v}$, $f_X(x) = \dfrac{dF_X(x)}{dx}$ and $f_Y(y) = \dfrac{dF_Y(y)}{dy}$. Equation (3) clearly shows that we can decouple the joint density $f_{X,Y}$ into the product of a dependence density function c and the marginal densities. Thus, copula provides flexibility for modeling dependence in terms of the choice of marginal distributions and dependence structure without restrictions.

Another useful property of copula is tail dependence. A copula $C(u, v)$ is said to have upper tail dependence λ^U if

$$\lambda^U = \lim_{\varepsilon \to 1^-} \frac{\overline{C}(\varepsilon, \varepsilon)}{1 - \varepsilon} \in [0, 1),$$

where $\overline{C}(u, v) = 1 - u - v + C(u, v)$ is the survival function of $C(u, v)$. Similarly, a copula $C(u, v)$ is said to have lower tail dependence λ^L if

$$\lambda^L = \lim_{\varepsilon \to 0^+} \frac{C(\varepsilon, \varepsilon)}{\varepsilon} \in [0, 1).$$

If $\lambda^U = 0$ ($\lambda^L = 0$), a copula $C(u, v)$ has no upper (lower) tail dependence.

We consider several kinds of copula functions for modeling various types of dependence between movements of CDS spreads: (1) Gaussian (GA) copula as the benchmark, (2) Gumbel (GM) copula for the upper-tail dependence, (3) Gumbel-Survival (GS) copula for the lower-tail dependence, and (4)

Symmetrized Joe-Clayton (SJC) copula for the asymmetric dependence. Dependence parameters of individual copulas are assumed to follow the step-wise function in accordance with the crisis regimes discussed in Section 3.2.3. For estimation, we employ the canonical maximum likelihood (CML) method.

3.3.1 Gaussian (GA) Copula

GA copula is defined as

$$C_{GA}(u,v;\rho) = \Phi_\rho\left(\Phi^{-1}(u), \Phi^{-1}(v)\right),$$

where $\Phi_\rho(\cdot,\cdot)$ is the joint distribution function of the two-dimensional $N(0,1)$ with correlation ρ and $\Phi(\cdot)$ is the distribution function of $N(0,1)$. Therefore, the GA copula can be represented as

$$C_{GA}(u,v;\rho) = \int_{-\infty}^{\Phi^{-1}(v)}\int_{-\infty}^{\Phi^{-1}(u)} \frac{1}{2\pi\sqrt{1-\rho^2}}\exp\left\{-\frac{r^2-2\rho rs+s^2}{2(1-\rho^2)}\right\} drds.$$

Note that it has neither upper nor lower tail dependence unless the correlation is equal to 1. That is,

$$\lambda_{GA}^U = \lambda_{GA}^L = \begin{cases} 0 & \text{if } \rho \neq 1 \\ 1 & \text{if } \rho = 1 \end{cases}.$$

Therefore, extreme comovements can not be captured by the GA copula.

3.3.2 Gumbel (GM) and Gumbel Survival (GS) Copula

GM copula is defined as

$$C_{GM}(u,v;\alpha) = \exp\left\{-\left([-\ln(u)]^\alpha + [-\ln(v)]^\alpha\right)^{1/\alpha}\right\},$$

where $\alpha \geq 1$. Tail dependences of the GM copula are given by

$$\begin{aligned}\lambda_{GM}^U &= 2-2^{1/\alpha}\\ \lambda_{GM}^L &= 0.\end{aligned}$$

Thus, the GM copula is suitable for describing variables with extreme comovements in upward direction.

GS copula is defined by using the survival function of C_{GM} as

$$\begin{aligned} C_{GS}(u,v;\beta) &= \bar{C}_{GM}(1-u,1-v;\beta) \\ &= u+v-1+\exp\left\{-\left([-\ln(1-u)]^{\beta}+[-\ln(1-v)]^{\beta}\right)^{1/\beta}\right\}, \end{aligned}$$

where $\beta \geq 1$. Tail dependences of the GS copula are given by

$$\begin{aligned} \lambda_{GS}^{U} &= 0 \\ \lambda_{GS}^{L} &= 2-2^{1/\beta}. \end{aligned}$$

Therefore, the GS copula is proper to describe variables with extreme comovements in downward direction.

3.3.3 Symmetrized Joe-Clayton (SJC) Copula

Joe-Clayton (JC) copula is another name of the "BB7" copula of Joe (1997). If we parameterize it using the upper and the lower tail dependence (λ_{JC}^{U} and λ_{JC}^{L}),

$$C_{JC}(u,v,;\lambda_{JC}^{U},\lambda_{JC}^{L}) = 1-\left(1-\{[1-(1-u)^{\kappa}]^{-\gamma}+[1-(1-v)^{\kappa}]^{-\gamma}-1\}^{1/\gamma}\right)^{1/\kappa},$$

where

$$\kappa = \frac{1}{\log_2(2-\lambda_{JC}^{U})} \text{ and } \gamma = \frac{1}{\log_2(\lambda_{JC}^{L})}.$$

A critical drawback of the JC copula is that some asymmetry remains even in the case of $\lambda_{JC}^{U} = \lambda_{JC}^{L}$.

SJC copula proposed by Patton (2006) is an extension of the JC copula to overcome this drawback. It is defined as

$$\begin{aligned} C_{SJC}(u,v,;\lambda_{SJC}^{U},\lambda_{SJC}^{L}) &= \frac{1}{2}\{C_{JC}(u,v,;\lambda_{SJC}^{U},\lambda_{SJC}^{L}) \\ &\quad +\bar{C}_{JC}(1-u,1-v,;\lambda_{SJC}^{U},\lambda_{SJC}^{L})\} \\ &= \frac{1}{2}\{C_{JC}(u,v,;\lambda_{SJC}^{U},\lambda_{SJC}^{L}) \\ &\quad +[u+v-1+C_{JC}(1-u,1-v,;\lambda_{SJC}^{U},\lambda_{SJC}^{L})]\} \end{aligned}$$

and symmetric when $\lambda_{JC}^{U} = \lambda_{JC}^{L}$ by definition.

3.3.4 Dependence Parameterization

In order to inference structural changes in dependence between the CDS spreads of EU sovereigns in the progress of the GFC and the EDC, we assume the following dependence parameters of step-wise function in time:

$$
\begin{aligned}
\theta_t &= \bar{\theta}_0 I_{0,t} + \bar{\theta}_1 I_{1,t} + \bar{\theta}_2 I_{2,t} + \bar{\theta}_3 I_{3,t}\,, \\
(\theta_t &= \bar{\theta}_{Pre} I_{Pre,t} + \bar{\theta}_{GFC} I_{GFC,t} + \bar{\theta}_{EDC} I_{EDC,t} + \bar{\theta}_{Post} I_{Post,t})
\end{aligned}
\tag{4}
$$

where θ_t is a dependence parameter of a copula and $I_{k,t}$'s are the indicator functions defined in Section 3.2.3. Figure 5 graphically illustrates how θ_t evolves in time.

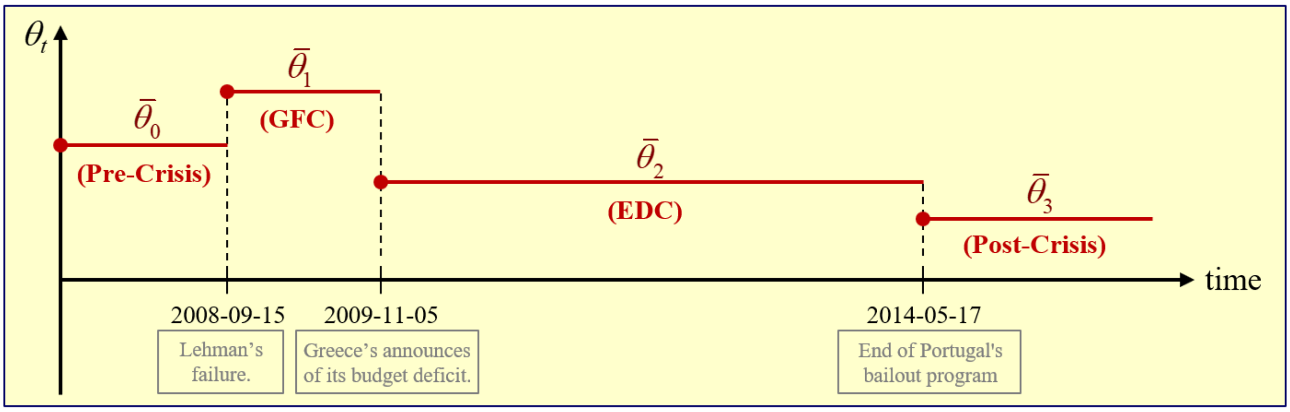

Figure 5: Step-wise dependence parameterization for copula functions

4 Data

In this paper, we investigate USD-denominated 5-year CDS spreads for 14 EU economies, which comprise Austria (AUD), Belgium (BEL), Finland (FIN), France (FRA), Germany (GER), Netherlands (NET), Greece (GRE), Ireland (IRL), Italy (ITA), Portugal (POR), Spain (SPA), Poland (POL), Sweden (SWE), and the United Kingdom (UK) among the 28 EU countries. The period covers from 16 May 2007 to 29 March 2017 and amounts to a total of 516 weekly observations for each country. The choice of the countries and the beginning of this sample period is mainly due to data availability. We use weekly average values of the CDS spreads.[9] Our selection of weekly frequency is to avoid noise

[9]In fact, the use of weekly averaged value is not common although it exists. Chiarella et al. (2015), who also empirically study European sovereign CDS spreads using weekly averaged values. Similarly, Giordano et al. (2013) take

contained in daily data and the choice of the average value is to fully reflect information during a week to our analysis.[10]

Panel A and B of Table 1 report summary statistics of the weekly average of the CDS spreads and their 1st differences (in bps), respectively, for the 14 EU economies by sub-periods defined in Section 2.3. Before Lehman Brother's bankruptcy (sub-period 0), the mean CDS premium was as low as 5.2 bps for GER, but no higher than 35.3 bps for POL in Panel A. This narrow dispersion among the sample economies is in line with the minimal standard deviations for this period in Panel B. Note that the CDS spreads of *GIIPS* economies are already somewhat higher than of those of EMU Cores even before outbreak of the crisis due to investor's anxiety about a possible crisis originating from the events of BNP Paribas or Northern Rock.

The GFC period (sub-period 1) shows the range of 37.8 bps (GER) - 199.7 bps (POL) for the mean values of the CDS premiums in Panel A. This amounts to five times of the range in the Pre-crisis period and makes sense with the increased standard deviations for all countries in this period in Panel B.

In the EDC period (sub-period 2), the average CDS premiums range from 38.3 bps (FIN) - 3,558.0 bps (GRE) in Panel A and the highest is obtained for GRE, who triggers the outbreak of the EDC and has the largest standard deviation and kurtosis in Panel B. Also, in Panel B of Table 1, all EMU peripheries show increased standard deviations from the previous period whereas 2 of the 6 EMU core and all non-EMU economies exhibit decreased standard deviations. In addition, the kurtosises increase from the GFC to the EDC period for all countries, which is not the case from the pre-crisis to the GFC period and EMU peripheries show the largest increase among the three groups. These observations stem from investor's reaction to the fact that the EMU peripheral economies are source of the EDC and imply that the EDC was an extreme tail event for the EMU peripheral economies rather than the other groups. The Post-crisis period (sub-period 3) shows lower average levels of the CDS spreads than the previous two crisis periods, however, still higher compared to the pre-crisis period. This is the case of the standard deviations, too, especially for the EMU periphery group, and indicates investors are still watching the EMU peripheries with cautions.

monthly average of sovereign bond yield spreads (with respect to Germany) of Eurozone countries to investigate financial contagion in the Eurozone sovereign bond market.

[10]For example, if we use CDS spreads on every Wednesday and an important event take place on a Thursday resulting in a surge of the CDS spreads which comes back to its original level within the week, then the impacts of this event will be discarded in the empirical results.

Table 1: **Summary statistics.** This table describes summary statistics of the weekly averages of USD-denominated 5-year CDS spreads of the 14 EU sovereigns and their changes (in bps) for each sub-period defined in Section 2.3.

		Pre-crisis (sub-period 0) (16 May 2007 - 14 Sep 2008)				GFC (sub-period 1) (15 Sep 2008 - 04 Nov 2009)				EDC (sub-period 2) (05 Nov 2009 - 16 May 2014)				Post-crisis (sub-period 3) (17 May 2014 - 29 Mar 2017)			
Panel A: Summary satistics of the CDS spreads																	
Country		Mean	Std	Min	Max	Mean	Std	Min	Max	Mean	Std	Min	Max	Mean	Std	Min	Max
EMU	AUS	6.3	3.9	1.4	13.4	106.8	54.4	13.0	265.7	83.1	50.8	26.0	229.1	27.1	3.1	21.3	34.8
Core	BEL	13.0	8.9	1.5	29.5	66.4	33.5	21.7	148.8	132.9	84.3	37.1	374.0	41.2	7.3	27.0	58.2
	FIN	6.1	3.5	1.4	13.2	40.2	19.8	12.4	90.2	38.3	19.3	17.1	87.2	24.1	2.5	18.4	30.1
	FRA	6.9	4.4	1.5	16.7	42.7	19.8	12.3	94.1	98.6	53.4	23.0	244.0	38.4	8.4	25.5	67.1
	GER	5.2	2.8	1.1	12.2	37.8	18.5	8.7	89.2	48.6	24.9	20.1	108.6	18.0	3.1	12.4	24.9
	NET	6.4	3.9	1.4	15.2	57.5	31.5	11.6	125.9	58.9	27.8	26.8	130.2	23.2	4.9	15.5	32.5
EMU	GRE	29.5	20.4	4.5	66.4	162.0	59.1	52.4	286.4	3,558	4,433	151.8	23,976	1,255	804.2	448.5	6,579
Peri	IRL	16.0	10.9	1.9	31.8	187.3	75.3	31.9	378.1	373.9	250.5	61.8	1,059	56.5	8.7	40.3	83.0
	ITA	24.0	14.9	5.5	47.8	111.9	43.9	41.8	193.8	260.5	128.9	74.2	564.9	128.2	24.7	85.1	196.1
	POR	22.3	14.4	3.6	48.3	80.6	28.1	40.8	149.6	542.8	331.4	61.0	1,404	220.5	58.2	120.4	350.4
	SPA	21.2	14.1	2.7	46.3	90.6	27.8	40.0	158.8	275.4	124.3	74.0	606.6	88.8	13.2	60.8	119.3
Non-	POL	35.3	22.8	7.7	93.0	199.7	81.3	59.4	405.6	139.5	60.2	60.3	321.3	72.3	11.0	53.9	101.5
EMU	SWE	6.0	3.9	1.2	14.3	75.0	35.9	12.6	151.0	34.9	17.0	13.6	80.3	18.4	4.6	13.0	27.1
	UK	8.3	6.1	1.1	19.1	82.6	35.4	23.9	164.5	58.3	20.8	22.1	99.8	25.7	8.0	15.6	43.4
Panel B: Summary satistics of the changes in the CDS spreads																	
Country		Mean	Std	Skew	Kurt	Mean	Std	Skew	Kurt	Mean	Std	Skew	Kurt	Mean	Std	Skew	Kurt
EMU	AUS	0.15	0.85	0.31	6.14	0.78	18.44	0.26	6.87	-0.13	7.84	0.42	7.39	-0.03	1.30	0.63	5.29
Core	BEL	0.29	1.47	0.34	7.87	0.23	9.33	-0.07	4.43	0.01	12.06	0.20	5.99	-0.06	1.83	0.92	6.49
	FIN	0.14	0.81	-0.04	7.15	0.11	5.69	0.30	4.70	0.03	2.92	0.57	6.47	0.00	0.95	0.45	6.23
	FRA	0.16	0.89	0.05	6.19	0.18	5.51	-0.21	5.07	0.09	8.39	0.19	6.56	0.05	2.52	0.58	6.09
	GER	0.10	0.84	-0.64	7.41	0.21	5.37	-0.16	5.32	-0.00	4.13	-0.10	6.13	-0.02	1.03	1.46	12.60
	NET	0.13	0.90	0.22	6.87	0.25	8.57	0.68	5.09	0.01	4.50	0.32	6.48	-0.03	1.14	-0.03	6.10
EMU	GRE	0.69	2.89	-0.86	6.03	1.54	16.95	-0.17	3.46	1.60	1,181	-1.96	61.49	2.65	512.3	-0.76	62.11
Peri	IRL	0.43	1.50	0.05	5.64	1.87	24.65	0.50	4.77	-0.35	33.49	0.82	19.63	-0.06	2.96	-0.00	6.50
	ITA	0.53	2.21	-0.09	4.13	0.51	12.41	0.35	3.71	0.15	22.68	0.24	5.44	0.43	8.90	-0.12	4.33
	POR	0.52	2.18	-0.39	5.38	0.32	10.16	0.22	3.00	0.46	47.40	-0.21	7.66	0.53	15.52	0.38	7.60
	SPA	0.54	2.11	-0.39	5.05	0.56	10.89	0.19	3.08	0.04	21.46	-0.34	4.52	-0.06	6.69	-0.25	4.73
Non-	POL	1.01	5.51	0.62	6.41	0.69	24.90	0.53	3.15	-0.25	10.77	0.08	5.36	0.05	3.50	1.97	16.89
EMU	SWE	0.15	0.85	-0.24	9.62	0.64	11.28	0.11	3.43	-0.15	2.85	1.34	9.85	0.04	0.86	0.93	6.96
	UK	0.25	1.01	0.31	6.14	0.56	10.02	0.27	4.08	-0.13	3.59	0.06	4.33	0.04	1.68	1.49	10.16

Our main data source is Bloomberg. The CDS spreads are collected from CMA closing prices in Bloomberg and iTraxx Europe index is obtained from JP Morgan's quote in Bloomberg. Other financial market data including 3-month EURIBOR, 3-month EONIA rate, and Eurosroxx50 index are also collected from Bloomberg except for EUR currency rate against USD. We use the EUR/USD currency rates downloaded from FRED.

5 Empirical Results

5.1 Estimated Results of Marginals

We estimate the AR(4)-EGARCH(1,1) model specified in Equation (1) by maximum likelihood. Table 2 presents estimated results of the parameters in the marginal processes[11] for individual sovereigns and Table 3 reports their goodness-of-fits.

The results coincide with the previous studies on sovereign CDS premium. Market liquidity proxied by the bid-ask spread increases the CDS premiums for the sample economies, as expected in Section 3.2.2, except for FIN and the UK. The global sovereign credit risk proxied by US CDS, the overall credit condition of companies in Europe measured by iTraxx Europe index, and the outlook of the overall state of the economy in Europe represented by Eurostoxx50 stock market index show the expected effects on the all sovereigns except for one country, respectively. The overall strong significance of these common factors is consistent to related literature such as Longstaff et al. (2011) who report global variables play more important roles than local variables in determining sovereign CDS premiums, and Amstad et al. (2016) finding empirical evidence that global risk factors explain up to 77.6% of variations in sovereign CDS spreads.

The remaining two variables are related to EUR currency. The value of Euro currency proxied by EUR/USD exchange rate decreases the CDS premiums in general. Note that the impact is strongest for EMU peripheries among the three groups: All the five countries in the EMU peripheral group are significantly affected by the EUR/USD exchange rate whereas only two of the six EMU cores and two of the three Non-EMUs show significances for this factor. This indicates that investors on the EMU peripheries have reacted more sensitively to the value of EUR.

The funding liquidity has relatively unclear effects. Only half of the sample sovereigns show significance for this variable and the signs are mixed. A possible interpretation of this vague result is

[11] The results of the autocorrelation equations are not reported here.

that investors in the European sovereign debt markets do not worry about the EUR funding liquidity since the European Central Bank (ECB) who is the liquidity controller in the EUR currency funding market shows its strong willingness[12] to relieve the situation of the debt crisis and uses policies such as OMT (Outright Monetary Transactions) programs convincing the investors that the region's economy will not break out.

Our main interests in Table 2 are the coefficients (γ_{GFC}, γ_{EDC} and γ_{Post}) of the dummy variables. If we look into the conditional mean equations, the two crises seem to have little relation with structural changes in the movements of the CDS spreads after controlling for their common determinants: (1) There is no significant dummy for EMU core economies. (2) Among EMU peripheries, only GRE and IRL show positive structural increase for the GFC period and only GRE has the significantly positive dummy for the EDC period. (3) Furthermore, POL among the Non-EMUs, experiences even structurally decreased movement for the EDC period. These results imply that the extreme jumps in the level of CDS spreads in Figure 1 are mostly originated from the global and Euro-regional risk factors.

The conditional variances are strongly affected by the crises since most dummies in the conditional variances exhibit positive significance. Table 4 summarizes the estimated values of γ_k's in the conditional variance equations by averaging the values of the significant estimates of γ_k's in each group. If we look into Table 4 by sub-periods, the three groups exhibit similar structural increments for the GFC period. However, it is not the case for the other two sub-periods: the EMU periphery group shows the highest increment followed by the EMU core group for the EDC period and by the Non-EMU group for the Post-crisis period. This result is an evidence that (1) investors in the European sovereign debt market have treated the EU member states as a homogeneous group at most before the onset of the EDC, (2) however, they perceive the the EU economies as heterogeneous groups by their economic status and use of Euro currency from the EDC.

[12]The most clear and effective message was "Whatever it takes" speech on 26 July 2012 by Mario Draghi, the president of the ECB.

Table 2: **Estimated results of the marginal processes.** This table provides the estimates of the conditional mean and variance equations for the individual markets. Values in parentheses are standard errors. ^{a}, ^{b} and ^{c} indicate statistical significances at the 1%, 5%, and 10% significance levels, respectively. Bolds are significant dummy variables.

	EMU Core						EMU Periphery					Non-EMU		
	AUS	BEL	FIN	FRA	GER	NET	GRE	IRL	ITA	POR	SPA	POL	SWE	UK
Conditional mean														
β_0	0.08	0.15	0.06	0.09	0.00	0.04	0.14	0.03	-0.09	0.10	0.24	0.79^{b}	0.14^{c}	0.01
β_{BA}	0.56^{a}	0.44^{a}	0.18	0.38^{a}	0.68^{a}	0.45^{a}	1.54^{a}	0.89^{a}	1.49^{a}	1.27^{a}	0.36^{a}	0.67^{a}	0.24^{a}	0.25
β_{US}	0.16^{a}	0.32^{a}	0.26^{a}	0.43^{a}	0.27^{a}	0.28^{a}	1.49^{a}	0.08	0.98^{a}	0.96^{a}	0.79^{a}	0.31^{a}	0.13^{a}	0.36^{a}
β_{Corp}	0.05^{a}	0.12^{a}	0.05^{a}	0.09^{a}	0.04^{a}	0.07^{a}	0.07	0.09^{a}	0.20^{a}	0.09^{b}	0.17^{a}	0.47^{a}	0.05^{a}	0.07^{a}
β_{Stock}	-0.11^{a}	-0.07^{c}	-0.13^{a}	-0.21^{a}	-0.10^{a}	-0.05	-0.22^{b}	-0.12^{b}	-0.52^{a}	-0.34^{a}	-0.29^{a}	-0.62^{a}	-0.04^{c}	-0.11^{b}
β_{EUR}	-0.08	-0.10	-0.05	-0.19^{a}	-0.16^{a}	-0.07	-0.42^{a}	0.30^{a}	-0.36^{b}	-0.36^{a}	-0.44^{a}	-0.76^{a}	-0.06	-0.13^{c}
β_{Liq}	-0.01	0.03^{a}	0.00	-0.01	-0.01^{c}	-0.01^{b}	0.00	0.04^{a}	0.00	0.01	0.01	-0.07^{a}	0.03^{a}	-0.02^{a}
γ_{GFC}	0.11	0.72	-0.05	0.16	0.08	0.40	$\mathbf{2.35}^{c}$	$\mathbf{3.10}^{a}$	0.74	0.63	0.63	-1.09	-0.06	0.88
γ_{EDC}	0.08	-0.10	0.08	-0.12	-0.02	0.00	$\mathbf{6.84}^{b}$	0.46	0.96	1.67	0.61	-0.43	-0.07	0.09
γ_{Post}	-0.19	-0.25	0.21	-0.18	-0.10	-0.04	-8.05	-0.30	0.01	0.22	-0.42	$\mathbf{-0.61}^{c}$	0.09	0.12
Conditional variance														
a_0	-0.08	-0.01	0.00	0.04	-0.02	0.01	0.02	-0.01	0.12^{c}	0.11	0.09^{a}	0.35^{a}	-0.05	0.06
a_1	0.60^{a}	0.65^{a}	0.39^{a}	0.46^{a}	0.44^{a}	0.40^{a}	0.78^{a}	0.79^{a}	0.38^{a}	0.57^{a}	0.36^{a}	0.67^{a}	0.58^{a}	0.42^{a}
b_1	0.91^{a}	0.95^{a}	0.96^{a}	0.93^{a}	0.95^{a}	0.95^{a}	0.94^{a}	0.96^{a}	0.92^{a}	0.88^{a}	0.94^{a}	0.90^{a}	0.93^{a}	0.93^{a}
θ	0.22^{a}	0.21^{a}	0.18^{c}	0.26^{a}	0.38^{a}	0.48^{a}	0.23^{a}	0.29^{a}	0.55^{a}	0.40^{a}	0.55^{a}	0.01	0.27^{a}	0.36^{a}
γ_{GFC}	$\mathbf{0.54}^{a}$	$\mathbf{0.25}^{b}$	$\mathbf{0.11}^{c}$	0.05	0.10	$\mathbf{0.16}^{b}$	$\mathbf{0.31}^{a}$	$\mathbf{0.31}^{a}$	$\mathbf{0.23}^{a}$	$\mathbf{0.28}^{a}$	0.12	$\mathbf{0.18}^{c}$	$\mathbf{0.38}^{a}$	$\mathbf{0.26}^{a}$
γ_{EDC}	$\mathbf{0.34}^{a}$	$\mathbf{0.21}^{a}$	0.07	$\mathbf{0.19}^{a}$	$\mathbf{0.13}^{b}$	$\mathbf{0.11}^{c}$	$\mathbf{0.65}^{a}$	$\mathbf{0.27}^{a}$	$\mathbf{0.36}^{a}$	$\mathbf{0.75}^{a}$	$\mathbf{0.26}^{a}$	-	$\mathbf{0.15}^{a}$	0.08
γ_{Post}	$\mathbf{0.13}^{c}$	0.09	$\mathbf{0.09}^{c}$	$\mathbf{0.12}^{b}$	0.07	0.05	$\mathbf{0.52}^{a}$	0.10	$\mathbf{0.17}^{b}$	$\mathbf{0.43}^{a}$	0.10	-	$\mathbf{0.17}^{a}$	0.07
AIC	-2,550	-2,811	-1,915	-2,624	-2,039	-2,229	-5,516	-3,563	-3,705	-4,173	-3,623	-3,222	-1,956	-2,300
SBC	-2,639	-2,900	-2,004	-2,713	-2,128	-2,318	-5,605	-3,652	-3,794	-4,262	-3,712	-3,311	-2,045	-2,389

Table 3: **Goodness-of-fits of the marginal distributions.** This table reports the results of goodness-of-fit tests of the estimated marginal distributions. Q_n(6-12) stands for the Ljung-Box statistic with the minimum p-value among $Q_n(6)$ and $Q_n(12)$, where $Q_n(m)$ represents the Ljung-Box statistic of order m for n^{th} moments. LM(1-12) stands for the Engle's LM statistics with the minimum p-value among $LM(1)$ - $LM(12)$, where $LM(m)$ represents the LM statistic of order m. Values in brackets are the p-values against the null hypothesis of no autocorrelation in the corresponding moments.

Statistic	AUS	BEL	FIN	FRA	GER	NET	GRE	IRL	ITA	POR	SPA	POL	SWE	UK
Q_1(6-12)	3.91	7.90	12.66	12.19	4.67	7.38	3.26	4.54	7.20	16.02	1.19	11.44	17.77	3.43
	[0.69]	[0.25]	[0.39]	[0.43]	[0.59]	[0.83]	[0.78]	[0.13]	[0.30]	[0.19]	[0.98]	[0.49]	[0.12]	[0.75]
Q_2(6-12)	8.95	6.87	6.16	6.59	2.60	2.44	5.05	17.54	12.07	4.33	5.34	14.22	3.94	5.65
	[0.18]	[0.33]	[0.41]	[0.36]	[0.86]	[0.87]	[0.54]	[0.62]	[0.44]	[0.63]	[0.50]	[0.29]	[0.68]	[0.46]
Q_3(6-12)	3.18	4.78	4.38	4.12	0.69	2.87	3.47	15.81	3.83	16.55	6.18	7.66	2.41	3.34
	[0.79]	[0.57]	[0.63]	[0.66]	[0.99]	[0.82]	[0.99]	[0.01]	[0.70]	[0.17]	[0.91]	[0.81]	[0.88]	[0.98]
Q_4(6-12)	4.93	2.87	1.99	1.61	0.23	0.97	1.14	10.33	3.61	3.48	1.97	4.63	0.75	0.91
	[0.55]	[0.83]	[0.92]	[0.95]	[1.00]	[0.99]	[0.98]	[0.11]	[0.73]	[0.75]	[0.92]	[0.97]	[0.99]	[0.99]
LM(1-12)	2.12	0.81	12.10	5.54	0.61	0.10	3.53	0.82	5.39	4.03	5.89	0.29	3.18	7.72
	[0.15]	[0.37]	[0.10]	[0.24]	[0.74]	[0.75]	[0.32]	[0.35]	[0.25]	[0.26]	[0.32]	[0.15]	[0.44]	[0.46]

Table 4: **Summary of the structural changes in $\ln(\sigma_t^2)$.** This table shows the average values of significant γ_k's, the coefficients of the dummy variables (I_k's) in in Equation (1). Values in parentheses are the number of the economies with significant dummy. γ_k^{core}, γ_k^{peri} and γ_k^{non} represent γ_k of EMU core, EMU peripheral, and Non-EMU economies, respectively.

Period	EMU Core	EMU Periphery	Non-EMU	Summary
GFC	0.2635 (4)	0.2573 (4)	0.2707 (3)	$\gamma_{Post}^{core} \approx \gamma_{Post}^{peri} \approx \gamma_{Post}^{non}$
EDC	0.2162 (5)	0.4008 (5)	0.1517 (1)	$\gamma_{EDC}^{peri} > \gamma_{EDC}^{core} \approx \gamma_{EDC}^{non}$
Post-crisis	0.1123 (3)	0.3743 (3)	0.1715 (1)	$\gamma_{Post}^{peri} > \gamma_{Post}^{core} \approx \gamma_{Post}^{non}$
Summary	$\gamma_{GFC}^{core} \approx \gamma_{EDC}^{core} > \gamma_{Post}^{core}$	$\gamma_{EDC}^{peri} \approx \gamma_{Post}^{peri} > \gamma_{GFC}^{peri}$	$\gamma_{GFC}^{non} > \gamma_{EDC}^{non} \approx \gamma_{Post}^{non}$	

5.2 Estimated Results of Copulas

We consider various types of dependence to investigate structural changes in comovements of the standardized residuals (η_t^i's) in Equation (1): (i) GA copula as the benchmark, (ii) GM copula for the upper-tail dependence, (iii) GS copula for the lower-tail dependence, and (iv) SJC copula for the asymmetric tail dependence. Each dependence parameter in a copula is assumed to be a step-wise function defined in Equation (4). We apply the CML method to parameter estimation.

Note that we are focusing on the cross-sectional distributions of the dependence parameters. Since we divide the sample economies into EMU cores (C), EMU peripheries (P), and non-EMUs (N), we have six types of pairs: (C,C), (C,P), (P,P), (C,N), (P,N), (N,N). In order to analyze how differently have the dependences evolve in the progress of the recent financial turmoils across the types of pairs, we consider the following simple regression:

$$\bar{\theta}_k^{(i,j)} - \bar{\theta}_0^{(i,j)} = \sum_{l=1}^{6} \delta_l T_l(i,j) + \xi^{(i,j)} \tag{5}$$

for each k (=1, 2, 3), where $\theta_k^{(i,j)}$ is the dependence parameter for the pair (i,j) of economies during the sub-period k, $T_l^{(i,j)}$ is the variable for indicating the type the country pair (i,j), and $\xi^{(i,j)}$ is an *i.i.d.* $N(0,1)$. We regard the values of insignificant dependence parameters as 0 for this regression.

Table 5 reports the estimated results of the cross-sectional regression (5). Panel A of Table 5 shows that (C,C) and (N,N) experience structural increase in both Gaussian and tail dependences during the two crisis periods compared to the Pre-crisis period. On the other hands, (P,P) exhibits no or structural decrease in dependences during the GFC and the EDC periods, which is opposite to Silvapulle et al. (2016) that analyze EU peri countries' daily sovereign bond yield spreads relative to Germany by using a similar approach to ours. Furthermore, (P,P) shows smaller dependences for the Post-crisis period than the Pre-crisis period.

Panel B of Table 5 presents estimated results from the SJC copula. Here, note that we substitute the values of the insignificant dependence parameter estimates in the SJC copula to 0 for the calculation of the asymmetries between tail dependences. The asymmetry is skewed to the lower tail for the GFC period overall, however, not for the EDC period.[13]

[13] More analyses of the dependences are required. Firstly, the structural changes in dependences do not show clear patterns, which means grouping the EU economies as the three groups is not enough to analyze dependence and investors are focusing not only on the sovereigns' market based label such as *GIIPS* but also on other characteristics of each economies. A possible resolution is wake-call contagion theory which can provide us with backgrounds on the fundamental

Table 5: **Structural changes in dependences.** This table reports the estimated results of the cross-sectional regression (5) with dependence parameters from for GA, GM, GS, and SJC copula. The "Asymmetry" in Panel B is the difference between δ_l's of λ^U and λ^L in 5. [a], [b] and [c] indicate statistical significances at the 1%, 5%, and 10% significance levels, respectively.

Panel A: Single-parameter copulas

Pair		GA (ρ)			GM (λ^U)			GS (λ^L)		
i	j	GFC	EDC	Post	GFC	EDC	Post	GFC	EDC	Post
C	C	**0.191**^{a}	**0.161**^{a}	0.048	**0.159**^{a}	**0.151**^{a}	0.048	**0.157**^{a}	**0.105**^{b}	0.032
C	P	**0.073**^{b}	0.013	**-0.106**^{b}	**0.051**^{c}	0.006	**-0.103**^{a}	**0.092**^{a}	-0.011	**-0.062**^{c}
P	P	0.020	-0.029	**-0.156**^{b}	-0.007	-0.037	**-0.191**^{a}	0.026	-0.026	**-0.113**^{c}
C	N	**0.205**^{a}	**0.126**^{b}	-0.051	**0.157**^{a}	**0.107**^{a}	-0.053	**0.127**^{a}	0.016	**-0.089**^{b}
P	N	**0.145**^{a}	-0.007	**-0.193**^{a}	**0.104**^{a}	0.011	**-0.086**^{b}	**0.142**^{a}	-0.040	**-0.110**^{b}
N	N	**0.364**^{a}	**0.260**^{b}	0.030	**0.230**^{b}	**0.181**^{b}	-0.013	**0.218**^{b}	0.064	-0.034
R^2		0.141	0.132	0.113	0.152	0.171	0.153	0.073	0.076	0.069

Panel B: Two-parameter copula (SJC)

Pair		Asymmetry ($\lambda^U - \lambda^L$)			SJC (λ^U)			SJC (λ^L)		
i	j	GFC	EDC	Post	GFC	EDC	Post	GFC	EDC	Post
C	C	-0.040	0.166	0.000	**0.138**^{a}	**0.166**^{a}	0.060	**0.178**^{a}	0.100	0.051
C	P	-0.141	0.000	-0.090	-0.033	-0.002	**-0.090**^{a}	**0.141**^{a}	-0.013	-0.021
P	P	-0.131	0.000	-0.224	**-0.131**^{b}	-0.066	**-0.224**^{a}	0.100	-0.012	-0.080
C	N	0.146	0.106	0.136	**0.146**^{a}	**0.106**^{a}	0.019	0.083	-0.053	**-0.136**^{b}
P	N	-0.147	0.000	0.139	0.076	0.042	0.028	**0.147**^{a}	-0.082	**-0.139**^{b}
N	N	0.000	0.000	0.000	0.129	0.120	-0.008	0.197	-0.050	-0.069
R^2		-	-	-	0.231	0.173	0.231	0.026	0.059	0.085

6 Conclusion

This paper empirically investigates how have European Union (EU) sovereign CDS spreads evolved during the Global Financial Crisis (GFC) and the Eurozone Debt Crisis (EDC) in terms of their conditional means, conditional volatilities, and dependences. We especially focus on the difference among the EU sovereign CDS markets' reactions to the crises across types of EU countries – 6 EMU core (AUD, BEL, FIN, FRA, NET, GER and NET), 5 EMU peripheral (*GIIPS*), and 3 Non-EMU (POL, SWE and the UK) economies. We control for market liquidity, global sovereign credit risk, euro regional variables, crisis dummies, and heteroscedasticity in the marginal process and apply various types of copulas to time-varying dependence. In this paper, we interpret the CDS spread as a market perceived risk of sovereign default.

We find structural increases in the idiosyncratic volatilities. The three groups exhibit similar structural increments during the GFC period. On the other hands, during the EDC period, the EMU periphery group shows the highest increment relative to the Pre-crisis period. Regarding dependence, (EMU core, EMU core) and (Non-EMU, Non-EMU) pairs generally experience structural increase in both the Gaussian and the tail dependence during the two crisis periods compared to the Pre-crisis period. However, (EMU periphery, EMU periphery) overall exhibits no or structural decrease in dependence during both the GFC and the EDC period. Lastly, the asymmetry in dependence is skewed to the lower tail for the GFC period overall, whereas no for the EDC period.

This paper requires further investigations on the dependence analysis since the structural changes in the dependences do not show a clear pattern. This means the grouping the EU economies as the three group is not enough to analyze the changes in dependences and investors are focusing on more than sovereigns' market based label such as *GIIPS.* A possible resolution would be wake-call contagion theory which can provide us with backgrounds on the fundamental (economy-specific) determinants of the dependence changes.[14]

(economy-specific) determinants of the dependence changes. Secondly, R^2's for the regressions with λ^L in Panel B of Table 5 are very small.

[14]Actually, literature review and related economic interpretations of the current empirical results are not enough, neither. We will complemet these aspects in the presentation in the conference. I am sorry to the discussant about the lack of completion.

References

Alter, A. and Beyer, A. (2014). The dynamics of spillover effects during the european sovereign debt turmoil. *Journal of Banking & Finance*, 42:134 – 153.

Amstad, M., Remolona, E., and Shek, J. (2016). How do global investors differentiate between sovereign risks? the new normal versus the old. *Journal of International Money and Finance*, 66:32 – 48. The New Normal in the Post-Crisis Era.

Ang, A. and Longstaff, F. A. (2013). Systemic sovereign credit risk: Lessons from the u.s. and europe. *Journal of Monetary Economics*, 60(5):493 – 510. Aggregate Implications of Local Public Finance.

Bernoth, K. and Erdogan, B. (2012). Sovereign bond yield spreads: A time-varying coefficient approach. *Journal of International Money and Finance*, 31(3):639 – 656. Financial Stress in the Eurozone.

Bongaerts, D., De Jong, F., and Driessen, J. (2011). Derivative pricing with liquidity risk: Theory and evidence from the credit default swap market. *The Journal of Finance*, 66(1):203–240.

Chiarella, C., ter Ellen, S., He, X.-Z., and Wu, E. (2015). Fear or fundamentals? heterogeneous beliefs in the european sovereign cds market. *Journal of Empirical Finance*, 32:19 – 34.

De Santis, R. A. (2014). The euro area sovereign debt crisis: Identifying flight-to-liquidity and the spillover mechanisms. *Journal of Empirical Finance*, 26:150 – 170.

De Santis, R. A. and Stein, M. (2016). Correlation changes between the risk-free rate and sovereign yields of euro area countries. Working Paper 1979, ECB.

EU (2018). *The European Union - What it is and what it does.* Luxembourg: Publications Office of the European Union.

Fabozzi, F. J., Giacometti, R., and Tsuchida, N. (2016). Factor decomposition of the eurozone sovereign cds spreads. *Journal of International Money and Finance*, 65:1 – 23.

Giordano, R., Pericoli, M., and Tommasino, P. (2013). Pure or wake-up-call contagion? another look at the emu sovereign debt crisis. *International Finance*, 16(2):131–160.

Gorea, D. and Radev, D. (2014). The euro area sovereign debt crisis: Can contagion spread from the periphery to the core? *International Review of Economics & Finance*, 30:78 – 100.

Joe, H. (1997). *Multivariate Models and Multivariate Dependence Concepts.* London: Chapman and Hall/CRC.

Longstaff, F. A., Pan, J., Pedersen, L. H., and Singleton, K. J. (2011). How sovereign is sovereign credit risk? *American Economic Journal: Macroeconomics*, 3(2):75–103.

Ludwig, A. (2014). A unified approach to investigate pure and wake-up-call contagion: Evidence from the eurozone's first financial crisis. *Journal of International Money and Finance*, 48:125 – 146.

Paniagua, J., Sapena, J., and Tamarit, C. (2017). Sovereign debt spreads in emu: The time-varying role of fundamentals and market distrust. *Journal of Financial Stability*, 33:187 – 206.

Patton, A. J. (2006). Modeling asymmetric exchange rate dependence. *International Economic Review*, 47(2):527–556.

Pesaran, M. H. and Pick, A. (2007). Econometric issues in the analysis of contagion. *Journal of Economic Dynamics and Control*, 31(4):1245 – 1277.

Silvapulle, P., Fenech, J. P., Thomas, A., and Brooks, R. (2016). Determinants of sovereign bond yield spreads and contagion in the peripheral eu countries. *Economic Modelling*, 58:83 – 92.

Sklar, A. (1959). Fonctions de rÃ©partition Ã n dimensions et leurs marges. *UniversitÃ© Paris*, 8:229–231.

Wong, A. Y.-T. and Fong, T. P. W. (2011). Analysing interconnectivity among economies. *Emerging Markets Review*, 12(4):432 – 442.