Contagion and exposure between sovereign and financial credit risk: A Delta Conditional approach to the ECB announcements in the European sovereign debt crisis. *

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This version: November 10, 2017

Abstract

The timely identification of spillovers between the financial and sovereign sectors is a crucial topic for preventing undergoing scenarios such as the European sovereign debt crisis. To assess the dependence between financial and sovereign credit risk I employ Delta Conditional measures, $\Delta CoVaR$ and $\Delta CoES$. These measures are mainly used in financial sector for assessing the Systemically Important Financial Institutions but its application for analysing contagion to other sectors is almost non-existent so far. I use a copula approach with time-varying parameters for capturing changes in the tail dependence. The results show the importance of some measures taken by the ECB to reduce the exposure of the sovereign credit risk to the financial sector and the influence of the Greek referendum announcements on this relationship. I also show that the effects of the policy measures in terms of spillover between sectors can be assessed accurately using Delta Conditional measures.

Keywords: Δ *CoVaR, Copula, Contagion, Systemic risk, European sovereign debt crisis.*
JEL classification : G18, G20, G21, G23, G32, G38, C58, G01

1 Introduction

Can't see the wood for the trees

English proverb

Systemic risk in biological terms can be defined as a possible global disaster arising from the behaviour of a single individual of the species that coexist in the same environment. Likewise, in economics terms, systemic risk is the threat of a system breakdown because of short-sighted behaviour and the undervaluing of externalities. Government guarantees and bailouts have helped to build a closer relationship between the financial and sovereign

*Any comment or suggestion is very welcome. Parts of this work were completed while visiting the JRC (Joint Research Centre) of the European Commission in Ispra (Italy). This article was presented at the Finance & Economy Unit's internal seminar in the JRC of the European Commission on August 29^{th}, 2017. I am indebted to the JRC staff in Ispra for their helpful comments and hospitality. In particular, I want to mention Elisa Ossola, Eduardo Rossi, Dimitrios Exadaktylos and Marco Pinchetti. I thank to my PhD supervisor, Prof. Alfonso Novales Cinca, and the Research Institute of Economic Analysis (ICAE) for the support in the production of this article. This research was supported by the Ministry of Education of Spain (FPU grant FPU15/04241).The usual disclaimers apply.

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sectors triggering ultimately massive damages to the welfare state as well as political reactions in the form of populist movements along Europe. Since systemic risk affects by nature all sectors, it should be computed not only within the financial system but between the financial and other sectors such as the sovereign one. Comparing systemic risk with the proverb that heads this section, Trichet (2009) said that *'systemic risk is about seeing the wood and not only the trees'*.

Since the European sovereign debt crisis, the connection between financial and sovereign sector has been extensively studied. Most research on this topic has been conducted in a Vector Autoregression (VAR) framework (Alter and Beyer (2012), Bicu and Candelon (2012), Kok and Gross (2013),Alter and Schüler (2012), Chudik and Fratzscher (2012), Candelon et al. (2011)). Following the VAR methodology, the impulse response function is employed to assess the effect on all sectors of a shock in a given sector, which is produced in economic distress situations. Conditional Value at Risk ($CoVaR$) is a cross-sector measure indicating a low quantile of benchmark returns. Therefore, CoVaR framework can capture better the behaviour of sovereign and financial credit risk in distress conditions. To date, market price-based systemic risk measures have been mainly focused on analysing the systemic risk of a given firm in its own sector. For instance, Reboredo and Ugolini (2015b) employed a CoVaR framework to measure the contagion from the Greek debt crisis to sovereign debt sector. To my knowledge, the only article focusing on the link between sovereign and financial sector under CoVaR methodology is Reboredo and Ugolini (2015a). These authors employed a vine-copula approach using as underlying debt and equity returns from the end of 1999 to mid-2012. However, the chosen period leaves out the most stressful moments for Spanish and Italian sovereign debt, the summer of 2012 when the President of the ECB had to explicitly support the Monetary Union. Moreover, it is widely accepted that the European sovereign debt crisis was led by a crisis of confidence on the institutions, consequently employing a credit risk underlying as the CDS seems more coherent.

This work deals with the link between European sovereign and financial credit risk during the 2009-2016 period using a CoVaR framework. This methodology allows to assess the change in financial credit risk when the sovereign sector is taking into account and vice versa. Indeed, the Delta Conditional measures derived from CoVaR framework, Delta Conditional Value-at-Risk ($\Delta CoVaR$) and Delta Conditional Expected Shortfall ($\Delta CoES$), capture the credit risk dependence between sectors. Conditional measures incorporate directionality providing information about contagion and exposure of sovereign credit risk to the financial sector. To compute conditional probabilities I employ a copula approach due to its straightforward decomposition of the joint distribution which eases the interpretation of the dependence between both credit risks, apart from the fact of having lower computational cost and being less time expensive than other approaches that imply numerical integration, such as the GARCH proposal by Girardi and Ergün (2013).

The CoVaR model approach is validated not only using backtesting but also employing Delta Conditional measures to identify the main stress events during the analysed period. Additionally, an event study is conducted for assessing the efficacy of the ECB's measures considered by Lucas et al. (2013) according to the Delta Conditional measures. The results suggest that tail dependence in the relationship between financial sector and peripheral sovereign credit risk implies higher values in Delta Conditional measures than core countries, that means higher sensitivity to the financial system changes. ECB measures had an heterogeneous effect on the credit link between banks and countries risk. While the European Financial Stability Facility (EFSF) acted in fact as a contagion channel between the sovereign and the financial sector, the Draghi's speech on July 26^{th} 2012 and the disclosure of the details of the Outright Monetary Transactions (OMT) program reduce the exposure of the sovereign sector to the financial sector, specially in peripherical countries. These results are in line with the literature about the effectiveness of the ECB's policy during the European sovereign credit crisis (Wyplosz et al. 2011, Altavilla et al. 2016). The Greek referendum announcements from 2011 and 2015 played also an important role in the evolution of the relationship between sovereign and financial credit risk. The present article points out the possibilities of CoVaR and Delta Conditional as useful measures for assessing spillovers between sectors in the economy as well as to evaluate the collateral effect of policy choices.

The remainder of this paper is divided into five sections. The following section presents the idea of the CoVaR and Delta Conditional measures. Then, Section 3 suggests the copula approach for assessing the CoVaR measure. The data employed for the empirical application is presented in section 4. The empirical case in section 5 includes an unconditional and conditional backtesting, an event study and stress testing on the CoVaR, Conditional Expected Shortfall (CoES) and Delta Conditional measures. Finally, the most relevant results, their implications and some policy recommendations are pointed out in the concluding section.

2 CoVaR background

CoVaR was introduced by Adrian and Brunnermeier (2011) as a systemic risk measure for identifying Systemically Important Financial Institutions (SIFIs) in the financial sector. The original scope of CoVaR was to measure the capital needs of the financial system when a certain institution i is on distress. The question to answer was how large are the maximum losses of the financial system with a $\beta 100\%$ confidence level in a certain time horizon given that institution i is in the $\alpha 100$-th quantile of loss distribution, and $CoVaR$ is obtained by solving the implicit equation

$$P_{t-1}[-r_{m,t} \leq CoVaR_{m|i,t}(\alpha, \beta)|r_{i,t} = -VaR_{i,t}(\alpha)] = \beta, \tag{1}$$

where m stands for the financial sector as a whole. Concerning the subscripts in this work, i stands for each of the European countries considered whereas m represents the global European financial sector proxy in order to analyse spillovers between financial and sovereign credit risk. $CoVaR$ and VaR express required capital buffer, consequently they are positive values, then in Equation (1) are introduced preceded by a minus.

The level α of the conditioning event is usually fixed at $\alpha = \beta$. $\alpha, \beta \in (0, 1)$ and given that VaR is measured as a loss percentile, α and β would be close to one in a distressed scenario. $\alpha 100$-th loss percentile correspond to $1 - \alpha 100$-th returns percentile, so the corresponded return percentile of $VaR(\alpha)$ is $1 - \alpha$. The fact of employing a conditional event as the VaR, which is independent of the conditioning institution riskiness, allows us to compare the results conditional to different financial institutions. The maximum losses with β confidence level for the financial system may be different for different risk profiles. However, loses not considered in normal scenarios can trigger out a systemic event because of the lack of liquidity, i.e., in a normal scenario the capital needs of the financial system can be fulfilled by their institutions, but in a distressed scenario capital needs could suppose bankrupt and bailout processes. Therefore, Equation (1) is unsatisfactory for assessing the systemic risk of a financial institution. Indeed, it may be enough to capture the losses but not the loss change when the scenario for the conditioning event changes. The change in maximum losses for the financial system with $\beta 100\%$ confidence level when financial institution i changes from a normal scenario to its $(1-\alpha)100\%$ worst case scenario is known as $\Delta CoVaR$, i.e.,

$$\Delta CoVar_{m|i,t}(\beta) = CoVar_{m|i,t}(\alpha, \beta) - CoVar_{m|i,t}(0.5, \beta), \tag{2}$$

where the normal scenario is defined as the median loss for financial firm i.
Most systemic risk measures, such as MES or SRISK (Acharya et al. 2012, Brownlees and Engle 2016), see systemic risk on the opposite way, i.e., measuring losses for financial institution i given a stress scenario for the financial system. Adrian and Brunnermeier (2011) denote the measure with shifted variables as exposure $CoVaR$, i.e., $\Delta CoVar_{i|m,t}(\beta)$. Exposure CoVaR is a risk management tool similar to the stress test that is useful for tracking banks performance in a situation of systemic risk. Whereas $\Delta CoVaR$ measures which financial institution contributes more to a financial crisis, the exposure CoVaR measures which financial institution is more exposed to contagion from the financial sector.
A number of studies have noticed that CoVaR as defined by Equation (1) is not a monotonic function of the dependence parameter and it can not be validated using backtesting (Mainik and Schaanning 2014, Zhang 2015, Girardi and Ergün 2013). Previous drawbacks can be overcome if the definition of CoVaR is slightly modified, i.e.,

$$P_{t-1}[-r_{m,t} \leq CoVaR_{m|i,t}(\alpha, \beta) | r_{i,t} \leq -VaR_{i,t}(\alpha)] = \beta. \tag{3}$$

Consequently, $CoVaR_{m|i,t}(\alpha, \beta)$ expresses the maximum losses for the financial system with $\beta 100\%$ confidence level given that financial firm i is below its $(1-\alpha)100\%$ worst case scenario. Similarly, the $\Delta CoVar_{m|i,t}(\beta)$ interpretation changes expressing the loss change of the financial system with confidence level $\beta 100\%$ when the financial firm changes from a situation where it is below its 50% worst case scenario to being below its $(1-\alpha)100\%$ worst case scenario.
Although several modifications for $\Delta CoVar$ have been put forward trying to express a change from the normal to a distress scenario , e.g., Zhang (2015) and Girardi and Ergün (2013), it is out of the scope of this work to analyse them. Thereby, I take definitions of $CoVaR$ and $\Delta CoVaR$ choice to be closer to the original Adrian and Brunnermeier (2011) definition while keeping the possibility of backtesting and dependence consistent feature, i.e., $CoVaR$ is a monotonic function of the dependence parameter between the variables.
Even though under Equation (3) the $CoVaR$ properties improve, it has some limitation given the nature of $CoVaR$, i.e., it looks only to a certain percentile and consequently is not subadditive. These features can be enhanced if the Value-at-Risk dimension is moved to a Expected Shortfall framework. The Conditional Expected Shortfall, $CoES_{m|i,t}(\alpha, \beta)$, measures the average losses in the financial system with $\beta 100\%$ confidence level when financial firm i is below its $(1-\alpha)100\%$ worst case scenario, i.e.,

$$CoES_{m|i,t}(\alpha, \beta) = \frac{1}{1-\beta} \int_{\beta}^{1} CoVaR_{m|i,t}(\alpha, q) dq,$$

where $CoVaR_{m|i,t}(\alpha, q)$ is given by Equation (3). $\Delta CoES$ can be computed following the same procedure as in Equation (2).

3 Methodology

The structure model of the CoVaR can be divided into three steps: the marginal model structure, the copula choice and the copula time-varying parameter. The assessment of $CoVaR$ is straightforward given these three essential stages.

To begin with, Equation (3) can be expressed as a ratio following Bayes' theorem, i.e.,

$$P_{t-1}[r_{m,t} < -CoVaR_{m|i,t}(\alpha,\beta)|r_{i,t} \leq -VaR_{i,t}(\alpha)] = \frac{P_{t-1}[r_{m,t} < -CoVaR_{m|i,t}(\alpha,\beta), r_{i,t} < -VaR_{i,t}(\alpha)]}{P_{t-1}[r_{i,t} < -VaR_{i,t}(\alpha)]}.$$

Expressing the previous equation in terms of copula functions[1]

$$\begin{aligned} P_{t-1}[r_{m,t} < -CoVaR_{m|i,t}(\alpha,\beta)|r_{i,t} < -VaR_{i,t}(\alpha)] &= \frac{C\left(F_{r_{m,t}}(-CoVaR_{m|i,t}(\alpha,\beta)), F_{r_{i,t}}(-VaR_{i,t}(\alpha))\right)}{F_{r_{i,t}}(-VaR_{i,t}(\alpha))} \\ &= \frac{C(u_m, 1-\alpha)}{1-\alpha}. \end{aligned} \tag{4}$$

Using generator functions ϕ for the Archimedean copula C I get[2]

$$C(u_m, 1-\alpha) = \phi^{-1}\left[\phi(u_m) + \phi(1-\alpha)\right]. \tag{5}$$

Equation (4) can be rewritten as

$$\frac{\phi^{-1}\left[\phi(u_m) + \phi(1-\alpha)\right]}{1-\alpha} = 1-\beta \Rightarrow \phi^{-1}\left[\phi(u_m) + \phi(1-\alpha)\right] = (1-\beta)(1-\alpha).$$

Solving for u_m

$$u_m = \phi^{-1}\left[\phi\left((1-\alpha)(1-\beta)\right) - \phi(1-\alpha)\right].$$

Finally the $CoVaR_{m|i,t}(\alpha,\beta)$ is obtained as

$$CoVaR_{m|i,t}(\alpha,\beta) = -\left[\mu_{m,t} + \sigma_{m,t} F^{-1}_{\xi_{m},t}(u_{m,t})\right]. \tag{6}$$

where $\mu_{m,t}$ is the conditional mean and $\sigma_{m,t}$ is the conditional standard deviation for the financial system, $F^{-1}_{\xi_m,t}$ is the inverse cumulative distribution function of the financial system's innovation and $u_{m,t}$ is an uniform distributed value obtained from the copula relationship. The assessment for $CoVaR_{i|m,t}(\alpha,\beta)$ would be conducted following the same procedure. Notice that $CoVaR$ and $CoES$ refers to losses, so high values in this indicators mean bad news.

[1] Observe than although VaR is defined as a quantile of loss distribution, the copula framework is employed in returns distribution. Therefore the $-VaR(\alpha)$ for losses, i.e., $P_{t-1}(r_{i,t} > -VaR_{i,t}(\alpha)) = P_{t-1}(-r_{i,t} < VaR_{i,t}(\alpha)) = \alpha$, is equivalent to $VaR(1-\alpha)$ for returns, i.e., $P_{t-1}(r_{i,t} < VaR_{i,t}(1-\alpha)) = 1-\alpha$.

[2] The t-Student copula is not an Archimedian copula. The t-Student copula is an implicit copula and thus there is not a closed form for the expression $C(u_m, 1-\alpha)$. The t-Student copula can not be presented through generator functions as the Archimedean copulas in equation (5). However there is an expression for the conditional quantile copula. The Rotated Gumbel copula suffers from the same drawback because it is also not an Archimedean copula (Fengler and Okhrin, 2012).

Marginal model. The chosen model for the marginal distributions should take into account not only the time-varying mean and volatility but also the asymmetry and the heavy tails in the probability distribution for the innovation. An ARMA(1,0) process with skewed-t Student innovation meets the desired goals , i.e.,

$$r_{j,t} \;=\; \underbrace{\phi_{j,0} + \phi_{j,1} r_{j,t-1}}_{\mu_{j,t}} + \epsilon_{j,t}, \qquad j = m, i \tag{7}$$

with $\epsilon_{j,t} = \sigma_{j,t}\xi_{j,t}$ where $\sigma^2_{j,t}$ is the conditional variance given by a TGARCH(1,1) specification, i.e.,

$$\sigma^2_{j,t} \;=\; \omega_i + \alpha_j(1 + \theta_j \mathbb{1}_{j,t-1})\epsilon^2_{j,t} + \beta_j \sigma^2_{j,t-1},$$

where the indicator function $\mathbb{1}_{j,t-1}$ values 1 if $\epsilon_{j,t} < 0$ and zero otherwise. The innovation influence in the variance for the next period is different if the analyzed return is negative ($\alpha_j + \theta_j$) or positive (α_j) . β_j is the persistence parameter in past variance.
The innovations are assumed to have an univariate skewed-t distribution in order to capture skewness and the kurtosis, i.e., $\xi_{j,t} \sim f(\xi_{j,t}; \eta_j, \lambda_j)$ where f is the probability distribution function of the skewed-t distribution, η_j denotes the degrees of freedom and λ_j the asymmetry parameter, $j = i, m$. Because of its properties this marginal distribution is widely employed in the systemic risk literature[3].
The density of Hansen (1994)'s skewed-t distribution is

$$h(\xi_t|\eta,\lambda) = \begin{cases} bc(1 + \frac{1}{\eta-2}(\frac{b\xi_t+a}{1-\lambda})^2)^{-(\eta+1)/2} & \xi_t < -a/b \\ bc(1 + \frac{1}{\eta-2}(\frac{b\xi_t+a}{1+\lambda})^2)^{-(\eta+1)/2} & \xi_t \geq -a/b \end{cases}, \tag{8}$$

where $2 < \eta < \infty$ and $-1 < \lambda < 1$. The constants a, b and c are given by

$$a = 4c\lambda\left(\frac{\eta-2}{\eta-1}\right), b = \sqrt{1 + 3\lambda^2 - a^2}, c = \frac{\Gamma(\frac{\eta+1}{2})}{\sqrt{\pi(\eta-2)}\Gamma(\frac{\eta}{2})}.$$

Note that when $\lambda = 0$ and as $\eta \to \infty$, Equation (8) reduces to the standard Gaussian distribution. When $\lambda = 0$ and η is finite, we obtain the standardized symmetric-t distribution. From Equation (8) the log-Likelihood function that should be maximized is

$$\begin{aligned} lnL &= \sum_{t=1}^{T} \log(h(\xi_t|\eta,\lambda)) \\ &= \sum_{t=1}^{T}\left[\log(bc) - \frac{\eta+1}{2}\log\left(1 + \frac{1}{\eta-2}\left(\frac{b\xi_t + a}{1 + 2\lambda\mathbb{1}_{(\xi_t \geq -a/b)} - \lambda}\right)^2\right)\right] \\ &= T\log(bc) - \sum_{t=1}^{T}\frac{\eta+1}{2}\log\left(1 + \frac{1}{\eta-2}\left(\frac{b\xi_t + a}{1 + 2\lambda\mathbb{1}_{(\xi_t \geq -a/b)} - \lambda}\right)^2\right), \end{aligned}$$

where $\mathbb{1}$ is an indicator function that takes the value one if the condition between brackets holds and zero otherwise.

[3]See for instance Engle et al. (2015), Karimalis and Nomikos (2014), Girardi and Ergün (2013) or Reboredo and Ugolini (2015b)

Copula specification. The copula choice determines the relationship between a couple of marginal distribution. A inaccurate copula choice would suppose missleading of $CoVaR$, $\Delta CoVaR$, and ultimately a wrong interpretation of these values. In order to diminish that chance a broad range of copula choices are compared using Information Criteria. The considered Information Criteria are the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC)[4]which are also employed by Reboredo and Ugolini (2015b) and Karimalis and Nomikos (2014). However, a misspecified marginal distribution could also lead to a wrong copula choice. Using Pseudo Maximum- Likelihood Method (PML) apart from the Maximum Likelihood Method (ML) allows to prevent from making this mistake and to have a second check for the Information Criteria choice.

I consider 7 copulas that are broadly employed in financial studies. Each copula implies different tail dependence. Lower tail dependence is allowed by Clayton and Rotated Gumbel but no upper tail dependence, whereas the opposite situation is found in Gumbel copula. Joe-Clayton (BB7) Student's and Clayton-Gumbel (BB1) copula allows either upper and lower tail dependence (Table 1).

[Insert Table 1 here]

A description of the main features of the considered copulas, the uniform value obtained for Equation (6) and the copula density function can be checked in Appendix B. Table 2 sums up the conditional quantile u_m and the copula density function for each copula.

[Insert Table 2 here]

Time-varying copula parameter dependence. The joint tail dependence is established by the copula parameter. A time-varying copula parameter allows tail dependence to change as time goes by, as a result, the model is more flexible for tracking changes in the relationships between sovereign and financial credit risk. I propose the following parametric representation based on Karimalis and Nomikos (2014) for the Clayton, Gumbel and Rotated Gumbel copulas

$$\theta_t = \Lambda_1 \left(\omega + \beta \theta_{t-1} + \alpha \frac{1}{10} \sum_{k=1}^{10} |u_{i,t-k} u_{m,t-k}| \right), \tag{9}$$

where Λ_1 is $\exp(x)$ for Clayton copula and $(\exp(x)+1)$ for the Gumbel in order to keep the values in the feasible area. The evolution for the parameter δ of Frank copula is represented by

$$\delta_t = \omega + \beta \delta_{t-1} + \alpha \frac{1}{10} \sum_{k=1}^{10} |u_{i,t-k} u_{m,t-k}|. \tag{10}$$

Regarding BB7 copula, the relationship between parameters and coefficients of the upper and low tail dependence is: $\theta = \frac{1}{\log_2(2-\tau^U)}$, $\delta = \frac{-1}{\log_2(\tau^L)}$ and $\tau^U, \tau^L \in (0,1)$. For the BB1 copula I employ the formula below giving the relation between parameters and tail dependence in Table 1, i.e., $\delta = \frac{1}{\log_2(2-\tau^U)}$ and $\theta = \frac{-\log_2(2-\tau^U)}{\log_2(\tau^L)}$. Consequently the following representation is proposed

$$\tau_t^K = \Lambda_2 \left(\omega_K + \beta_K \tau_{t-1}^K + \alpha_K \frac{1}{10} \sum_{k=1}^{10} |u_{i,t-k} u_{m,t-k}| \right), \qquad K = U, L$$

[4] $AIC = 2k - 2\log(\hat{L})$ and $BIC = \log(T)k - 2\log(\hat{L})$, where $\hat{L}$ is the maximized value of the likelihood function, T is the sample data and k is the number of estimated parameters.

where $\Lambda_2(x) \equiv (1+\exp(-x))^{-1}$ is the logistic transformation in order to keep the coefficient of tail dependence between 0 and 1.
For the Student's t copula I assume that the degrees of freedom paramater is constant (Elliott and Timmermann, 2013, p. 932 , Reboredo and Ugolini, 2016) and only the correlation parameter, i.e., ρ_t, is time-varying. Equation (9) is employed where $\Lambda_1(x) \equiv \frac{1-\exp(-x)}{1+\exp(-x)}$. In other words, the modified logistic transformation allows for a value of $\rho_t \in (-1,1)$.
Equations (9) and (10) have a similar form to a GARCH model if we look just inside the brackets, with a long term component, an innovation influence component and a past persistence component. The next table provides a summary of the time-varying parameters representation proposed for each copula.

[Insert Table 3 here]

Estimation approach The joint density function is obtained combining the marginal probability distribution functions $(f_i(r_i), f_m(r_m))$ and the density copula function, i.e.,

$$f(r_1, r_2) = c(F_i(r_i;\theta_i)F_m(r_m;\theta_i);\gamma)f_m(r_m;\theta_m)f_i(r_i;\theta_i). \tag{11}$$

Using Equation (11) the log-Likelihood function to be maximized is

$$\begin{aligned} lnL((r_i, r_m);\gamma,\theta_i,\theta_m) &= \sum_{t=1}^{T}(\log(c(F_i(r_{i,t};\theta_{i,t})F_m(r_{m,t};\theta_{m,t});\gamma_t)) + \log(f_m(r_{m,t};\theta_{m,t})) + \log(f_i(r_{i,t};\theta_{i,t}))) \\ &= \underbrace{\sum_{t=1}^{T}(\log(c(F_i(r_{i,t};\theta_{i,t})F_m(r_{m,t};\theta_{m,t});\gamma_t)))}_{2^{nd}\quad step} \\ &\quad \underbrace{+\sum_{t=1}^{T}(\log(f_m(r_{m,t};\theta_{m,t}))) + \sum_{t=1}^{T}(\log(f_i(r_{i,t};\theta_{i,t})))}_{1^{st}\quad step}. \end{aligned} \tag{12}$$

I choose the Inference Functions for Margins (IFM) approach for estimating the parameters, i.e., first the marginal distribution parameters are estimated and later the copula parameter as it is showed in Equation (12). As initial parameter values I take $\alpha_0 = \beta_0 = 0$, i.e., the ML optimum value for the copula parameter constant over the time.
If the marginal distribution is misspecified, estimation errors are large under this approach. To avoid them, the copula estimation is performed also taking into account the pseudo maximum likelihood method (PML) in which no assumption about the marginal distribution is made. The empirical joint observations $\hat{\xi}_t = (\hat{\xi}_{i,t}, \hat{\xi}_{m,t})$ are transformed into so-called pseudo-observations $\hat{u}_t = (\hat{u}_{i,t}, \hat{u}_{m,t})$ according to

$$\hat{u}_{k,t} = \frac{1}{T+1}\sum_{s=1}^{T}\mathbb{1}_{\hat{\xi}_{k,s}\leq\hat{\xi}_{k,t}}, \qquad k = i, m$$

where $\mathbb{1}_{\hat{\xi}_{k,s}\leq\hat{\xi}_{k,t}}$ is an indicator function that takes a value of 1 if $\hat{\xi}_{k,s} \leq \hat{\xi}_{k,t}$ and zero otherwise. Copula parameters are estimated via maximum likelihood estimation given these pseudo-observations.

4 Data

The raw data for drawing up the $CoVaR$ measure are daily CDS quotations from Datastream from May 20^{th}, 2009 to May 13^{th}, 2016. The total number of observations is 1691. I use the standard credit event and the most liquid maturity, i.e., complete restructuring event (CR) and 5-year contract Moreover, the CDS employed in this study are those which underlying is the senior debt, given the fact that is the most traded branch of the CDS categories. For the financial firms' CDS the same type, seniority and maturity is chosen.

I consider sovereign CDS from Austria, Belgium, Denmark, France, Germany, Italy, Netherlands and Spain. A total of 25 European bank CDS meet the criteria for the considered period, 14 being banks from the core European area whereas 11 are in the periphery. The number of banks and their countries are: Austria (2), Belgium (1), Finland (1), France (5), Germany (5), Italy (4), Netherland(3), Portugal (1) and Spain (3).

[Insert Table 4 here]

I employ an approach similar to the one used in Chamizo and Novales Cinca (2016) for obtaining the returns of the financial system credit risk[5]. First of all, I construct CDS indices for each domestic sector by taking the daily median CDS return for the financial firms in each country. After that, I build common financial risk index as result of choosing the 1^{st} PCA among the country level financial CDS returns[6]. According to Rodríguez-Moreno and Peña (2013), the first principal component of a CDS portfolio is the best systemic measure in the macro group.
As a robustness check, the equally-weighted portfolio as well as the weights given by % GDP are also employed for building the financial credit risk measure. The chosen copulas don't change under these alternative indicators. Table 5 shows the considered weight and the alternative weights criteria for checking robustness of the financial system indicator.

[Insert Table 5 here]

CDS spreads are transformed in returns following Berndt and Obreja (2010) and Ballester et al. (2016).

$$\begin{aligned} r_{i,t} &= -\Delta CDS_t A_t(T) \\ &= -\Delta CDS_t \frac{1}{4} \sum_{j=1}^{4T} \delta\left(\frac{j}{4}\right) q\left(\frac{j}{4}\right), \end{aligned} \tag{13}$$

where $\Delta CDS_t(T)$ is the daily change in CDS spreads with maturity T and $A_t(T)$ is the value of a defaultable quarterly annuity over the next T years. T is equal to five years, given the data of the CDS spreads. The risk-free discount factor for day t and s quarter is $\delta(t,s)$, fitted from Euribor rates[7]. The risk-neutral survival probability of the bank or government over the next s quarters can be written as $q(t,s) = \exp(-\lambda_t(s))$ where λ_t is the risk-neutral default intensity. λ_t is computed directly from observed CDS spreads by

[5] Chamizo and Novales Cinca (2016) build CDS indices for each sector by taking the median CDS spread in a given sector each day, they obtain then a common risk factor among CDS spread using principal component analysis. My approach is analogous building bank CDS indices by country and using CDS returns instead of logarithmic change

[6] In order to avoid giving excessive weight to the most volatile country-level CDS returns, the PCA is performed on the correlation matrix instead of the covariance matrix.

[7] Euribor rates are obtained from the European Money Markets Institute (EMMI) and floored at 0%.

$\lambda_t = 4\log(1 + CDS_t/4L)$, which is employed to assess the annuity and then, the CDS return. L denotes the risk neutral expected loss given default (LGD), fixed at 60% for corporate firms and 40% for governments. It has to be pointed out that the change in CDS spreads enters into the return procedure preceded by a minus, so an increase in credit risk, i.e., an increase in CDS spreads, supposes a decrease in CDS returns whereas a reduction of credit risk reflects a rise in CDS returns.

5 Empirical results

Estimated values of the parameter λ shows a negative asymmetry for the financial sector and positive for the sovereign credit risk. Spanish and Italian sovereign CDS and the European financial index have higher degrees of freedom and more persistence of past returns (Table 6).

[Insert Table 6 here]

AIC and BIC estimated under the likelihood obtained from the ML or PML estimation coincide in the choice of copula (Table 7 and 8). Frank copula is selected for all the countries with the exception of Spain and Italy, which select a copula with tail dependence as the Student t copula. The fact that PML and ML coincide in the choice of copula suggests that the marginal distribution is not misspecified.

[Insert Table 7 here]

[Insert Table 8 here]

The choice of copula is a key feature that determines the behaviour of *Delta* measures, i.e., $\Delta CoVaR$ and $\Delta CoES$, because it is where the joint tail dependence is reflected. A different copula would suppose a different tail dependence and ultimately different values of $\Delta CoVaR$ and $\Delta CoES$. It is important to be aware of model risk. Taking into account a comprehensive range of copulas, considering different information criteria and using not only the maximum likelihood value, but also the pseudo maximum likelihood value for the information criterion are three ways of reducing the possibility of choosing an inaccurate copula.

Figure 1 shows the different values of $CoVaR$ and $\Delta CoVaR$ for Italy on July 26^{th}, 2012 using several copulas and different levels of stress for the conditioning variable, i.e., α. $\Delta CoVaR_{Italy|m,t}(\alpha, 0.95)$ values are higher than $\Delta CoVaR_{m|Italy,t}(\alpha, 0.95)$ values which suggests that Italy has a higher exposure to the financial system that the financial system to Italy sovereign credit risk on July 26^{th}, 2012, no matter what copula we are employing. Student's t copula arises lower maximum daily credit losses with 95% confidence level than Frank copula for a wide confidence level α range whether as $CoVaR_{Italy|m,t}(\alpha, 0.95)$ or $CoVaR_{m|Italy,t}(\alpha, 0.95)$. In relation to $\Delta CoVaR$ values, Student's t copula has a similar behaviour to the Gumbel copula although they have different $CoVaR$ values. The different values on α allows us to see the tail dependence in the copulas through the convex shape of $CoVaR$ and $\Delta CoVaR$ with the exception of Frank copula. The Frank copula shows a linear increase as α is increasing probably due to its lack of tail dependency. The tail dependence of Student's t copula is clearly observed in Figure 2, where the observations are gathered on the left bottom corner and the right top corner of the graphs, behavior that is not shared by Frank copula.

[Insert Figure 1 here]
[Insert Figure 2 here]

The general image emerging from Figure 1 is that the Frank copula give us higher values of $CoVaR$ but lower values of $\Delta CoVaR$ than the Student's t copula for a wide range of α given equal marginal features. The graphs presented in Figure 3 provide evidence about the copula role in the $CoVaR$ and $\Delta CoVaR$ behaviour.

[Insert Figure 3 here]

In fact, Figure 3 shows the maximum conditional quantile of institution j returns conditioned to a quantile $1-\alpha$ or lower for institution l's returns with a confidence level of $1-\beta$, i.e.,

$$C(u_j|u_l \leq 1-\alpha) = 1-\beta$$

where u_j, u_l are the quantile of institution j and l's returns. Its focus is on the left tail of the joint distribution of returns due to $\alpha, \beta \in (0.9, 0.995)$. Conditioning to values of $1-\alpha = 0.1$ and $1-\beta = 0.1$ the quantile for institution j, i.e., u_j, under the Frank copula is half than under Student's t copula (0.04 against 0.08), which could explain the higher values of $CoVaR$ under Frank copula. Given a value of $1-\beta = 0.1$, u_j changes by less than 0.01 under the Frank copula for values of $1-\alpha$ between 0.005 and 0.1 while for Student's t copula the change is almost 0.08, which could explain the higher value of $\Delta CoVaR$ under this copula.

Overall, Figure 4 provides support to the validity of the model. $CoVaR_{i|m,t}(0.95, 0.95)$ is like assessing $VaR_{i,t}(0.95)$ for country i under a stressed scenario in the financial sector, i.e., $CoVaR$ is a Stressed VaR. The difference between the unconditional VaR and the $CoVaR$ could been seen as a measure the relevance of the conditioning event in VaR assessment. Figure 4 shows lower values for $VaR_{i,t}(0.95)$ than $CoVaR_{i|m,t}(0.95, 0.95)$ as it would be expected due to the positive dependence between financial market and the sovereign sector. $CoES_{i|m,t}(0.95, 0.95)$ is considering more severe scenarios than $CoVaR_{i|m,t}(0.95, 0.95)$, specifically $CoES$ is looking beyond 95% percentile, thus $CoES$ should have higher values than $CoVaR$.Figure 5 provides a similar interpretation but shifting the conditioning and conditioned variable, i.e., $VaR_{m,t}(0.95)$, $CoVaR_{m|i,t}(0.95, 0.95)$ and $CoES_{m|i,t}(0.95, 0.95)$.

Table 9 shows the estimated values for the risk measures in four different days. The maximum losses with a 95% confidence level for each country are represented by the Value at Risk (VaR_i) The highest $VaR_{i,t}$ is observed in Spanish sovereign sector on May 8^{th}, 2010, following by the Italian sovereign sector on August 2^{nd}, 2012. If maximum losses with 95% confidence level for each country are assessed in a stressed scenario where the financial sector is below its 5% percentile, i.e., $CoVaR_{i|m,t}$, losses are higher. For the Spanish case those losses increases from 4.05% to 5.47% on May 8^{th}, 2010. The cost of suffering an extreme event in the Spanish sovereign sector if it is produced in a financial crisis environment is 1.42%. For the Italian sovereign sector on August 2^{nd},2012, the extra losses for suffering a distress event when the financial sector is facing a fragile situation is 0.76%. On the other hand, the maximum losses for the financial sector with a 95% confidence level given that a certain country is on distress is represented by $CoVaR_{m|i,t}$. The highest losses are obtained if the conditioning country is Belgium, followed by Denmark

and Netherlands, all of them on May 8^{th}, 2010. Danish financial authority identified on 2014 six SIFIs in Denmark and Dutch financial regulator three banks with high systemic risk. Belgian banks' authority pointed out six Belgian SIFIS[8]. $\Delta CoVaR_{i|m}$ measures the change in the maximum losses for the sovereign sector when the financial market moves from a normal scenario to a distress one. This change implies dependency in the behaviour of the conditional variable to the specific scenario for the conditioning variable. According to $\Delta CoVaR$, Spain and Italy are the countries that are more exposed to financial sector and are more likely to produce contagion to financial markets. $\Delta CoES$ shows the same behaviour than $\Delta CoVaR$ in this sense.
$CoES_{m|i,t}$ shows the expected losses of the financial sector as a whole in a distress scenario given a crisis period on a certain country. The highest values coincide with the countries identified in $\Delta CoVaR_{m|i,t}$, i.e., Belgium, Denmark and Netherlands on the 8^{th} of May 2010.

[Insert Table 9 here]

Figures 6 and 7 show a strong distinct pattern between core and periphery countries. The behaviour of Spain and Italy is different from the rest of countries having high values with greater volatility. These Δ measures allow us to have a clue about the contagion and countries' exposure to the financial system. The findings concerning $\Delta CoVaR$ and $\Delta CoES$ can be really useful in order to analyse the ECB's policy effect during the sovereign credit crisis.

[Insert Figure 6 here]
[Insert Figure 7 here]

5.1 Event study

November 2009 has been identified as the initial point for the European sovereign debt crisis (Bhanot et al. 2014, Reboredo and Ugolini 2015b). It is when investors became concerned about the Greek government problems because of the announcement of an unexpected higher deficit.
Following Lucas et al. (2013) I distinguish two main key policy announcements during the European sovereign credit risk crisis. On May 8^{th}, 2010 started the European Financial Stability Facility (EFSF) and the ECB's Securities Market Program (SMP). The second key policy announcement began on 26^{th} July 2012, when Draghi pledged to do *"whatever it takes"* to preserve the euro, and that *"it will be enough"*. On 2^{nd} August 2012 it was announced a new asset purchase program, the Outright Monetary Transactions (OMT). The details of this program were published on the 6^{th} September 2012.

I assess the 1^{st} principal component of the time-series of $\Delta CoVaR_{i|m,t}(\beta)$, $\Delta CoES_{i|m,t}(\beta)$, $\Delta CoVaR_{m|i,t}(\beta)$, $\Delta CoES_{m|i,t}(\beta)$ across countries. Principal component analysis is employed due to its efficiency for gathering volatility patterns in one indicator. As a result four indicators for systemic risk derived from Δ measures are obtained, two related to contagion from countries to financial credit risk, i.e., $\Delta CoVaR^{1^{st}PC}_{m|i,t}$, $\Delta CoES^{1^{st}PC}_{m|i,t}$, and two concerning sovereign credit risk exposure to the financial sector, i.e., $\Delta CoVaR^{1^{st}PC}_{i|m,t}$,

[8]For the Danish case those banks were Danske Bank, Nykredit Realkredit, Nordea Bank Danmark, Jyske Bank, Sydbank and DLR Kredit while for the Dutch authority the most systematically important banks were ING Bank, Rabobank and ABN AMRO. For the Belgian supervisor the most systematically important domestic banks were KBC Groep KBC Bank NV, Belfius Banque SA, Euroclear Bank SA and Investeringsmaatschappij Argenta Argenta Bank

$\Delta CoES^{1^{st}PC}_{i|m,t}$.

Lets define the abnormal $\Delta - measure_{i|j,t}(\beta)$, i.e., $A\Delta - measure_{i|j,t}(\beta)$ as

$$A\Delta - measure(\beta) = \Delta - measure_{i|j,t}(\beta) - E_{t-1}(\Delta - measure_{i|j,t}(\beta)), \qquad (14)$$

where $E_{t-1}(\Delta - measure_{i|j,t}(\beta))$ is supposed to be a constant, i.e., $E_{t-1}(\Delta - measure_{i|j,t}(\beta)) = b_0$, and $\Delta - measure_{i|j,t}(\beta)$ can be any of the four European-level systemic risk measures built using principal component analysis.

The estimation window has a length between half a month and six month and the length of the event window is 4 days. Using several estimation windows prevents results to be dependant of the length of previous considered returns. Following Abad et al. (2011) I compute a t-standard ratio for testing the zero-mean hypothesis for the cumulative abnormal $\Delta - measure_{i|j,t}(\beta)$, i.e., $CA\Delta - measure_{i|j,\tau_1:\tau_2}(\beta) = \sum_{t=\tau_1}^{\tau_2} A\Delta\Delta - measure_{i|j,t}(\beta)$. A non-parametric test, Wilcoxon signed-rank test, is employed in case normality assumption is not hold for $A\Delta - measure_{i|j,t}(\beta)$.
The policy measures are divided in four measures or announcements.

May 8^{th}, 2010 announcement: European Financial Stability Facility (EFSF) and the ECB's Securities Market Program (SMP). The study event is performed employing an event window from May 6^{th}, 2010 to May 11^{th}, 2010.

July 26^{th}, 2012 announcement: Draghi's speech The study event is performed employing an event window from July 24^{th}, 2012 to July 30^{th}, 2012, i.e., two business days before and after the announcement.

August 2^{nd}, 2012 announcement: first news about the Outright Monetary Transactions (OMT) program The study event is performed employing an event window from July 31^{th}, 2012 to August 6^{th}, 2012.

September 6^{th}, 2012 announcement: disclosure of the details about the Outright Monetary Transactions (OMT) program The study event is performed employing an event window from September 4^{th}, 2012 to September 10^{th}, 2012.

[Insert Table 10 here]

There is considered that a measure had an effect only when the null hypothesis for both test, parametric and non-parametric are rejected. Concerning to May 8^{th}, 2010, the Δ conditional measures capture a change in systemic risk between sovereign and financial sectors. Indeed, Figures 4 and 5 show a peak in that date indicating a raise in contagion and exposure of sovereign sector to financial sector. This result coincides with the one obtained by Wyplosz et al. (2011). According to them, the ESFS acted as a channel of contagion. Indeed, it change a country indebtness problem to an European general problem, consequently it was implicitly as sharing debt issues. It also supposed a contagion channel through European banks that were highly recommended to not sell European foreign sovereign bonds, e.g., Greece, by their national government. When a sovereign default occurs, it produces twice contagion to the other European sovereign credit risk. First because of the losses of the ESFS guarantees and the second due to the recapitalization of domestic banks that were recommended to keep the exposure to defaulted country.

The speech of Mario Draghi also seemed to have an effect reducing the credit exposure of the sovereign sector to the financial system. In Figures 11a, 11a , 11a and 11a the same exercise is performed at a country level, where the only country than had a significant effect in its exposure to the financial sector on July 26^{th}, 2012 was Spain for estimation windows above two months.
Finally the disclosure of the OMT program seemed to trigger a reduction in the exposure of the sovereign to the financial sector. Specifically, Italy and Spain were the main countries that reduced their exposure to the financial sector. Recent literature coincides in similar results about the effect ofthe OMT. Altavilla et al. (2016) analysed the effect of the OMT program using high-frequency data. They conclude that the OMT program implied the reduction of the interest rate paid by the Italian and Spanish government.

The Δ Conditional measures appear to be a good indicator for tracking the effectiveness of the measures taken by the ECB as can be seen in the similar conclusion of the event study with other articles about this topic. Nevertheless, Δ Conditional measures may have also power to find out stress moments in the sovereign debt crisis period without laying down an specific event.
The top 5 most stressful days are identified in terms of the highest systemic risk values obtained in the sample. Table 12 shows that the most relevant moments for driving exposure and contagion between sovereign and financial credit risk are the May 8^{th}, 2010 announcement and the Greek referendum announcements. In Figure 8 the black vertical lines that refer to those three announcements. Firstly, the May 8^{th}, 2010 announcement where the European Financial Stability Facility (EFSF) and the ECB's Securities Market Program (SMP) are presented. Secondly, November 1^{st}, 2011 is the day after the Greek prime minister Papandreou announced his will of proposing a referendum about the bailout conditions. Third, June 30^{th}, 2015 the Greek government deal with problems for repaying IMF. The same day Jeroen Dijsselbloem, the head of the Eurogroup, said that *'Greece is in default or will be in default tomorrow morning on the IMF'*[9]. The Greek prime minister Tsipras had announced a referendum three days before for the July 5^{th}, 2015 in order to ask to the Greek people if they should accept the third bailout conditions.

[Insert Table 12 here]
[Insert Figure 8 here]

5.2 Backtesting and stress testing

Backtesting on CoVaR. The proportion of exceedances over the threshold of the CoVaR should approximately equal the confidence level and they should take place independently, not in clusters. Consequently for checking the accuracy of the proposed model the statistical tests for unconditional coverage from Kupiec (1995) and the conditional coverage from Christoffersen (1998) are computed. The null hypothesis of the unconditional and conditional coverage is performed at 5% level of significance under skewed-t margins and the best fit according to the Bayesian Information Criterion (BIC).

For the conditional institution of $CoVaR_{j|l}(\alpha, \beta)$ I built the indicator function that values one if the past ex-post losses of l crossed the past ex-ante VaR forecast and zero

[9] `https://www.nytimes.com/2015/07/01/world/europe/greece-alex-tsipras-debt-emergency-bailout.html`

otherwise, i.e.,

$$\mathbb{1}_{l,t} = \begin{cases} 1 & if \quad r_{l,t} \leq -VaR_{l,t}(\alpha) \\ 0 & if \quad r_{l,t} > -VaR_{l,t}(\alpha) \end{cases} .$$

For those days t where $\mathbb{1}_{l,t} = 1$ I use a second indicator function that values one if the past ex-post losses of j crossed the past ex-ante CoVaR forecast and zero otherwise, i.e.,

$$\mathbb{1}_{j|l,t} = \begin{cases} 1 & if \quad r_{j,t} \leq -CoVaR_{j,t}(\alpha, \beta) \\ 0 & if \quad r_{j,t} > -CoVaR_{j,t}(\alpha, \beta) \end{cases} .$$

For this last hit sequence I have $T_{\mathbb{1}_{l,t}=1}$ observations , i.e., the observations where $r_{l,t} \leq -VaR_{l,t}$, where $j, l = i, m$.

Unconditional coverage test from Kupiec (1995). If $CoVaR_{j|l}(\alpha, \beta)$ satisfies the unconditional coverage property, $P(\mathbb{1}_{j|l,t+1} = 1) = 1 - \beta$, i.e., the proportion of exceedances over the threshold is equal to the significance level. Consequently the null and alternative hypothesis in this test would be

$$\begin{cases} H_0 : E[\mathbb{1}_{j|l,t}] \equiv p = 1 - \beta, \\ H_1 : E[\mathbb{1}_{j|l,t}] \equiv p \neq 1 - \beta. \end{cases}$$

Let us define $X = \sum_{t=1}^{T_{\mathbb{1}_{l,t}=1}} \mathbb{1}_{j|l,t}$, then the likelihood ratio of Kupiec (1995) is given by

$$LR = \frac{p^X (1-p)^{T_{\mathbb{1}_{l,t}=1} - X}}{\left(\frac{T_{\mathbb{1}_{l,t}=1} - X}{T_{\mathbb{1}_{l,t}=1}} \right)^{T_{\mathbb{1}_{l,t}=1} - X} \left(\frac{X}{T_{\mathbb{1}_{l,t}=1}} \right)^X},$$

where $-2\log(LR) \sim \chi_1^2$ under the null hypothesis.

[Insert Table 13 here]

The results for the conditional and unconditional coverage test for $CoVaR_{m|i,t}(\alpha, \beta)$ are in line with the $CoVaR_{m|i}$ backtest results in Karimalis and Nomikos (2014) and Girardi and Ergün (2013) with a mean p-value of 0.3418. As a consequence, the hypothesis that the proportion of exceedances over the threshold is equal to the confidence level in the case of $CoVaR_{m|i}(0.95)$ can not be rejected that . If the same test under normality assumption for the marginal is performed the mean p-value is below 0.05 for the $CoVaR_{m|i}(0.95)$ with enough exceedances for the conditioning variable, which can be seen as an advantage of the proposed model over the simple Gaussian model.
Table 13 shows besides the p-value, the lower and the upper bound of the non-rejection area, i.e., the number of exceedances that are considered normal with a confidence level of 95%, the number of exceedances and the size of the sample for assessing the backtesting.

Conditional coverage test from Christoffersen (1998). If the $CoVaR_{j|l}(\alpha, \beta)$ satisfies the conditional coverage property, $P_t(\mathbb{1}_{j|l,t+1} = 1) = 1 - \beta$. Given the assumption that $\mathbb{1}_{j|l,t}$ follows a first-order Markov sequence with transition probability matrix

$$P_1 = \begin{bmatrix} 1 - p_{01} & p_{01} \\ 1 - p_{11} & p_{11} \end{bmatrix},$$

where $p_{k,q}$ indicate the probability of having in t+1 $\mathbb{1}_{j|l,t+1} = q$ conditional to the scenario on t where $\mathbb{1}_{j|l,t} = k$ with $q, k = 0, 1$. If the conditional coverage property is satisfied, the probability of a exception in t+1 doesn't depend on the fact of having an exception on t, i.e., $P_t(\mathbb{1}_{j|l,t+1} = 1) = P(\mathbb{1}_{j|l,t+1} = 1)$. In conclusion, the null and the alternative hypothesis are

$$\begin{cases} H_0 : E[\mathbb{1}_{j|l,t}] \equiv p = p_{01} = p_{11}, \\ H_1 : E[\mathbb{1}_{j|l,t}] \equiv p \neq p_{01} = p_{11}, \end{cases}$$

Given the fact that there are $T_{\mathbb{1}_{l,t}=1}$ observations, a total of $T_{\mathbb{1}_{l,t}=1} - 1 \equiv T^{pair}_{\mathbb{1}_{l,t}=1}$ pair of observations can be obtained. The sample of pair of observations can be divided in four subsamples, i.e.,

$$T^{pair,00}_{\mathbb{1}_{l,t}=1} + T^{pair,01}_{\mathbb{1}_{l,t}=1} + T^{pair,10}_{\mathbb{1}_{l,t}=1} + T^{pair,11}_{\mathbb{1}_{l,t}=1} = T^{pair}_{\mathbb{1}_{l,t}=1},$$

where the superscripts indicate that if there was an exceedance in $t-1$ and t and the subscript indicate that all the observations hold $r_{l,t+1} \leq -VaR_{l,t+1}$.
Defining

$$\hat{p}_{01} = \frac{T^{pair,01}_{\mathbb{1}_{l,t}=1}}{T^{pair,00}_{\mathbb{1}_{l,t}=1} + T^{pair,01}_{\mathbb{1}_{l,t}=1}},$$

and

$$\hat{p}_{11} = \frac{T^{pair,11}_{\mathbb{1}_{l,t}=1}}{T^{pair,10}_{\mathbb{1}_{l,t}=1} + T^{pair,11}_{\mathbb{1}_{l,t}=1}},$$

H_0 holds if $\hat{p}_{01} \approx \hat{p}_{11}$, as a consequence the probability of having an exceedance in $t+1$ could be defined without taking into account the scenario in t, i.e.,

$$\hat{p} = \frac{T^{pair,01}_{\mathbb{1}_{l,t}=1} + T^{pair,11}_{\mathbb{1}_{l,t}=1}}{T^{pair,00}_{\mathbb{1}_{l,t}=1} + T^{pair,01}_{\mathbb{1}_{l,t}=1} + T^{pair,10}_{\mathbb{1}_{l,t}=1} + T^{pair,11}_{\mathbb{1}_{l,t}=1}}.$$

The likelihood ratio of Christoffersen (1998) is employed, i.e.,

$$\begin{aligned} LR &= \left(\frac{\hat{p}}{\hat{p}_{01}}\right)^{T^{pair,01}_{\mathbb{1}_{l,t}=1}} \left(\frac{\hat{p}}{\hat{p}_{11}}\right)^{T^{pair,11}_{\mathbb{1}_{l,t}=1}} \\ &\quad \left(\frac{1-\hat{p}}{1-\hat{p}_{01}}\right)^{T^{pair,00}_{\mathbb{1}_{l,t}=1}} \left(\frac{1-\hat{p}}{1-\hat{p}_{11}}\right)^{T^{pair,10}_{\mathbb{1}_{l,t}=1}}, \end{aligned}$$

where $-2\log(LR) \sim \chi^2_1$. The frequency with which consecutive exceedances are observed may be few due to the fact that they are rare events, as a consequence the power of this test is limited.
Table 14 shows, besides the p-value, the distribution of the pair of sample observations in order to detect possible clusters in the exceedances. The mean p-value for $CoVaR_{i|m,t}(\alpha, \beta)$ and for $CoVaR_{m|i,t}(\alpha, \beta)$ is respectively 0.2479 and 0.3525. Consequently the null hypothesis of independence of the exceedances can not be rejected.

[Insert Table 14 here

Stress testing CoVaR. The stress testing exercise can be performed taking into account different confidence levels for the $CoVaR$, i.e., different values of β. In that way the $CoVaR$ is assessed under different scenarios. In particular the following figures identify the $CoVaR$ in two selected days (May 10^{th}, 2010 and July 26^{th},2012) from $\beta = 0.99$ to 0.5.

[Insert Figure 9 here]
[Insert Figure 11 here]

On the one hand, the $CoVaR_{i|m,t}(\alpha, \beta)$ and $CoVaR_{m|i,t}(\alpha, \beta)$ are monotonic increasing functions of the confidence level β and the difference of CoVaR based on β leads to a different sort of institutions than based on α, i.e., $\Delta CoVaR_{i|m}(\beta = 0.95) = CoVaR_{i|m}(\alpha = 0.95, \beta = 0.95) - CoVaR_{i|m}(\alpha = 0.5, \beta = 0.95) \neq CoVaR_{i|m}(\alpha = 0.95, \beta = 0.95) - CoVaR_{i|m}(\alpha = 0.95, \beta = 0.5)$. For instance, Italy and Spain have the smallest value of $CoVaR_{i|m}(\alpha = 0.95\beta = 0.95) - CoVaR_{i|m}(\alpha = 0.95\beta = 0.5)$ and $CoVaR_{m|i}(\alpha = 0.95\beta = 0.95) - CoVaR_{m|i}(\alpha = 0.95\beta = 0.5)$ but they are on the top of the classification following $\Delta CoVaR_{i|m}(\beta = 0.95)$ and $\Delta CoVaR_{m|i}(\beta = 0.95)$. The reading of these figures can also be informative about the distress that could be expected in each moment t. For example, in the top Figure 11, i.e., $CoVaR_{i|m}(\beta)$, with a 90% of confidence ($\beta = 0.90$), given that the financial sector is below the 5% worst case scenario ($\alpha = 0.95$), the sovereign credit risk for Spain will not experience daily losses higher than 2.25% whereas for the same confidence level and situation for the financial system, Austria CDS losses returns will not be above 1.23% . This is the way these graphs should be read.
On the other hand, $\Delta CoVaR_{i|m,t}(\beta)$ and $\Delta CoVaR_{m|i,t}(\beta)$ are not monotonic increasing with the value of β as can be seen in 10 and 12, where the values for Spain and Italy are slightly decreasing although for high quantiles are again increasing. Moreover, there are not observable changes in the ranking of the countries according to their values of $\Delta CoVaR$. Concerning to the values of $\Delta CoES$ is remarkable that they seem monotonic increasing with the value of β.

[Insert Figure 10 here]
[Insert Figure 12 here]

6 Conclusions

The $CoVaR$ measure introduced by Adrian and Brunnermeier (2011) was drawn up for assessing the banks' systemic risk contribution to the financial system. In this article the $CoVaR$ is employed with a copula methodology to measure the interrelationship between sovereign and financial credit risk. The economic literature has not employed yet this approach to deal with the spillovers between sovereign and financial credit risk. This approach is a robust way for measuring systemic risk focusing on a low quantile of the returns' distribution.

Taken together, the data presented in this article provide evidence that the choice of copula determines the $CoVaR$ values and the tail dependence between financial and sovereign credit returns strongly influence $\Delta CoVaR$. The copula methodology allows to decompose in a understandable way the systemic risk measures, besides of being a time-saving and less computationally expensive method than other procedures. However, an inaccurate copula choice implies a model risk that can drive to a wrong measure of exposure and contagion. In order to prevent model risk, a wide range of copulas and several information criteria are considered, using ML and PML to maximize the possibility of choosing an accurate copula.

Taking into account the relationship between sovereign and financial sector when the credit risk is assessed supposed an average increase of 0.54% for the sovereign VaR and 0.45% for the financial VaR. The difference between core and peripherical countries is reflected in higher exposure and contagion to the financial credit risk for peripheral countries, i.e., higher $\Delta CoVaR$ and $\Delta CoES$. These findings are consistent with previous results, e.g. Alter and Beyer (2012) and Alter and Schüler (2012), showing that periphery countries were the ones that contributed more to the financial credit contagion and that they were the most affected due to the high exposure to the financial sector.

This diverse pattern in the systemic risk measures may emerge in the copula approach due to the different joint distribution. $\Delta CoES$ seems monotonic increasing with the confidence level of the conditional variable while $\Delta CoVaR$ does not seem to share this feature. $\Delta CoVaR$ as a function of the confidence level of the conditioning variable might reveal tail dependence features. However it is necessary to study more deeply how these systemic risk measures interact with different parameters as the confidence level for the conditional and conditioning variable. Future works might try to find out the impact of the choice of copula in the model risk of $CoVaR$ and $CoES$.

Policy makers need indicators for assessing the effectiveness and the collateral detrimental effects that some measure can have in the economy. The Δ Conditional measures provides support as a tool for the measurement of contagion and spillover effects. These measures have showed that the ECB's actions had an powerful effect limiting the exposure of European countries to the financial credit risk, specially the exposure of Spain and Italy. Some policy measures had also augmented the contagion effects between sovereign and the financial sector as the EFSF. These results are in line with recent literature about the effect of ECB's measures during the European sovereign credit crisis (Wyplosz et al. 2011, Altavilla et al. 2016). The Greek referendum announcement on November 1^{st}, 2011 and on June 30^{th}, 2015 also had an effect on the systemic risk measures computed in this article. These findings reveal Δ Conditional measures, i.e., $\Delta CoVaR$ and $\Delta CoES$ as suitable tools to provide reliable information for take effective and efficient policy measures.

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Appendices

A Tables

Table 1: Main tail dependence features for each copula

Family	**Lower tail dependence**	**Upper tail dependence**
Clayton	$2^{-1/\theta}$	$-$
Gumbel	$-$	$2-2^{1/\theta}$
Frank	$-$	$-$
BB7 (Joe-Clayton)	$2^{-1/\delta}$	$2-2^{1/\theta}$
Rotated Gumbel	$2-2^{1/\theta}$	$-$
Student's	$2t_{v+1}\left(-\sqrt{\frac{(v+1)(1-\theta)}{1+\theta}}\right)$	$2t_{v+1}\left(-\sqrt{\frac{(v+1)(1-\theta)}{1+\theta}}\right)$
BB1 (Clayton-Gumbel)	$2^{-1/\theta\delta}$	$2-2^{1/\delta}$

Note: $-$ represents that there is no tail dependency.
Source: (Ao et al., 2017, p. 22) and Jiang (2012).

Table 2: Conditional quantile u_m and copula density function $c(u_{m,t}, u_{i,t}; \theta)$

Copula	**Conditional quantile:** u_m	**Copula density function:** $c(u_{i,t}, u_{m,t}; \theta)$
Clayton	$\left(1 + ((1-\alpha)(1-\beta))^{-\theta} - (1-\alpha)^{-\theta}\right)^{-\frac{1}{\theta}}$	$(\theta+1)\left(u_{i,t}^{-\theta} + u_{m,t}^{-\theta} - 1\right)^{-2-\frac{1}{\theta}} u_{i,t}^{-\theta-1} u_{m,t}^{-\theta-1}$
Gumbel	$\exp\left(-\left[(-\log((1-\alpha)(1-\beta)))^{\theta} - (-\log(1-\alpha))^{\theta}\right]^{\frac{1}{\theta}}\right)$	$(A+\theta-1)\, A^{1-2\theta} \exp(-A)$ $(u_{m,t}u_{i,t})^{-1}(-\log u_{m,t})^{\theta-1}(-\log u_{i,t})^{\theta-1}$
Frank	$-\frac{1}{\theta}\log\left(1 - \frac{(1-\exp(-\theta))-(1-\exp(-\theta))(\exp(-\theta(1-\beta)(1-\alpha)))}{(1-\exp(-\theta(1-\beta)))}\right)$	$\frac{\theta(1-\exp(-\theta))\exp(\theta(u_{i,t}+u_{m,t}))}{(1-\exp(-\theta)-(1-\exp(-\theta u_{i,t}))(1-\exp(-\theta u_{m,t})))^2}$
BB7	$\psi^{-1}\left[\psi\left((1-\beta)(1-\alpha)\right) - \psi(1-\alpha)\right]$	$\left[T_1(u_{i,t})T_1(u_{m,t})\right]^{-1-\delta}$ $T_2(u_{i,t})T_2(u_{m,t})L_1^{-2(1+\delta)/\delta}$ $(1-L_1^{-1/\delta})^{1/\theta-2}$ $\left[(1+\delta)\theta L_1^{1/\delta} - \theta\delta - 1\right]$
Rotated Gumbel	$C^R_{Gumbel}(1-\alpha, u_m) = (1-\beta)(1-\alpha)$	$(A+\theta-1)A^{1-2\theta}\exp(-A)((1-u_i)(1-u_m))^{-1}$ $(-\log(1-u_i))^{\theta-1}(-\log(1-u_m))^{\theta-1}$
Student's t	$\int_{-\infty}^{u_m} C_{i\|m}((1-\alpha)\|s)ds = (1-\beta)(1-\alpha)$	$K\frac{1}{\sqrt{1-\rho^2}}$ $\left[1 + \frac{T_\eta^{-1}(u_{i,t})^2 - 2\rho T_\eta^{-1}(u_{i,t})T_\eta^{-1}(u_{m,t}) + T_\eta^{-1}(u_{m,t})^2}{\eta(1-\rho^2)}\right]^{-\frac{\eta+2}{2}}$ $\left[(1+\eta^{-1}T_\eta^{-1}(u_{i,t})^2)(1+\eta^{-1}T_\eta^{-1}(u_{m,t})^2)\right]^{-\frac{\eta+1}{2}}$
BB1	$\left[\left\{\left[((1-\beta)(1-\alpha))^{-\theta} - 1\right]^{\delta} - ((1-\alpha)^{-\theta}-1)^{\delta}\right\}^{\frac{1}{\delta}} + 1\right]^{-\frac{1}{\theta}}$	$(u_{i,t}u_{m,t})^{-\theta-1}(ab)^{\delta-1}c^{\frac{1}{\delta}-2}d^{-\frac{1}{\theta}-1}$ $\left\{d^{-1}c^{\frac{1}{\delta}}(1+\theta)+\theta(\delta-1)\right\}$

Note:

in BB7 copula conditional quantile formula: $\psi(x;\theta,\delta) = [1-(1-x)^{-\theta}]^{\delta} - 1$, $\psi^{-1}(x;\theta,\delta) = 1-[1-(1+x)^{-\frac{1}{\delta}}]^{\frac{1}{\theta}}$ and $\psi'(x;\theta,\delta) = -[1-(1-x)^{\theta}]^{-\delta-1}\delta[-(1-x)^{\theta}\theta/(-1+x)]$.

in BB7 copula density function: $T_1(s) = 1-(1-s)^{\theta}$, $T_2(s) = (1-s)^{\theta-1}$ and $L_1 = T_1(v)^{-\delta} + T_1(s)^{-\delta} - 1$.

in Rotated Gumbel conditional quantile formula : $C^R_{Gumbel}(u_i, u_m; \theta) = u_i + u_m - 1 + C_{Gumbel}(1-u_i, 1-u_m; \theta)$.

in Rotated Gumbel copula density function: $A = [(-\log(1-u_i))^{\theta} + (-\log(1-u_m))^{\theta}]^{1/\theta}$.

in Student's t copula conditional quantile formula: $C_{i|m}(\alpha_i|s;\eta,\rho) = T_{\eta+1}\left(\sqrt{\frac{\eta+1}{\eta+(T_\eta^{-1}(\alpha_j))^2}}\frac{T_\eta^{-1}(s)-\rho T_\eta^{-1}(\alpha_j)}{\sqrt{1-\rho^2}}\right)$, T_η is the cdf of a t-Student with η degrees of freedom and T_η^{-1} represents its inverse.

in BB1 copula density function $a = u_{i,t}^{-\theta} - 1$, $b = u_{m,t}^{-\theta} - 1$, $c = a^{\delta} + b^{\delta}$ and $d = 1 + c^{\frac{1}{\delta}}$.
The conditional uniform values are obtained from returns' distribution, hence for instance looking above the 95% percentile of losses for the conditional and conditioning variable means that α and β value 0.05.

Table 3: Time-varying parameter representation for each copula

General model	$\Lambda\left(\omega_K + \beta_K \theta_{t-1}^K + \alpha_K \frac{1}{10}\sum_{k=1}^{10} \lvert u_{i,t-k} u_{m,t-k} \rvert\right)$	
Copula	**Parameter** θ	**Function** $\Lambda(x)$
Clayton	θ	$\exp(x)$
Gumbel	θ	$(\exp(x)+1)$
Frank	θ	x
BB7	τ^L; τ^U	$(1+\exp(-x))^{-1}$
Rotated Gumbel	θ	$(\exp(x)+1)$
Student's t	ρ	$\frac{1-\exp(-x)}{1+\exp(-x)}$
BB1	τ^U: τ^L	$(1+\exp(-x))^{-1}$

Note:

$\tau^U, \tau^L \in (0,1)$.

For the BB7 copula $\theta = \frac{1}{\log_2(2-\tau^U)}$ and $\delta = \frac{-1}{\log_2(\tau^L)}$.

For the BB1 copula $\delta = \frac{1}{\log_2(2-\tau^U)}$ and $\theta = \frac{-\log_2(2-\tau^U)}{\log_2(\tau^L)}$.

Table 4: European banks employed for building the financial system credit risk index

Name	**Country**
Banca Monte dei Paschi di Siena	Italy
Banco Comercial Português	Portugal
Banco Popular Español	Spain
Banco Santander	Spain
Bayerische Landesbk	Germany
BBVA	Spain
BNP Paribas	France
Commerzbank AG	Germany
Cooptieve Cente Rabo BA	Netherland
Credit Agricole	France
Credit Lyonnais	France
Danske Bank A/S	Finland
Deutsche bank AG	Germany
Erste Group Bank AG	Austria
ING Bank N.V.	Netherland
Intesa Sanpaolo Spa	Italy
KBCA Bank	Belgium
Lb Badenwuerttemberg	Germany
Mediobanca Spa	Italy
Natixis	France
Portigon AG	Germany
SNS Bank N.V.	Netherland
Societé Générale	France
Unicredit	Italy
Unicredit Bank AG	Austria

Table 5: Different weights for building the financial sector proxy.

Countries	1^{st} PCA	Equal	% GDP
Austria	10.83%	11.11%	3.25%
Belgium	8.02%	11.11%	4.00%
Finland	9.95%	11.11%	2.07%
France	12.73%	11.11%	22.81%
Germany	11.73%	11.11%	28.36%
Italy	11.95%	11.11%	17.81%
Netherland	12.62%	11.11%	7.36%
Portugal	9.64%	11.11%	1.96%
Spain	12.53%	11.11%	12.39%

1^{st} PCA column expresses the weights obtained by the first principal component.
Equal indicates the equally weighted portfolio.
% GDP column shows the weights according to the percentage of total GDP in the first quarter of 2009.

B Set of considered Copulas

The demonstration of some of the hereinbelow formulas can be seen in Karimalis and Nomikos (2014) and in Bernardi et al. (2017).
In the following equations $F_{\xi_{m,t}}(\xi_{m,t}) = u_{m,t}$ and $F_{\xi_{i,t}}(\xi_{i,t}) = u_{i,t}$.

Clayton copula. This copula allows positive dependence and asymmetric lower tail dependence. The Clayton copula has a dependence parameter $\theta \in (0, +\infty)$. When $\theta \to 0$ implies independence and when $\theta \to \infty$ implies perfect dependence.
Following the Girardi and Ergün (2013)'s definition , the uniform value is given by the following formula

$$u_m = \left(1 + ((1-\alpha)(1-\beta))^{-\theta} - (1-\alpha)^{-\theta}\right)^{-\frac{1}{\theta}}.$$

In order to estimate the parameter θ it is necessary to employ the copula density function according to Equation (12)

$$c(u_{i,t}, u_{m,t}; \theta) = (\theta + 1)\left(u_{i,t}^{-\theta} + u_{m,t}^{-\theta} - 1\right)^{-2-\frac{1}{\theta}} (u_{i,t}u_{m,t})^{-\theta-1}.$$

Gumbel copula. This copula allows positive dependence and asymmetric upper tail dependence. The Gumbel copula has a dependence parameter $\theta \in [1, +\infty)$. When $\theta = 1$ implies independence and when $\theta \to \infty$ implies perfect dependence.
Following Girardi and Ergün (2013)'s $CoVaR$ definition, the analytical expression for the conditional quantile employed in Equation (6) is

$$u_m = \exp\left(-\left[(-\log((1-\alpha)(1-\beta)))^{\theta} - (-\log(1-\alpha))^{\theta}\right]^{\frac{1}{\theta}}\right).$$

In order to estimate the parameter θ we should employ the copula density function in equation (12)

$$\begin{aligned} c(u_{i,t}, u_{m,t}; \theta) &= (A + \theta - 1)\, A^{1-2\theta} \exp(-A) \\ &\quad (u_{i,t} u_{j,t})^{-1} (-\log u_{i,t})^{\theta-1} (-\log u_{m,t})^{\theta-1}, \end{aligned}$$

where $A = \left[(-\log u_{m,t})^{\theta} + (-\log u_{i,t})^{\theta}\right]^{\frac{1}{\theta}}$.

Frank copula. This copula allows positive and negative dependence structures without implying tail dependence. The Frank copula has a dependence parameter $\theta \in (-\infty, +\infty) \backslash \{0\}$. When $\theta \to 0$ implies independence, when $\theta \to \infty$ implies positive perfect dependence and when $\theta \to -\infty$ implies negative perfect dependence.
The expression of the conditional quantile following the definition of Girardi and Ergün (2013) is

$$u_m = -\frac{1}{\theta} \log \left(1 - \frac{(1 - \exp(-\theta)) - (1 - \exp(-\theta))(\exp(-\theta(1-\beta)(1-\alpha)))}{(1 - \exp(-\theta(1-\alpha)))} \right).$$

In order to estimate the parameter θ we need to employ the copula density function in equation (12)

$$c(u_{i,t}, u_{m,t}; \theta) = \frac{\theta(1 - \exp(-\theta)) \exp(-\theta(u_{i,t} + u_{m,t}))}{(1 - \exp(-\theta) - (1 - \exp(-\theta u_{i,t}))(1 - \exp(-\theta u_{m,t})))^2}.$$

BB7 copula. This copula is also known as Joe-Clayton copula [10]. This is a copula with parameters $\theta \geq 1$ and $\delta > 0$, where θ measures upper tail dependence and δ measures lower tail dependence. The Joe-Clayton copula captures positive dependence while it allows for asymmetric upper and lower tail dependence. When $\delta \to 0$ the Joe copula is obtained and Clayton copula is the resulted one when $\theta = 0$.
The conditioned quantile following Girardi and Ergün (2013) is

$$u_m = \psi^{-1} \left[\psi\left((1-\beta)(1-\alpha)\right) - \psi(1-\alpha) \right],$$

where $\psi(x; \theta, \delta) = [1 - (1-x)^{\theta}]^{-\delta} - 1$ and $\psi^{-1}(x; \theta, \delta) = 1 - [1 - (1+x)^{-\frac{1}{\delta}}]^{\frac{1}{\theta}}$.
In order to estimate the parameter θ we need to employ the copula density function in Equation (12)

$$\begin{aligned} c(u_{i,t}, u_{m,t}; \theta, \delta) &= [T_1(u_{i,t}) T_1(u_{m,t})]^{-1-\delta}\, T_2(u_{i,t}) T_2(u_{m,t}) \\ &\quad L_1^{-2(1+\delta)/\delta} (1 - L_1^{-1/\delta})^{1/\theta - 2} \left[(1+\delta)\theta L_1^{1/\delta} - \theta\delta - 1 \right], \end{aligned}$$

where $T_1(s) = 1 - (1-s)^{\theta}$, $T_2(s) = (1-s)^{\theta-1}$ and $L_1 = T_1(v)^{-\delta} + T_1(s)^{-\delta} - 1$.

Rotated Gumbel copula. The Gumbel copula has a asymmetric dependence in the tails. Actually, it has no tail dependency in the lower tail but positive dependence in the upper tail when the parameter $\theta > 1$. The opposite tail dependence is obtained if the copula is rotated. If (U_i,U_m) has a copula $C_\theta(u_i, u_m)$, then ($1 - U_i$,$1 - U_m$) is distributed according to the rotated copula $C_\delta^R(u_i, u_m)$.

$$\begin{aligned} C^R_{Gumbel}(u_m, u_i; \theta) &= u_m + u_i - 1 + C_{Gumbel}(1 - u_m, 1 - u_i; \theta) \\ &= u_m + u_i - 1 + \exp\{-[(-\log(1-u_m))^{\theta} + (-\log(1-u_i))^{\theta}]^{1/\theta}\}. \end{aligned}$$

[10]See De Luca and Rivieccio (2012) for more information about this copula.

The conditional quantile u_m is obtained given the relation between the copula and the levels of confidence as it is showed in Equation (4) due to the fact that in the rotated Gumbel copula there is not closed form expression for the conditional quantile like in the Gumbel copula.
In order to estimate the parameter θ we need to employ the copula density function in equation (12)

$$\begin{aligned} c^R_{Gumbel} &= c_{Gumbel}(1-u_i, 1-u_m) \\ &= (A+\theta-1)A^{1-2\theta}\exp(-A)((1-u_i)(1-u_m))^{-1}(-\log(1-u_i))^{\theta-1}(-\log(1-u_m))^{\theta-1}, \end{aligned}$$

where $A = [(-\log(1-u_i))^\theta + (-\log(1-u_m))^\theta]^{1/\theta}$.

Following Reboredo and Ugolini (2015b) two additional copulas are also considered: the t-Student copula and the Clayton-Gumbel copula (BB1 copula).

Student's t copula. This copula allows positive and negative symmetric tail dependence. The parameter ρ measures correlation and the parameter η, the degrees of freedom, controls the probability mass assigned to extreme joint co-movements of risk factors changes[11]. When $\eta \to \infty$ corresponds to the Gaussian copula[12]. Due to the fact that the t-Student copula is an implicit copula, we can not obtain a close form conditioned quantile. Given the conditional copula $C_{i|m}(\alpha|u_m)$ we can get the conditional quantile fom the following formula

$$\overbrace{\int_0^{u_m} \underbrace{C_{i|m}(1-\alpha|s)}_{P[F_{\xi_{i,t}}(\xi_{i,t})<1-\alpha|F_{\xi_{m,t}}(\xi_{m,t})=s]} ds}^{P[F_{\xi_{i,t}}(\xi_{i,t})<1-\alpha, F_{\xi_{m,t}}(\xi_{m,t})<u_m]} = (1-\beta)(1-\alpha),$$

where $C_{i|m}(1-\alpha|s;\eta,\rho) = T_{\eta+1}\left(\sqrt{\frac{\eta+1}{\eta+(T_\eta^{-1}(1-\alpha))^2}}\frac{T_\eta^{-1}(s)-\rho T_\eta^{-1}(1-\alpha)}{\sqrt{1-\rho^2}}\right)$, T_η is the cdf of a t-Student with η degrees of freedom and T_η^{-1} represents it inverse[13].
For estimating the degrees of freedom (η) and the correlation parameter ρ the copula density function ies employed in Equation (12)

$$\begin{aligned} c(u_{i,t}, u_{m,t}); \eta, \rho) &= K\frac{1}{\sqrt{1-\rho^2}} \\ &\quad \left[1 + \frac{T_\eta^{-1}(u_{i,t})^2 - 2\rho T_\eta^{-1}(u_{i,t})T_\eta^{-1}(u_{m,t}) + T_\eta^{-1}(u_{m,t})^2}{\eta(1-\rho^2)}\right]^{-\frac{\eta+2}{2}} \\ &\quad \left[(1+\eta^{-1}T_\eta^{-1}(u_{i,t})^2)(1+\eta^{-1}T_\eta^{-1}(u_{m,t})^2)\right]^{\frac{\eta+1}{2}}, \end{aligned}$$

where $K = \Gamma(\frac{\eta}{2})\Gamma(\frac{\eta+1}{2})^{-2}\Gamma(\frac{\eta+2}{2})$.

[11] For more information about the properties of the t-Student copula see Demarta and McNeil (2005)
[12] The Gaussian copula underestimates the probability of joint extreme co-movements in high volatility and correlation scenarios according to Aussenegg and Cech (2011)
[13] See for instance Cech (2006)

BB1 copula. The BB1 copula, also known as the Clayton-Gumbel copula, allows asymmetric tail dependence. The BB1 copula has two dependence parameters: one for the Clayton behavior $\theta \in (0, +\infty)$ and another one for the Gumbel behavior $\delta \in [1, +\infty)$. When $\delta = 1$ and $\theta > 0$ we get the Clayton copula and as a consequence upper tail independence and lower tail dependence. When $\theta \to 0$ and $\delta > 0$ the Gumbel copula is obtained with upper tail dependence only. In the case of $\theta \to 0$ and $\delta = 1$ we get upper and lower tail independence[14].
The expression of the conditional quantile following the $CoVaR$ definition of Girardi and Ergün (2013) is

$$u_m = \left[\left\{ \left[((1-\beta)(1-\alpha))^{-\theta} - 1 \right]^{\delta} - ((1-\alpha)^{-\theta} - 1)^{\delta} \right\}^{\frac{1}{\delta}} + 1 \right]^{-\frac{1}{\theta}}.$$

In order to estimate the parameter θ and δ we need to employ the copula density function in Equation (12) obtained from Cech (2006)

$$c(u_{i,t}, u_{m,t}; \theta, \delta) \quad = \quad (u_{i,t} u_{m,t})^{-\theta-1} (ab)^{\delta-1} c^{\frac{1}{\delta}-2} d^{-\frac{1}{\theta}-1} \left\{ d^{-1} c^{\frac{1}{\delta}} (1+\theta) + \theta(\delta - 1) \right\} \quad (15)$$

where $a = u_{i,t}^{-\theta} - 1$, $b = u_{m,t}^{-\theta} - 1$, $c = a^{\delta} + b^{\delta}$ and $d = 1 + c^{\frac{1}{\delta}}$.

C Tables of results

Table 6: Values obtained from the model structure of CDS returns

	$\hat{\alpha}_i$	$\hat{\beta}_i$	$\hat{\theta}_i$	$\hat{\phi}_{0,i}$	$\hat{\phi}_{1,i}$	$\hat{\eta}_i$	$\hat{\lambda}_i$
Financial sector	0.10	0.37	0.53	0.00	0.20	3.43	-0.02
Austria	0.08	0.27	0.65	0.00	0.01	2.16	0.06
Belgium	0.09	0.55	0.35	0.00	0.03	2.41	0.01
Denmark	0.09	0.00	0.91	0.00	0.00	2.07	0.05
France	0.10	0.56	0.34	0.00	0.04	2.41	0.00
Germany	0.09	0.25	0.65	0.00	0.01	2.20	0.03
Italy	0.09	0.40	0.51	0.00	0.13	3.00	0.00
Netherlands	0.07	0.52	0.42	0.00	-0.01	2.05	0.02
Spain	0.09	0.47	0.44	0.00	0.10	2.98	0.01

Equation (7) shows the model structure of returns and Equation (8) shows the probability density function of return innovations.

[14] See for instance Venter (2002) or Nicoloutsopoulos (2005)

Table 7: Values from the Aike Information Criterion (AIC) for the different selected copulas

		AIC							
		Austria	Belgium	Denmark	France	Germany	Italy	Netherlands	Spain
Based on ML estimation	Clayton	-867	-762	-1148	-736	-839	-1063	-927	-1038
	Gumbel	-227	-470	-149	-393	-277	-1214	-132	-1137
	Frank	**-8549**	**-5717**	**-9042**	**-8571**	**-8713**	1155	**-9245**	576
	BB7	-271	-546	-171	-455	-310	-1247	-166	-1182
	Rotated Gumbel	-257	-545	-168	-440	-295	-1189	-154	-1129
	Student's t	-300	-587	-196	-483	-343	**-1301**	-189	**-1242**
	BB1	-278	-551	-180	-458	-318	-1290	-172	-1215
Based on PML estimation	Clayton	-221	-447	-88	-348	-235	-973	-122	-966
	Gumbel	-230	-490	-157	-384	-290	-1225	-142	-1154
	Frank	**-7732**	**-3222**	**-8314**	**-7807**	**-1679**	958	**-8509**	303
	BB7	-269	-547	-173	-433	-312	-1260	-152	-1178
	Rotated Gumbel	-247	-537	-173	-415	-295	-1181	-149	-1123
	Student's t	-283	-588	-182	-456	-336	**-1298**	-170	**-1229**
	BB1	-272	-553	-177	-435	-316	-1291	-155	-1215

$AIC = 2k - 2\log(\hat{L})$ where $\hat{L}$ is the log-likelihood obtained from Maximum Likelihood method (ML) or from the Pseudo Maximum Likelihood method (PML).

Table 8: Values from the Bayesian Information Criterion (BIC) for the different selected copulas

		BIC							
		Austria	Belgium	Denmark	France	Germany	Italy	Netherlands	Spain
Based on ML estimation	Clayton	-851	-746	-1132	-720	-823	-1046	-910	-1022
	Gumbel	-210	-454	-132	-377	-260	-1198	-116	-1121
	Frank	**-8533**	**-5701**	**-9026**	**-8555**	**-8697**	1171	**-9229**	593
	BB7	-238	-514	-138	-423	-278	-1215	-133	-1150
	Rotated Gumbel	-240	-528	-152	-424	-278	-1173	-138	-1113
	Student's t	-279	-566	-174	-461	-321	**-1279**	-167	**-1221**
	BB1	-245	-518	-148	-426	-285	-1257	-140	-1182
Based on PML estimation	Clayton	-205	-431	-71	-332	-219	-957	-106	-950
	Gumbel	-213	-474	-141	-368	-274	-1208	-125	-1138
	Frank	**-7716**	**-3206**	**-8298**	**-7791**	**-1663**	975	**-8492**	319
	BB7	-236	-515	-140	-401	-279	-1228	-119	-1145
	Rotated Gumbel	-230	-520	-157	-398	-279	-1165	-133	-1106
	Student's t	-261	-567	-161	-435	-315	**-1277**	-149	**-1208**
	BB1	-239	-520	-145	-402	-284	-1259	-122	-1183

$BIC = \log(T)k - 2\log(\hat{L})$ where $\hat{L}$ is the log-likelihood obtained from Maximum Likelihood method (ML) or from the Pseudo Maximum Likelihood method (PML).

Table 9: Summary statistic for risk measures (%)

	Date	Austria	Belgium	Denmark	France	Germany	Italy	Netherlands	Spain
$VaR_{i,t}$	*May* 8^{th}, 2010	1.75	3.34	1.30	2.79	1.97	3.41	1.47	4.05
	July 26^{th}, 2012	1.34	1.89	1.11	2.07	2.08	2.11	1.39	2.24
	August 2^{nd}, 2012	1.39	3.26	1.14	2.19	2.11	3.63	1.34	3.15
	September 6^{th}, 2012	1.48	2.38	1.06	2.37	1.73	1.94	1.45	2.26
$CoVaR_{i\|m,t}$	*May* 8^{th}, 2010	2.24	4.81	1.74	3.46	2.57	4.92	1.95	5.47
	July 26^{th}, 2012	1.71	2.66	1.48	2.53	2.69	2.69	1.84	2.82
	August 2^{nd}, 2012	1.75	4.49	1.53	2.65	2.71	4.39	1.79	3.82
	September 6^{th}, 2012	1.89	3.35	1.42	2.88	2.24	2.61	1.91	2.99
$CoVaR_{m\|i,t}$	*May* 8^{th}, 2010	4.35	5.03	4.54	4.10	4.41	4.39	4.51	4.35
	July 26^{th}, 2012	2.01	2.22	2.08	1.95	2.04	2.04	2.07	2.03
	August 2^{nd}, 2012	2.92	3.17	3.02	2.85	2.97	2.97	3.01	2.96
	September 6^{th}, 2012	1.89	2.13	1.97	1.82	1.93	1.93	1.96	1.93
$\Delta CoVaR_{i\|m,t}$	*May* 8^{th}, 2010	0.25	0.79	0.23	0.34	0.31	6.38	0.26	6.02
	July 26^{th}, 2012	0.19	0.41	0.20	0.23	0.32	2.46	0.24	2.46
	August 2^{nd}, 2012	0.19	0.67	0.20	0.23	0.31	3.20	0.23	2.81
	September 6^{th}, 2012	0.21	0.52	0.19	0.26	0.27	2.81	0.24	3.06
$\Delta CoVaR_{m\|i,t}$	*May* 8^{th}, 2010	0.66	1.05	0.77	0.53	0.69	5.89	0.75	5.79
	July 26^{th}, 2012	0.20	0.31	0.24	0.16	0.22	1.84	0.23	1.81
	August 2^{nd}, 2012	0.22	0.36	0.27	0.18	0.25	2.13	0.27	2.11
	September 6^{th}, 2012	0.21	0.35	0.26	0.18	0.24	2.04	0.26	2.05
$CoES_{i\|m,t}$	*May* 8^{th}, 2010	8.18	16.04	6.76	12.15	9.47	9.63	7.62	10.06
	July 26^{th}, 2012	6.38	8.64	5.77	8.55	9.65	4.48	7.13	4.65
	August 2^{nd}, 2012	6.43	14.21	5.91	8.74	9.62	6.69	7.04	5.87
	September 6^{th}, 2012	7.00	10.93	5.53	9.74	8.06	4.63	7.34	5.16
$CoES_{m\|i,t}$	*May* 8^{th}, 2010	14.92	16.24	15.29	14.45	15.04	8.36	15.23	8.38
	July 26^{th}, 2012	5.26	5.67	5.41	5.15	5.33	3.25	5.39	3.26
	August 2^{nd}, 2012	6.66	7.16	6.86	6.54	6.76	4.36	6.83	4.36
	September 6^{th}, 2012	5.49	5.96	5.66	5.36	5.58	3.27	5.64	3.25
$\Delta CoES_{i\|m,t}$	*May* 8^{th}, 2010	0.85	2.31	0.84	0.98	1.03	8.71	0.93	8.26
	July 26^{th}, 2012	0.64	1.19	0.71	0.67	1.04	3.35	0.87	3.37
	August 2^{nd}, 2012	0.63	1.93	0.73	0.67	1.02	4.37	0.86	3.84
	September 6^{th}, 2012	0.70	1.52	0.68	0.76	0.87	3.82	0.89	4.16
$\Delta CoES_{m\|i,t}$	*May*; 8^{th}, 2010	1.28	2.04	1.49	1.02	1.34	7.59	1.45	7.47
	July 26^{th}, 2012	0.38	0.61	0.46	0.32	0.42	2.37	0.45	2.33
	August 2^{nd}, 2012	0.42	0.71	0.53	0.35	0.48	2.74	0.52	2.72
	September 6^{th}, 2012	0.42	0.68	0.51	0.34	0.46	2.62	0.50	2.62

The measures are computed using CDS data from May 20^{th}, 2009 to May 13^{th}, 2016.
All the measures are computed fixing $\alpha = \beta = 95\%$.
Subscript i indicates a country CDS returns and m the financial sector CDS returns.
$CoVaR$, $CoES$ and the derived Δ measures are obtain following Girardi and Ergün (2013) definition of $CoVaR$.

Table 10: Event study p-values for European PCA risk measures for different estimation windows

Months	May 8^{th},2010				July 26^{th},2012				August 2^{nd},2012				September 6^{th},2012			
	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D
0.5	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.00	0.00	0.00	0.00	**0.00**	**0.00**	0.00	0.00
	0.07	**0.07**	**0.07**	**0.07**	**0.04**	**0.08**	**0.04**	**0.04**	0.22	0.22	0.22	0.22	**0.04**	**0.04**	0.22	0.22
1	**0.00**	**0.00**	**0.00**	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.01**	**0.01**	0.00	0.00
	0.07	**0.07**	**0.07**	**0.07**	0.22	0.22	1.00	1.00	0.22	0.22	0.50	0.50	**0.08**	**0.04**	0.22	0.22
1.5	**0.00**	**0.00**	**0.00**	**0.00**	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.01**	**0.00**	0.00	0.00
	0.07	**0.07**	**0.07**	**0.07**	0.14	**0.08**	1.00	1.00	0.22	0.22	0.22	0.35	**0.08**	**0.04**	0.35	0.35
2	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	**0.00**	0.00	0.00
	0.07	**0.07**	**0.07**	**0.07**	**0.08**	**0.08**	0.50	0.50	0.22	0.22	0.22	0.22	**0.04**	**0.04**	0.22	0.22
2.5	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	**0.00**	0.00	0.00
	0.07	**0.07**	**0.07**	**0.07**	**0.08**	**0.08**	0.89	1.00	0.22	0.22	0.22	0.22	**0.08**	**0.04**	0.35	0.35
3	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	**0.00**	0.00	0.00
	0.07	**0.07**	**0.07**	**0.07**	**0.08**	**0.08**	0.89	0.89	0.22	0.14	0.22	0.22	**0.04**	**0.04**	0.35	0.35
3.5	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	**0.00**	0.00	0.00
	0.07	**0.07**	**0.07**	**0.07**	**0.08**	**0.04**	0.89	0.89	0.22	0.14	0.22	0.22	**0.04**	**0.04**	0.22	0.35
4	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	**0.00**	0.00	0.00
	0.07	**0.07**	**0.07**	**0.07**	**0.08**	**0.08**	1.00	1.00	0.14	0.14	0.50	0.50	**0.04**	**0.04**	0.35	0.35
4.5	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	**0.00**	0.00	0.00
	0.07	**0.07**	**0.07**	**0.07**	**0.08**	**0.04**	1.00	1.00	0.14	0.14	0.50	0.50	**0.04**	**0.04**	0.35	0.35
5	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	**0.00**	0.00	0.00
	0.07	**0.07**	**0.07**	**0.07**	**0.08**	**0.08**	1.00	1.00	0.14	0.14	0.50	0.50	**0.04**	**0.04**	0.35	0.50
5.5	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	**0.00**	0.00	0.00
	0.07	**0.07**	**0.07**	**0.07**	**0.08**	**0.08**	1.00	1.00	0.14	0.14	0.50	0.50	**0.04**	**0.04**	0.50	0.50
6	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	**0.00**	0.00	0.00
	0.07	**0.07**	**0.07**	**0.07**	**0.08**	**0.08**	1.00	1.00	0.22	0.22	0.50	0.50	**0.04**	**0.04**	0.50	0.50

A: $\Delta CoVaR^{1^{st}PC}_{i|m,t}$. B:$\Delta CoES^{1^{st}PC}_{i|m,t}$. C: $\Delta CoVaR^{1^{st}PC}_{m|i,t}$. D: $\Delta CoES^{1^{st}PC}_{m|i,t}$.

This table shows t test and Wilcoxon rank-signed test p-value using different estimation windows (from 0,5 months to 6 months). Bold numbers point out when both p-values are lower than 0.1 indicating a change in exposure or contagion. $\Delta CoVaR^{1^{st}PC}_{i|m,t}$ and $\Delta CoES^{1^{st}PC}_{i|m,t}$ measure exposure of the sovereign sector as a whole to the financial sector and $\Delta CoVaR_{m|i,t}$ and $\Delta CoES^{1^{st}PC}_{m|i,t}$ measure contagion to financial sector from the sovereign sector as a whole.

Standard t ratio is a parametric test. If the sample is not normally distributed, a non-parametric test as the Wilconxon signed-rank test should be employed because of it would be a more powerful test. Due to the fact that for the first policy announcement we are employing just 4 days, the Wilcoxon signed-rank test has not critical values significant at, or beyond, 5% significance level (see Lowry (2014)).

$\Delta CoVaR^{1^{st}PC}_{i|m,t}$, $\Delta CoES^{1^{st}PC}_{i|m,t}$, $CoVaR^{1^{st}PC}_{m|i,t}$ and $CoES^{1^{st}PC}_{m|i,t}$ are the 1^{st} principal components of the corresponding systemic risk measures along the studied countries.

Table 11a: Event study p-values at a country level for different estimation windows

		$\Delta CoVaR_{i\|m,t}$				$\Delta CoVaR_{m\|i,t}$			
	Months	May 8^{th},2010	July 26^{th},2012	August 2^{nd},2012	September 6^{th},2012	May 8^{th},2010	July 26^{th},2012	August 2^{nd},2012	September 6^{th},2012
Austria	0,5	0,57	0,00	0,00	**0,00**	**0,00**	**0,00**	0,00	0,00
		1,00	0,35	1,00	**0,04**	**0,07**	**0,04**	0,50	0,22
	1	0,44	0,00	0,00	**0,00**	**0,00**	0,00	0,00	**0,00**
		1,00	0,35	1,00	**0,04**	**0,07**	1,00	0,69	**0,08**
	1,5	0,35	0,00	0,00	**0,00**	**0,00**	0,00	0,00	0,00
		1,00	0,22	1,00	**0,04**	**0,07**	0,89	0,50	0,69
	2	0,29	0,00	0,00	**0,00**	**0,00**	0,00	0,00	0,00
		1,00	0,35	1,00	**0,04**	**0,07**	0,35	0,50	0,69
	2,5	0,51	0,00	0,00	**0,00**	**0,00**	0,00	0,00	0,00
		1,00	0,35	1,00	**0,08**	**0,07**	1,00	0,50	0,69
	3	0,48	0,00	0,00	**0,00**	**0,00**	0,00	0,00	0,00
		1,00	0,35	1,00	**0,04**	**0,07**	0,89	0,50	0,69
	3,5	0,46	0,00	0,00	0,00	**0,00**	0,00	0,00	0,00
		1,00	0,35	1,00	0,14	**0,07**	1,00	0,50	0,69
	4	0,46	0,00	0,00	0,00	**0,00**	0,00	0,00	0,00
		1,00	0,35	1,00	0,22	**0,07**	1,00	0,50	0,69
	4,5	0,47	0,00	0,00	0,00	**0,00**	0,00	0,00	0,00
		1,00	0,35	1,00	0,22	**0,07**	1,00	0,69	0,69
	5	0,52	0,00	0,00	0,00	**0,00**	0,00	0,00	0,00
		1,00	0,35	1,00	0,22	**0,07**	1,00	0,69	0,69
	5,5	0,59	0,00	0,00	0,00	**0,00**	0,00	0,00	0,00
		1,00	0,35	1,00	0,22	**0,07**	1,00	0,50	0,69
	6	0,61	0,00	0,00	0,00	**0,00**	0,00	0,00	0,00
		1,00	0,35	1,00	0,22	**0,07**	1,00	0,69	0,69
Belgium	0,5	0,01	0,00	0,04	0,93	**0,00**	**0,00**	0,00	0,00
		0,27	1,00	0,69	0,04	**0,07**	**0,04**	0,35	0,14
	1	**0,00**	0,00	0,01	0,97	**0,00**	0,00	0,00	0,00
		0,07	0,89	0,69	0,04	**0,07**	1,00	0,50	0,22
	1,5	**0,00**	**0,00**	0,01	0,97	**0,00**	0,00	0,00	0,00
		0,07	**0,08**	0,50	0,04	**0,07**	0,69	0,50	0,35
	2	**0,00**	**0,00**	0,01	0,97	**0,00**	0,00	0,00	0,00
		0,07	**0,04**	0,22	0,04	**0,07**	0,35	0,35	0,35
	2,5	**0,00**	**0,00**	0,00	0,97	**0,00**	0,00	0,00	0,00
		0,07	**0,04**	0,22	0,04	**0,07**	0,89	0,50	0,50
	3	**0,00**	**0,00**	0,00	0,96	**0,00**	0,00	0,00	0,00
		0,07	**0,04**	0,22	0,04	**0,07**	0,89	0,50	0,50
	3,5	**0,00**	**0,00**	0,00	0,96	**0,00**	0,00	0,00	0,00
		0,07	**0,04**	0,22	0,04	**0,07**	0,89	0,50	0,35
	4	**0,01**	**0,00**	0,00	0,96	**0,00**	0,00	0,00	0,00
		0,07	**0,04**	0,22	0,04	**0,07**	1,00	0,50	0,50
	4,5	**0,02**	**0,00**	0,00	0,96	**0,00**	0,00	0,00	0,00
		0,07	**0,04**	0,22	0,04	**0,07**	1,00	0,50	0,50
	5	**0,05**	**0,00**	0,00	0,96	**0,00**	0,00	0,00	0,00
		0,07	**0,04**	0,22	0,04	**0,07**	1,00	0,50	0,50
	5,5	0,11	**0,00**	0,00	0,96	**0,00**	0,00	0,00	0,00
		0,07	**0,04**	0,22	0,04	**0,07**	1,00	0,50	0,50
	6	0,12	**0,00**	0,00	0,95	**0,00**	0,00	0,00	0,00
		0,07	**0,08**	0,35	0,04	**0,07**	1,00	0,50	0,50

This table shows t test and Wilcoxon rank-signed test p-value using different estimation windows (from 0,5 months to 6 months). Bold numbers point out when both p-values are lower than 0.1 indicating a change in exposure or contagion. $\Delta CoVaR_{i|m,t}$ measures exposure of sovereign to the financial sector and $\Delta CoVaR_{m|i,t}$ measures contagion to financial sector from the sovereign sector.

Table 11b: Event study p-values at a country level for different estimation windows

		$\Delta CoVaR_{i\|m,t}$				$\Delta CoVaR_{m\|i,t}$			
	Months	May 8^{th},2010	July 26^{th},2012	August 2^{nd},2012	September 6^{th},2012	May 8^{th},2010	July 26^{th},2012	August 2^{nd},2012	September 6^{th},2012
Denmark	0,5	0,70	0,00	0,00	0,00	0,00	0,00	0,00	0,00
		1,00	0,50	1,00	0,14	0,14	0,04	0,50	0,14
	1	0,60	0,00	0,00	0,00	**0,00**	0,00	0,00	0,00
		0,47	0,69	1,00	0,14	**0,07**	1,00	0,69	0,22
	1,5	0,53	0,00	0,00	0,00	**0,00**	0,00	0,00	0,00
		0,27	0,35	0,89	0,35	**0,07**	0,89	0,50	0,35
	2	0,52	0,00	0,00	0,00	**0,00**	0,00	0,00	0,00
		0,27	0,22	0,89	0,50	**0,07**	0,50	0,50	0,35
	2,5	0,48	0,00	0,00	0,00	**0,00**	0,00	0,00	0,00
		0,27	0,22	0,89	0,35	**0,07**	1,00	0,50	0,50
	3	0,53	0,00	0,00	0,00	**0,00**	0,00	0,00	0,00
		0,27	0,22	0,50	0,35	**0,07**	1,00	0,50	0,50
	3,5	0,50	0,00	0,00	0,00	**0,00**	0,00	0,00	0,00
		0,27	0,35	0,89	0,35	**0,07**	1,00	0,50	0,35
	4	0,47	0,00	0,00	0,00	**0,00**	0,00	0,00	0,00
		0,27	0,35	0,89	0,35	**0,07**	1,00	0,50	0,50
	4,5	0,45	0,00	0,00	0,00	**0,00**	0,00	0,00	0,00
		0,27	0,35	0,89	0,35	**0,07**	1,00	0,50	0,50
	5	0,43	0,00	0,00	0,00	**0,00**	0,00	0,00	0,00
		0,14	0,22	0,89	0,35	**0,07**	1,00	0,50	0,50
	5,5	0,41	0,00	0,00	0,00	**0,00**	0,00	0,00	0,00
		0,14	0,35	0,89	0,35	**0,07**	1,00	0,50	0,50
	6	0,42	0,00	0,00	0,00	**0,00**	0,00	0,00	0,00
		0,14	0,35	0,89	0,35	**0,07**	1,00	0,50	0,50
France	0,5	**0,00**	0,58	0,40	**0,04**	0,00	**0,00**	0,00	0,00
		0,07	0,14	1,00	**0,08**	0,14	**0,04**	0,50	0,14
	1	**0,00**	0,49	0,31	**0,05**	**0,00**	0,00	0,00	0,00
		0,07	0,08	1,00	**0,08**	**0,07**	1,00	0,50	0,14
	1,5	**0,00**	0,42	0,27	0,26	**0,00**	0,00	0,00	0,00
		0,07	0,04	1,00	0,14	**0,07**	1,00	0,50	0,35
	2	**0,00**	0,39	0,21	0,23	**0,00**	0,00	0,00	0,00
		0,07	0,04	0,89	0,14	**0,07**	0,69	0,35	0,22
	2,5	**0,00**	0,39	0,22	0,21	**0,00**	0,00	0,00	0,00
		0,07	0,04	1,00	0,14	**0,07**	1,00	0,50	0,35
	3	**0,00**	0,36	0,19	0,17	**0,00**	0,00	0,00	0,00
		0,07	0,08	0,89	0,08	**0,07**	1,00	0,50	0,35
	3,5	**0,00**	0,33	0,17	0,17	**0,00**	0,00	0,00	0,00
		0,07	0,04	1,00	0,14	**0,07**	1,00	0,50	0,35
	4	**0,00**	0,30	0,14	0,17	**0,00**	0,00	0,00	0,00
		0,07	0,04	0,89	0,14	**0,07**	1,00	0,50	0,50
	4,5	**0,00**	0,30	0,14	0,15	**0,00**	0,00	0,00	0,00
		0,07	0,08	0,89	0,14	**0,07**	1,00	0,50	0,50
	5	**0,00**	0,28	0,12	0,13	**0,00**	0,00	0,00	0,00
		0,07	0,04	1,00	0,14	**0,07**	1,00	0,50	0,50
	5,5	**0,00**	0,37	0,11	0,12	**0,00**	0,00	0,00	0,00
		0,07	0,08	1,00	0,14	**0,07**	1,00	0,50	0,69
	6	**0,02**	0,41	0,22	0,12	**0,00**	0,00	0,00	0,00
		0,07	0,14	1,00	0,14	**0,07**	1,00	0,50	0,69

This table shows t test and Wilcoxon rank-signed test p-value using different estimation windows (from 0,5 months to 6 months). Bold numbers point out when both p-values are lower than 0.1 indicating a change in exposure or contagion. $\Delta CoVaR_{i|m,t}$ measures exposure of sovereign to the financial sector and $\Delta CoVaR_{m|i,t}$ measures contagion to financial sector from the sovereign sector.

Table 11c: Event study p-values at a country level for different estimation windows

		$\Delta CoVaR_{i\|m,t}$				$\Delta CoVaR_{m\|i,t}$			
	Months	May 8^{th},2010	July 26^{th},2012	August 2^{nd},2012	September 6^{th},2012	May 8^{th},2010	July 26^{th},2012	August 2^{nd},2012	September 6^{th},2012
Germany	0,5	0,76	0,00	**0,00**	0,00	0,00	**0,00**	0,00	0,00
		1,00	1,00	**0,08**	1,00	0,14	**0,04**	0,50	0,22
	1	0,72	0,00	**0,00**	0,00	**0,00**	0,00	0,00	0,00
		0,47	1,00	**0,04**	1,00	**0,07**	1,00	0,50	0,22
	1,5	0,68	0,00	**0,00**	0,00	**0,00**	0,00	0,00	0,00
		0,27	0,35	**0,04**	1,00	**0,07**	0,50	0,50	0,35
	2	0,65	0,00	**0,00**	0,00	**0,00**	0,00	0,00	0,00
		0,14	0,35	**0,04**	1,00	**0,07**	0,22	0,22	0,35
	2,5	0,63	0,00	**0,00**	0,00	**0,00**	0,00	0,00	0,00
		0,07	1,00	**0,08**	1,00	**0,07**	0,89	0,50	0,50
	3	0,60	0,00	**0,00**	0,00	**0,00**	0,00	0,00	0,00
		0,07	1,00	**0,08**	1,00	**0,07**	0,69	0,50	0,50
	3,5	0,59	0,00	**0,00**	0,00	**0,00**	0,00	0,00	0,00
		0,07	1,00	**0,08**	1,00	**0,07**	0,89	0,50	0,35
	4	0,57	0,00	**0,00**	0,00	**0,00**	0,00	0,00	0,00
		0,07	1,00	**0,08**	1,00	**0,07**	1,00	0,50	0,50
	4,5	0,56	0,00	**0,00**	0,00	**0,00**	0,00	0,00	0,00
		0,07	1,00	**0,08**	1,00	**0,07**	1,00	0,50	0,50
	5	0,55	0,00	**0,00**	0,00	**0,00**	0,00	0,00	0,00
		0,07	1,00	**0,08**	1,00	**0,07**	1,00	0,50	0,50
	5,5	0,62	0,00	**0,00**	0,00	**0,00**	0,00	0,00	0,00
		0,07	1,00	**0,08**	1,00	**0,07**	1,00	0,50	0,69
	6	0,68	0,00	**0,00**	0,00	**0,00**	0,00	0,00	0,00
		0,07	1,00	**0,08**	1,00	**0,07**	1,00	0,50	0,69
Italy	0,5	**0,00**	**0,00**	0,00	**0,06**	0,00	**0,00**	0,00	0,00
		0,07	**0,08**	0,22	**0,04**	0,14	**0,04**	0,22	0,22
	1	**0,00**	0,00	0,00	0,13	**0,00**	0,00	0,00	0,00
		0,07	0,35	0,22	0,08	**0,07**	1,00	0,50	0,22
	1,5	**0,00**	0,00	0,00	**0,08**	**0,00**	0,00	0,00	0,00
		0,07	0,22	0,22	**0,08**	**0,07**	1,00	0,50	0,35
	2	**0,00**	0,00	0,00	**0,06**	**0,00**	0,00	0,00	0,00
		0,07	0,14	0,22	**0,04**	**0,07**	0,50	0,22	0,22
	2,5	**0,00**	0,00	0,00	**0,06**	**0,00**	0,00	0,00	0,00
		0,07	0,22	0,22	**0,04**	**0,07**	1,00	0,22	0,50
	3	**0,00**	0,00	0,00	**0,04**	**0,00**	0,00	0,00	0,00
		0,07	0,14	0,22	**0,04**	**0,07**	0,69	0,50	0,35
	3,5	**0,00**	0,00	0,00	**0,04**	**0,00**	0,00	0,00	0,00
		0,07	0,08	0,22	**0,04**	**0,07**	0,89	0,22	0,35
	4	**0,00**	0,00	0,00	**0,03**	**0,00**	0,00	0,00	0,00
		0,07	0,14	0,22	**0,04**	**0,07**	1,00	0,50	0,50
	4,5	**0,00**	0,00	0,00	**0,02**	**0,00**	0,00	0,00	0,00
		0,07	0,14	0,22	**0,04**	**0,07**	1,00	0,50	0,35
	5	**0,00**	0,00	0,00	**0,02**	**0,00**	0,00	0,00	0,00
		0,07	0,14	0,22	**0,04**	**0,07**	1,00	0,50	0,50
	5,5	**0,00**	0,00	0,00	**0,02**	**0,00**	0,00	0,00	0,00
		0,07	0,14	0,22	**0,04**	**0,07**	1,00	0,50	0,50
	6	**0,00**	0,00	0,00	**0,01**	**0,00**	0,00	0,00	0,00
		0,07	0,22	0,22	**0,04**	**0,07**	1,00	0,50	0,50

This table shows t test and Wilcoxon rank-signed test p-value using different estimation windows (from 0,5 months to 6 months). Bold numbers point out when both p-values are lower than 0.1 indicating a change in exposure or contagion. $\Delta CoVaR_{i|m,t}$ measures exposure of sovereign to the financial sector and $\Delta CoVaR_{m|i,t}$ measures contagion to financial sector from the sovereign sector.

Table 11d: Event study p-values at a country level for different estimation windows

	Months	$\Delta CoVaR_{i\|m,t}$ May 8^{th},2010	$\Delta CoVaR_{i\|m,t}$ July 26^{th},2012	$\Delta CoVaR_{i\|m,t}$ August 2^{nd},2012	$\Delta CoVaR_{i\|m,t}$ September 6^{th},2012	$\Delta CoVaR_{m\|i,t}$ May 8^{th},2010	$\Delta CoVaR_{m\|i,t}$ July 26^{th},2012	$\Delta CoVaR_{m\|i,t}$ August 2^{nd},2012	$\Delta CoVaR_{m\|i,t}$ September 6^{th},2012
Netherlands	0,5	0,94	0,15	0,08	0,00	**0,00**	**0,00**	0,00	0,00
		1,00	1,00	1,00	0,22	**0,07**	**0,04**	0,50	0,14
	1	0,91	0,14	0,08	0,00	**0,00**	0,00	0,00	0,00
		0,14	1,00	1,00	0,22	**0,07**	1,00	0,69	0,14
	1,5	0,90	0,10	0,05	0,00	**0,00**	0,00	0,00	0,00
		0,07	1,00	1,00	0,22	**0,07**	0,89	0,50	0,35
	2	0,88	0,07	0,03	0,10	**0,00**	0,00	0,00	0,00
		0,07	1,00	1,00	1,00	**0,07**	0,50	0,50	0,22
	2,5	0,88	0,05	0,02	0,08	**0,00**	0,00	0,00	0,00
		0,07	1,00	1,00	1,00	**0,07**	1,00	0,50	0,35
	3	0,90	0,03	0,01	0,06	**0,00**	0,00	0,00	0,00
		0,07	1,00	1,00	1,00	**0,07**	1,00	0,50	0,35
	3,5	0,89	0,03	0,01	0,04	**0,00**	0,00	0,00	0,00
		0,07	1,00	1,00	0,89	**0,07**	1,00	0,50	0,35
	4	0,89	0,02	0,01	0,03	**0,00**	0,00	0,00	0,00
		0,07	1,00	1,00	0,89	**0,07**	1,00	0,50	0,50
	4,5	0,88	0,02	0,00	0,03	**0,00**	0,00	0,00	0,00
		0,07	1,00	1,00	0,89	**0,07**	1,00	0,50	0,50
	5	0,88	0,01	0,00	0,02	**0,00**	0,00	0,00	0,00
		0,07	1,00	1,00	0,89	**0,07**	1,00	0,50	0,50
	5,5	0,87	0,04	0,00	0,03	**0,00**	0,00	0,00	0,00
		0,07	1,00	1,00	1,00	**0,07**	1,00	0,50	0,50
	6	0,88	0,47	0,20	0,02	**0,00**	0,00	0,00	0,00
		0,07	1,00	1,00	1,00	**0,07**	1,00	0,50	0,50
Spain	0,5	**0,00**	**0,00**	0,00	**0,00**	0,00	0,00	0,00	0,00
		0,07	**0,04**	0,14	**0,04**	0,14	0,04	0,22	0,22
	1	**0,00**	0,00	0,00	**0,00**	**0,00**	0,00	0,00	0,00
		0,07	0,22	0,22	**0,08**	**0,07**	1,00	0,50	0,22
	1,5	**0,00**	0,00	0,00	**0,00**	**0,00**	0,00	0,00	0,00
		0,07	0,14	0,22	**0,08**	**0,07**	1,00	0,22	0,22
	2	**0,00**	**0,00**	0,00	**0,00**	**0,00**	0,00	0,00	0,00
		0,07	**0,08**	0,14	**0,08**	**0,07**	0,50	0,22	0,22
	2,5	**0,00**	**0,00**	0,00	**0,00**	**0,00**	0,00	0,00	0,00
		0,07	**0,04**	0,14	**0,08**	**0,07**	0,89	0,22	0,35
	3	**0,00**	**0,00**	**0,00**	**0,00**	**0,00**	0,00	0,00	0,00
		0,07	**0,04**	**0,08**	**0,04**	**0,07**	0,89	0,22	0,35
	3,5	**0,00**	**0,00**	**0,00**	**0,00**	**0,00**	0,00	0,00	0,00
		0,07	**0,04**	**0,08**	**0,04**	**0,07**	0,89	0,22	0,22
	4	**0,00**	**0,00**	**0,00**	**0,00**	**0,00**	0,00	0,00	0,00
		0,07	**0,04**	**0,08**	**0,04**	**0,07**	1,00	0,22	0,35
	4,5	**0,00**	**0,00**	**0,00**	**0,00**	**0,00**	0,00	0,00	0,00
		0,07	**0,04**	**0,08**	**0,04**	**0,07**	1,00	0,35	0,22
	5	**0,00**	**0,00**	**0,00**	**0,00**	**0,00**	0,00	0,00	0,00
		0,07	**0,04**	**0,08**	**0,04**	**0,07**	1,00	0,22	0,35
	5,5	**0,00**	**0,00**	**0,00**	**0,00**	**0,00**	0,00	0,00	0,00
		0,07	**0,04**	**0,08**	**0,04**	**0,07**	1,00	0,22	0,35
	6	**0,00**	**0,00**	**0,00**	**0,00**	**0,00**	0,00	0,00	0,00
		0,07	**0,04**	**0,08**	**0,04**	**0,07**	1,00	0,50	0,35

This table shows t test and Wilcoxon rank-signed test p-value using different estimation windows (from 0,5 months to 6 months). Bold numbers point out when both p-values are lower than 0.1 indicating a change in exposure or contagion. $\Delta CoVaR_{i|m,t}$ measures exposure of sovereign to the financial sector and $\Delta CoVaR_{m|i,t}$ measures contagion to financial sector from the sovereign sector.

Table 12: Top 5 most stressful moments according to the systemic risk measures

TOP	$\Delta CoVaR^{1^{st}PC}_{i\|m,t}$	$\Delta CoES^{1^{st}PC}_{i\|m,t}$	$\Delta CoVaR^{1^{st}PC}_{m\|i,t}$	$\Delta CoES^{1^{st}PC}_{m\|i,t}$
1#	10-May-10	10-May-10	10-May-10	10-May-10
2#	11-May-10	11-May-10	11-May-10	11-May-10
3#	12-May-10	12-May-10	12-May-10	12-May-10
4#	30-Jun-15	30-Jun-15	29-Jun-15	29-Jun-15
5#	01-Nov-11	01-Nov-11	04-May-10	04-May-10

This table shows the five days with the highest values for the different systemic risk measures in the sample. The dates can be linked to the announcement of ECB measures as the EFSF and SMP (May, 8^{th} 2010), the Greek referendum announcement by prime minister Papandreu (October, 30^{th} 2011) and the difficulties of Greek government to repay the IMF's loan after the Greek referendum announcement by prime minister Tsipras (June, 30^{th} 2015).

Table 13: Unconditional coverage test Kupiec (1995)

		Austria	Belgium	Denmark	France	Germany	Italy	Netherlands	Spain
$CoVaR_{i\|m,t}(\alpha,\beta)$	p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	lower bound exceedances	1	1	1	1	1	1	1	1
	higher bound exceedances	7	7	7	7	7	7	7	7
	$\sum_{t=0}^{T_{\mathbb{1}_{m,t}=1}} \mathbb{1}_{i\|m,t} = 1$	26	21	26	20	21	13	23	19
	$T_{\mathbb{1}_{m,t}=1}$	66	66	66	66	66	66	66	66
$CoVaR_{m\|i,t}(\alpha,\beta)$	p-value	0.9858	0.6166	0.4497	0.0321	0.5080	0.0035	0.3844	0.0026
	lower bound exceedances	4	3	6	3	4	2	6	2
	higher bound exceedances	15	12	18	13	15	9	17	9
	$\sum_{t=0}^{T_{\mathbb{1}_{m,t}=1}} \mathbb{1}_{i\|m,t} = 1$	9	8	9	14	11	12	8	12
	$T_{\mathbb{1}_{i,t}=1}$	180	134	228	152	180	94	213	91

Table 14: Conditional coverage test Christoffersen (1998)

		Austria	Belgium	Denmark	France	Germany	Italy	Netherlands	Spain
$CoVaR_{i\|m,t}(\alpha,\beta)$	p-value	0.0769	0.0718	0.0217	0.0153	0.0718	0.7596	0.2278	0.7383
	$T^{pair,00}_{\mathbb{1}_{i,t}=1}$	28	33	29	28	33	42	30	32
	$T^{pair,01}_{\mathbb{1}_{i,t}=1}$	12	11	11	18	11	10	13	14
	$T^{pair,10}_{\mathbb{1}_{i,t}=1}$	12	11	11	17	11	10	12	14
	$T^{pair,11}_{\mathbb{1}_{i,t}=1}$	13	10	14	2	10	3	10	5
$CoVaR_{m\|i,t}(\alpha,\beta)$	p-value	0.3289	0.4791	0.0383	0.5228	0.1515	0.6864	0.4282	0.1850
	$T^{pair,00}_{\mathbb{1}_{i,t}=1}$	161	118	211	125	159	71	196	70
	$T^{pair,01}_{\mathbb{1}_{i,t}=1}$	9	7	7	12	9	10	8	9
	$T^{pair,10}_{\mathbb{1}_{i,t}=1}$	9	7	7	12	9	10	8	8
	$T^{pair,11}_{\mathbb{1}_{i,t}=1}$	0	1	2	2	2	2	0	3

D Figures of results

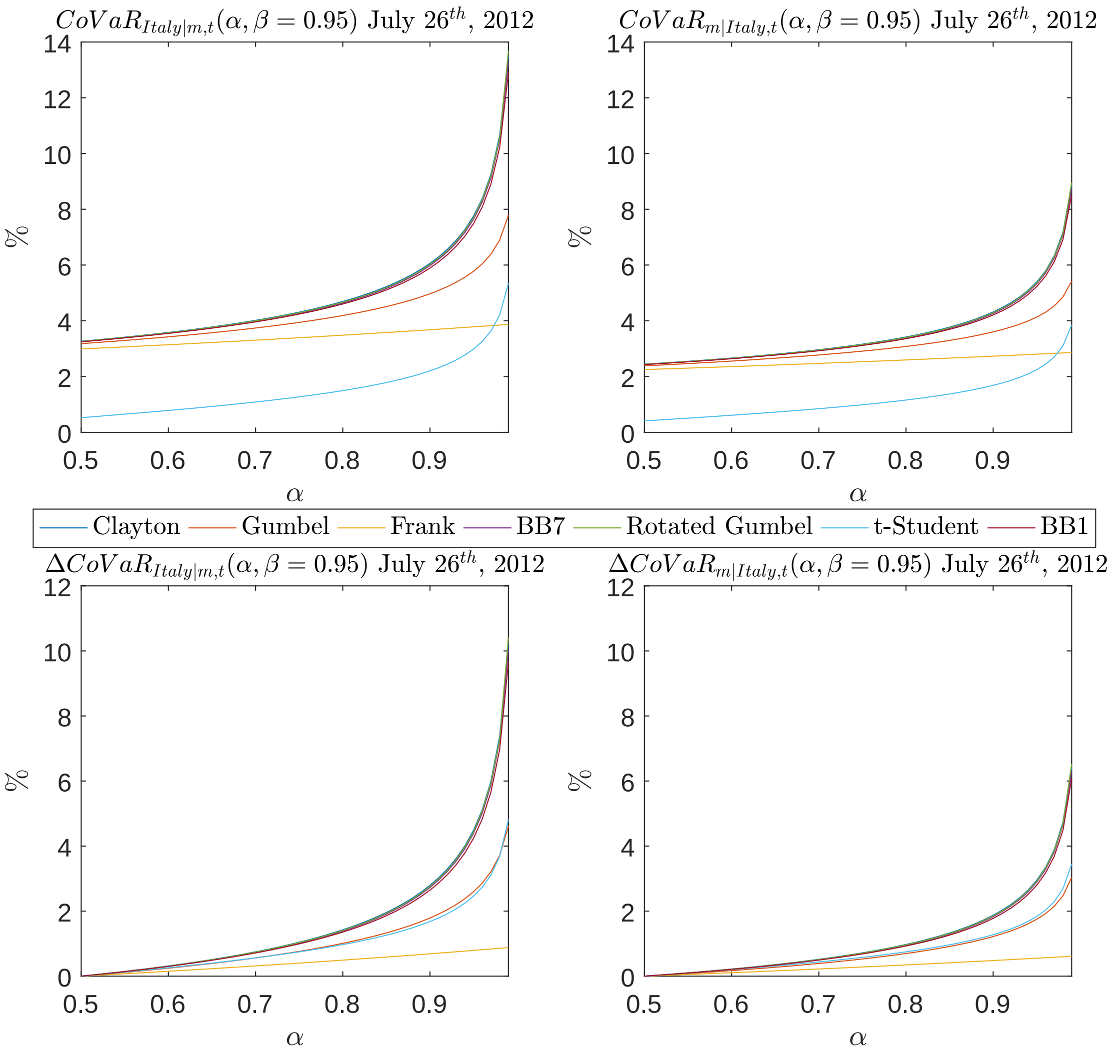

Figure 1: $CoVaR(\alpha, \beta = 0.95)$ and $CoVaR(\alpha, \beta = 0.95)$ for Italy on July, 26^{th}, 2012 for different copulas.
Top figures show (left) the maximum daily credit losses with a 95% level of confidence for Italy conditioned to the maximum daily credit losses for the financial system with a $\alpha * 100\%$ confidence level, i.e., $CoVaR_{Italy|m,t}(\alpha, 0.95)$ and (right) the maximum daily losses with a 95% level of confidence for the financial system conditioned to the maximum daily losses for Italian CDS with a $\alpha * 100\%$ confidence level, i.e., $CoVaR_{m|Italy,t}(\alpha, 0.95)$. Bottom figures show the change in $CoVaR$ when the conditioning variable changes from a stable situation , i.e., $\alpha = 0.5$ to the $\alpha * 100\%$ worst case scenario. The left column figures have as a conditioning variable the financial system, ie. m, and as conditioned variable $Italy$. The right column figures have the reverse conditioning and conditioned variables to the left column figures.

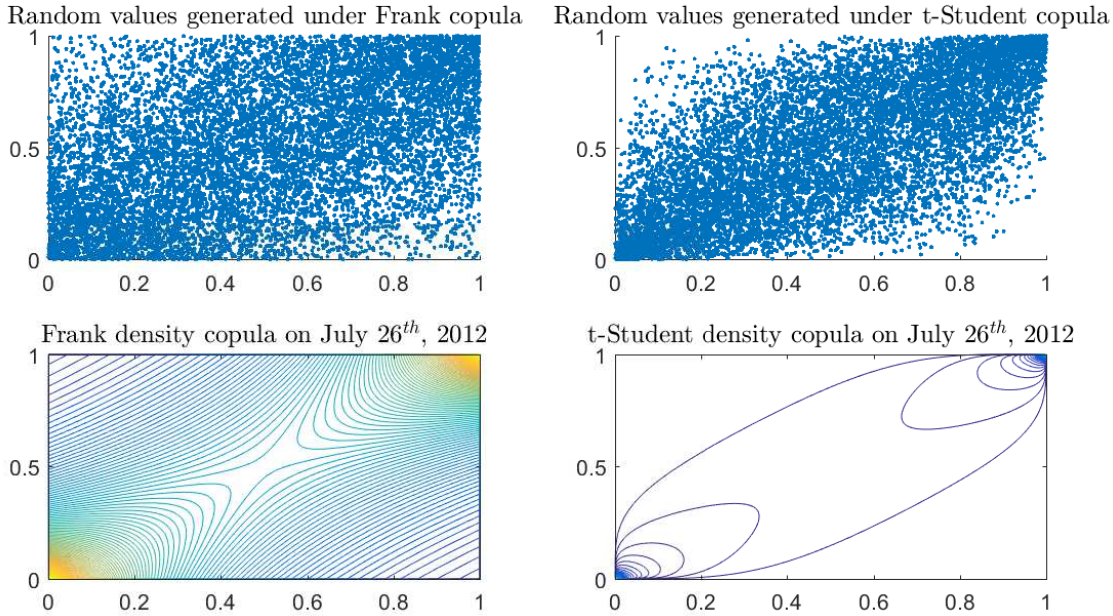

Figure 2: Comparison between Frank and Student's t copula for Italy on July, 26^{th}, 2012 given the estimated time-varying copula by maximum likelihood.
Top figures show uniform random values generated using Frank (left) or Student's t (right) copula given the estimated time-varying parameter on July, 26^{th}, 2012 for each copula. Note the saturation on the Student's t tails as a proof of the tail dependence. Bottom figures show the corresponding copula density function where each line correspond to a contour level for Frank (left) and Student's t (right) copula.

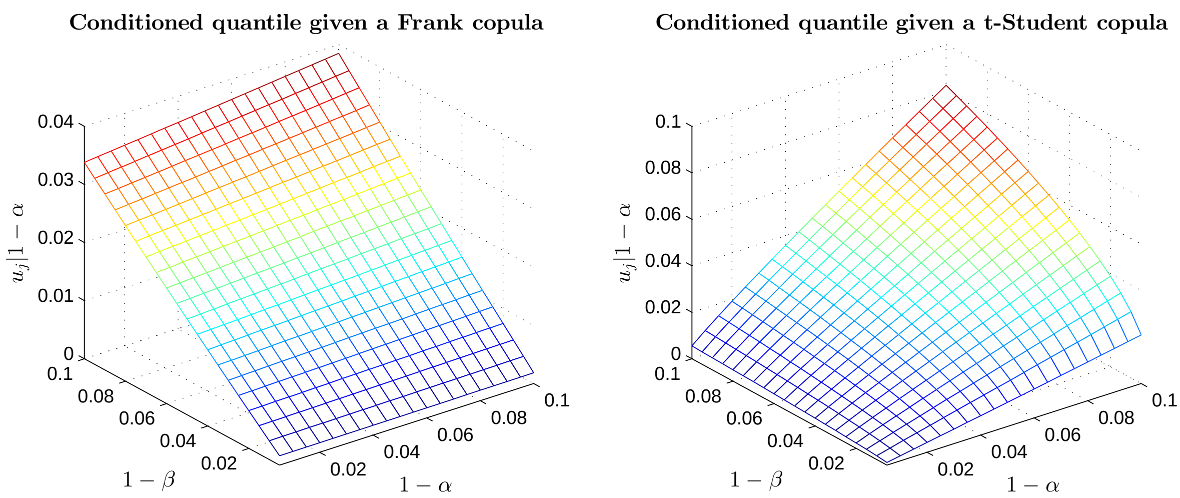

Figure 3: Returns' conditional quantile comparison between Frank and Student's t copula ($C(u_j, 1-\alpha) = (1-\beta)(1-\alpha)$) for Italy on July, 26^{th}, 2012.
These 3-D figures show the maximum conditional quantile of losses for institution j when the conditioning institution's returns are below its $1-\alpha$ quantile. Left figure is computed under the assumption that $C(\cdot,\cdot)$ is a Frank copula and right figure assumes a Student's t copula.

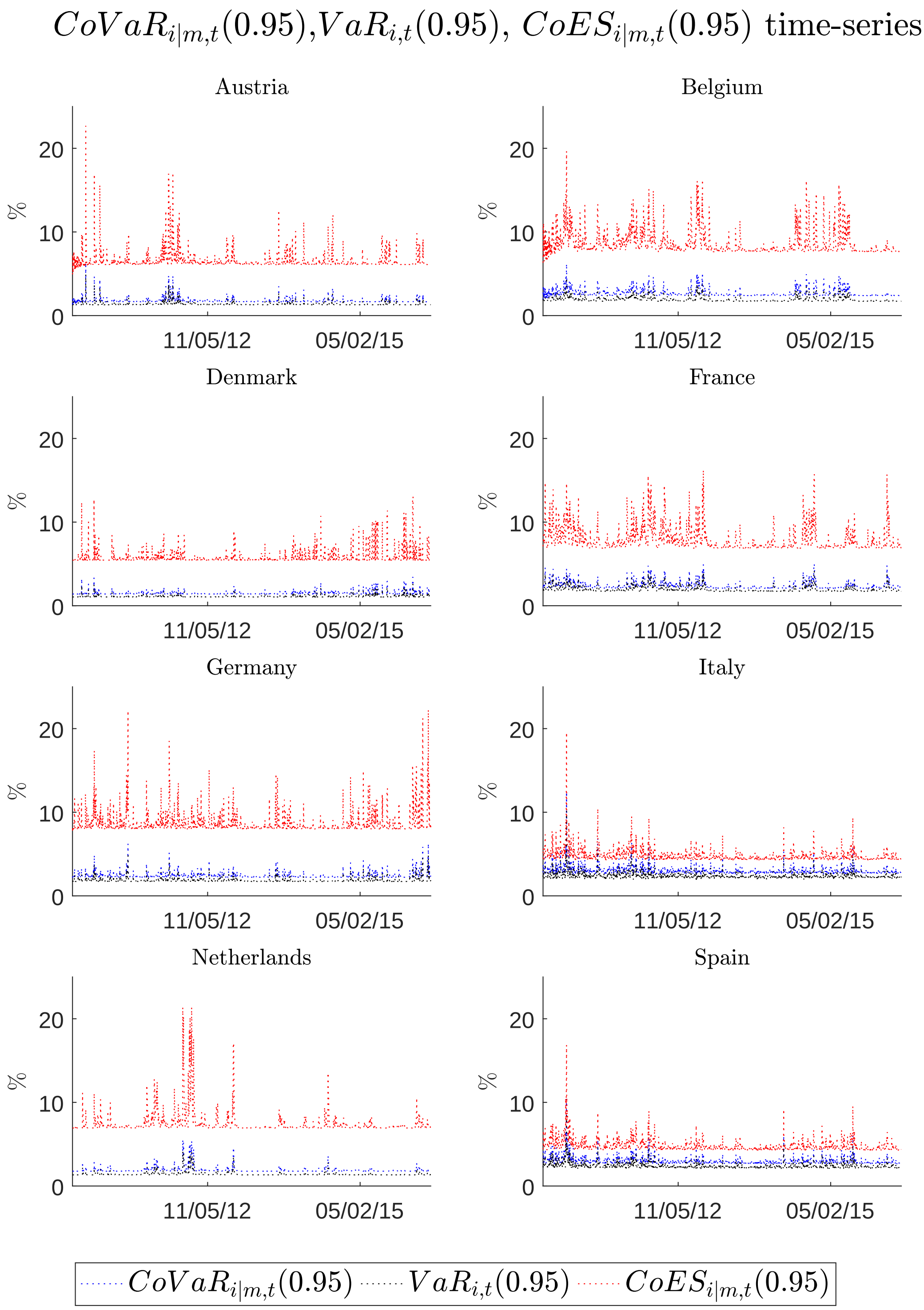

Figure 4: $CoVaR_{i|m,t}(0.95, 0.95)$, $VaR_{i,t}(0.95)$ and $CoES_{i|m,t}(0.95, 0.95)$
$VaR_{i,t}(0.95)$ expresses the maximum daily credit losses in percentage for country i with a 95% confidence level. $CoVaR_{i|m,t}(0.95, 0.95)$ expresses the maximum daily credit losses with a confidence level 95% that country i will face given that the financial sector's credit returns are below its $(1 - \alpha)$ percentile.

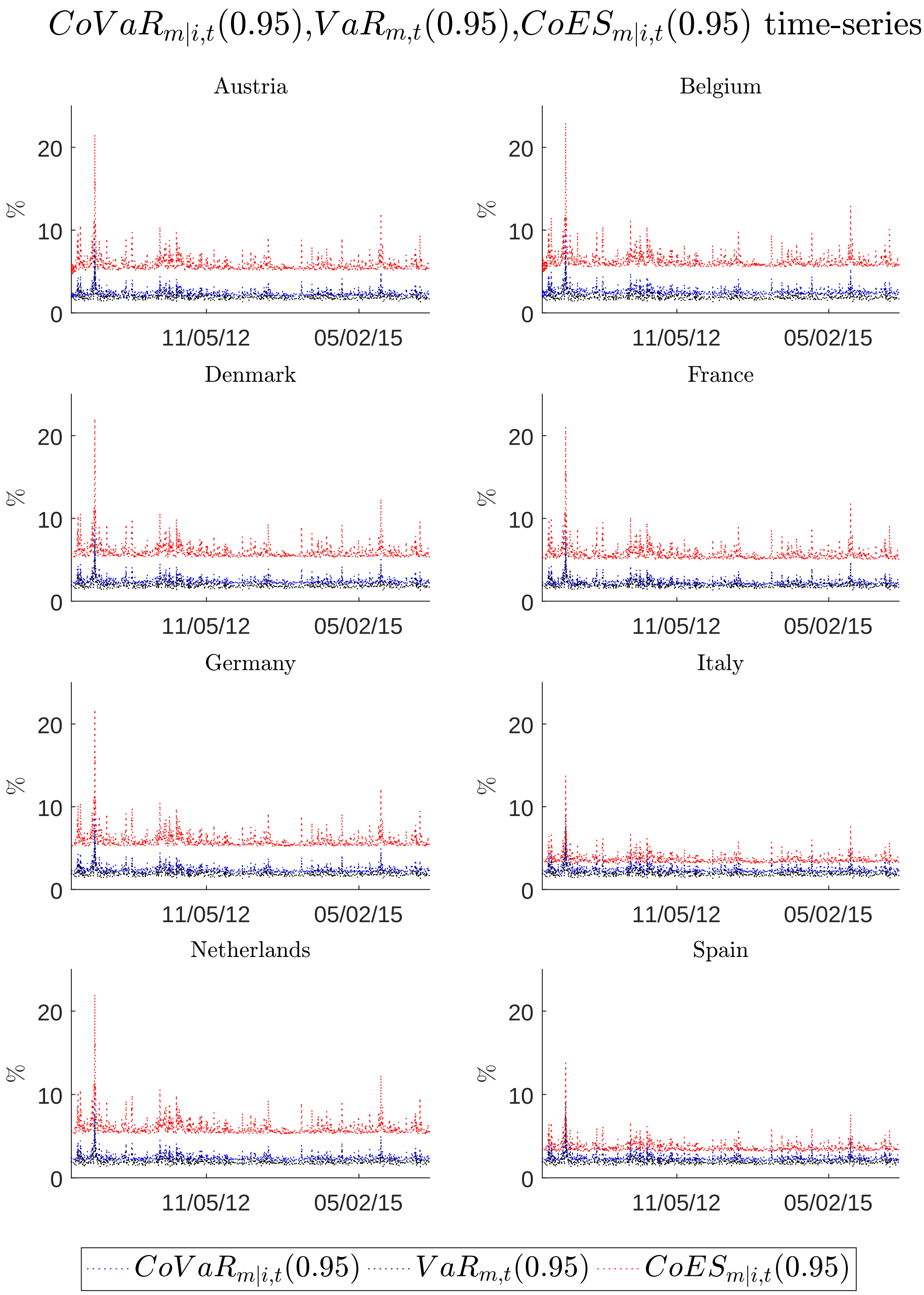

Figure 5: $CoVaR_{m|i,t}(0.95, 0.95)$, $VaR_{m,t}(0.95)$ and $CoES_{m|i,t}(0.95, 0.95)$
$VaR_{m,t}(0.95)$ expresses the maximum daily credit losses in percentage for the financial sector with a 95% confidence level. $CoVaR_{m|i,t}(0.95, 0.95)$ expresses the maximum daily credit losses with a confidence level 95% that the financial system will face given that the country i's credit returns are below its $(1-\alpha)$ percentile. Note that $CoVaR_{m|i,t}(0.95, 0.95) \geq VaR_{m,t}(0.95)$ because $CoVaR_{m|i,t}(0.95, 0.95)$ can be considered as assessing $VaR_{m,t}(0.95)$ under a stressed scenario in the country i, consequently its value should be higher. $CoES_{m|i,t}(0.95, 0.95)$ indicates the expected loss of the financial system if the losses are above its CoVaR given that the country i is below its $(1-\alpha)$ percentile. $CoES_{m|i,t}(0.95, 0.95) \geq CoVaR_{m|i,t}(0.95, 0.95)$due to considering more severe scenarios.

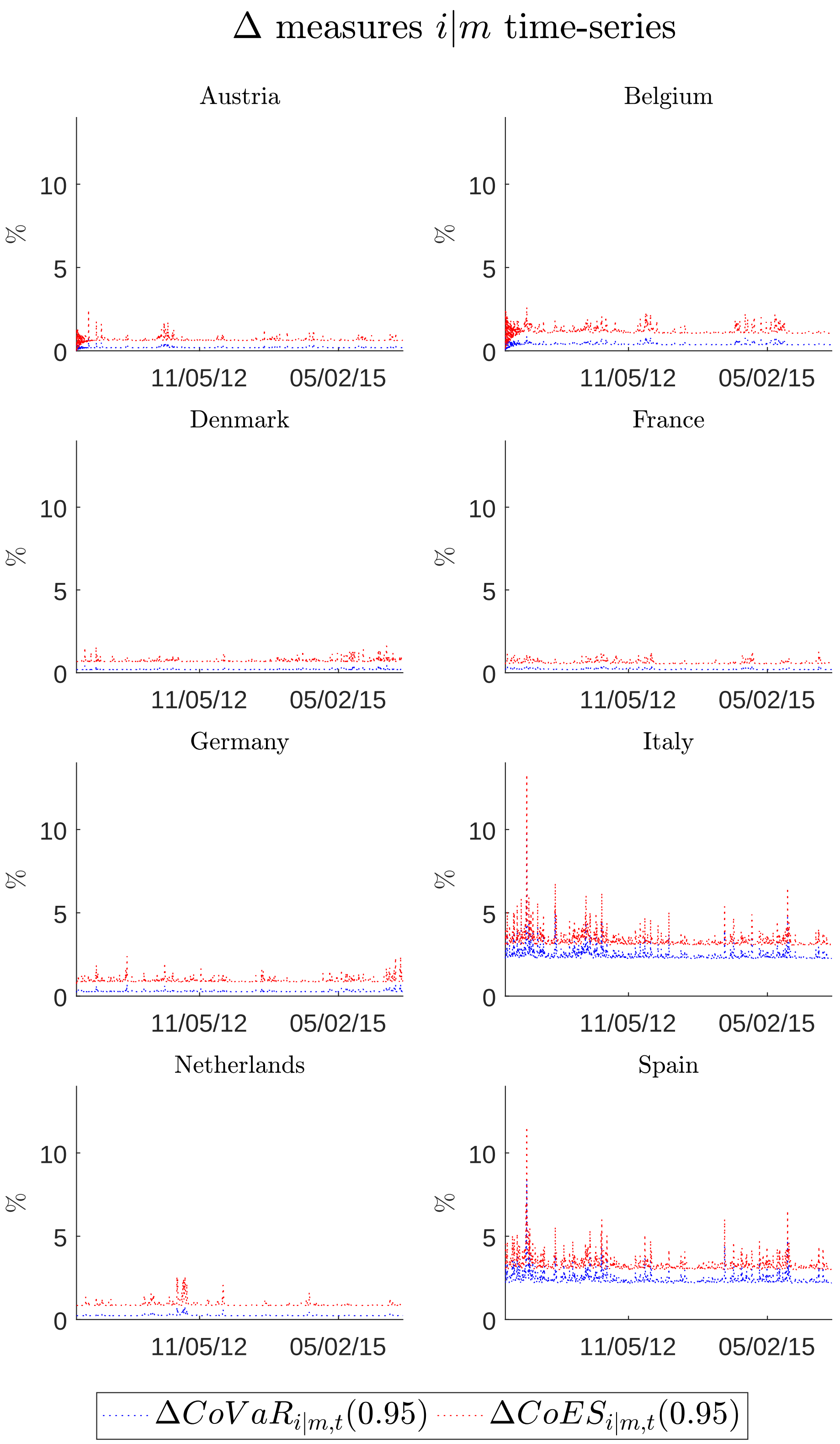

Figure 6: $\Delta CoVaR_{i|m,t}(0.95)$ and $\Delta CoES_{i|m,t}(0.95)$ time-series for each country $\Delta CoVaR_{i|m,t}(0.95)$ indicates the increase in $CoVaR_{i|m,t}(\alpha, 0.95)$ when the financial system suffers a change from a normal ($\alpha = 0.5$) to a distressed situation ($\alpha = 0.95$). $\Delta CoES_{i|m,t}(0.95)$ indicates the change in Expected Shortfall of i's sovereign credit risk if the losses are above its $CoVaR_{i|m,t}(\alpha, 0.95)$ when financial sector's situation is deteriorated, i.e., $CoES_{i|m,t}(0.95, 0.95) - CoES_{i|m,t}(0.5, 0.95)$. These measures assess the exposure of different countries to the financial sector.

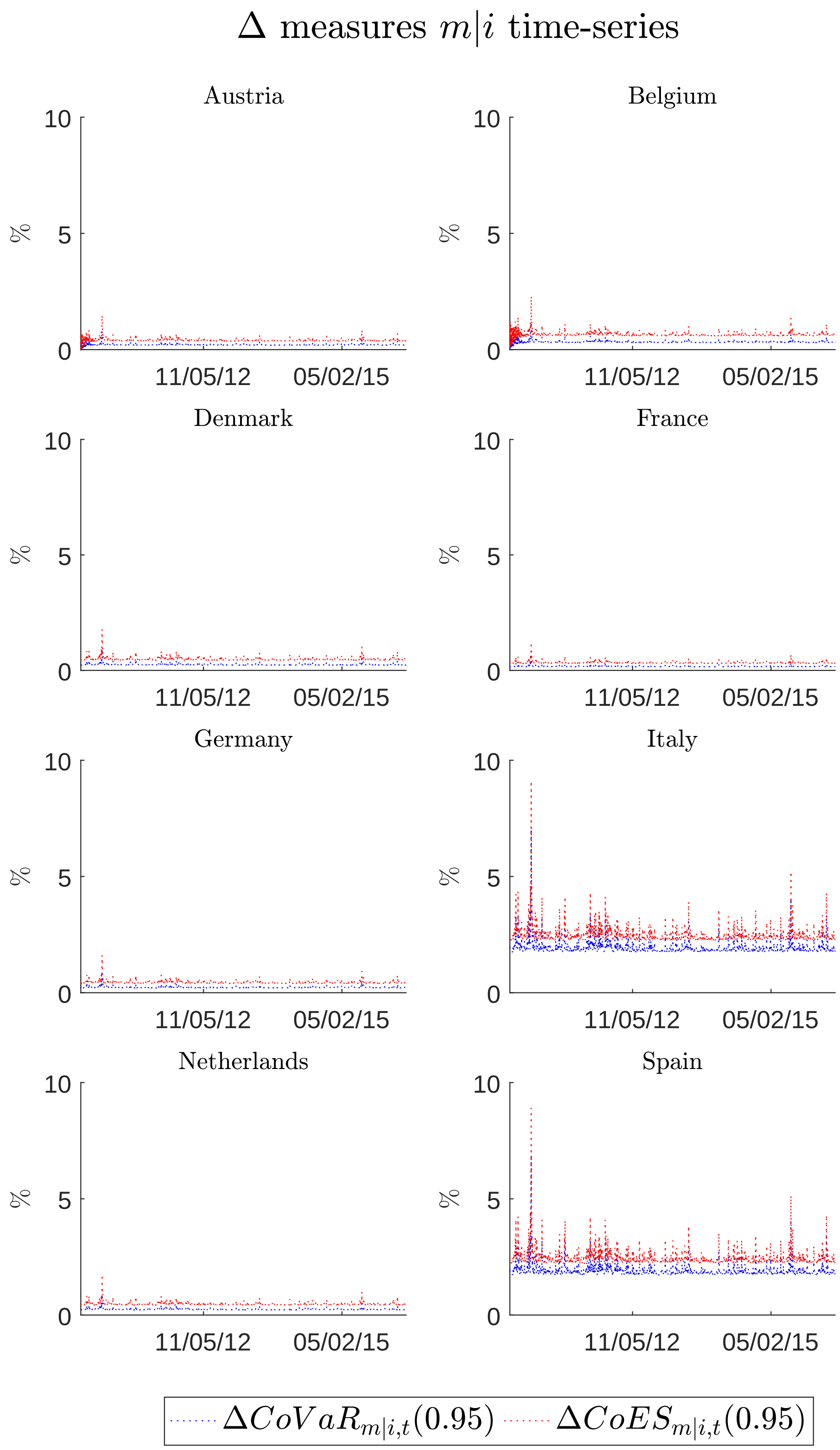

Figure 7: $\Delta CoVaR_{m|i,t}(0.95)$ and $\Delta CoES_{m|i,t}(0.95)$ time-series for each country $\Delta CoVaR_{m|i,t}(0.95)$ indicates the increase in $CoVaR_{m|i,t}(\alpha, 0.95)$ when the i's sovereign credit situation suffers a deterioration from a normal ($\alpha = 0.5$) to a distressed scenario ($\alpha = 0.95$). $\Delta CoES_{m|i,t}(0.95)$ indicates the change in Expected Shortfall of the financial system if the losses are above its $CoVaR_{m|i,t}(\alpha, 0.95)$ when i's sovereign credit risk situation is deteriorated, i.e., $CoES_{m|i,t}(0.95, 0.95) - CoES_{m|i,t}(0.5, 0.95)$. These measures assess the contagion from different countries to the financial sector.

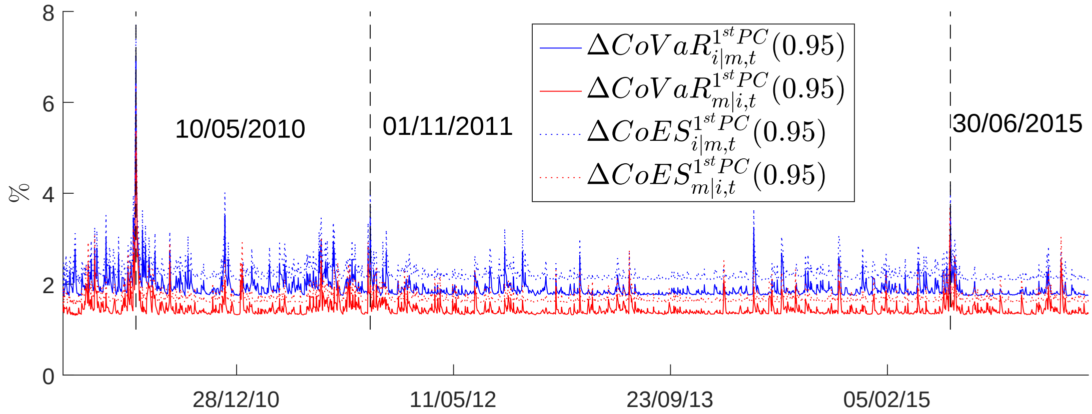

Figure 8: First principal component of $\Delta CoVaR_{i|m,t}(0.95)$, $\Delta CoVaR_{m|i,t}(0.95)$, $\Delta CoES_{i|m,t}(0.95)$ and $\Delta CoES_{m|i,t}(0.95)$

Red lines indicate measures of contagion from the sovereign credit risk to the financial sector, whilst blue lines represent systemic risk measures of exposure of sovereign credit risk to the financial credit risk. The black vertical lines refer to three announcements: the ECB's announcement where the European Financial Stability Facility (EFSF) and the Securities Market Program (SMP) were presented (May 8^{th}, 2010), the day after the Greek prime minister Papandreou announced his will of proposing a referendum about the bailout conditions (November 1^{st}, 2011) and the Greek government payback-problems with IMF (June 30^{th}, 2015).

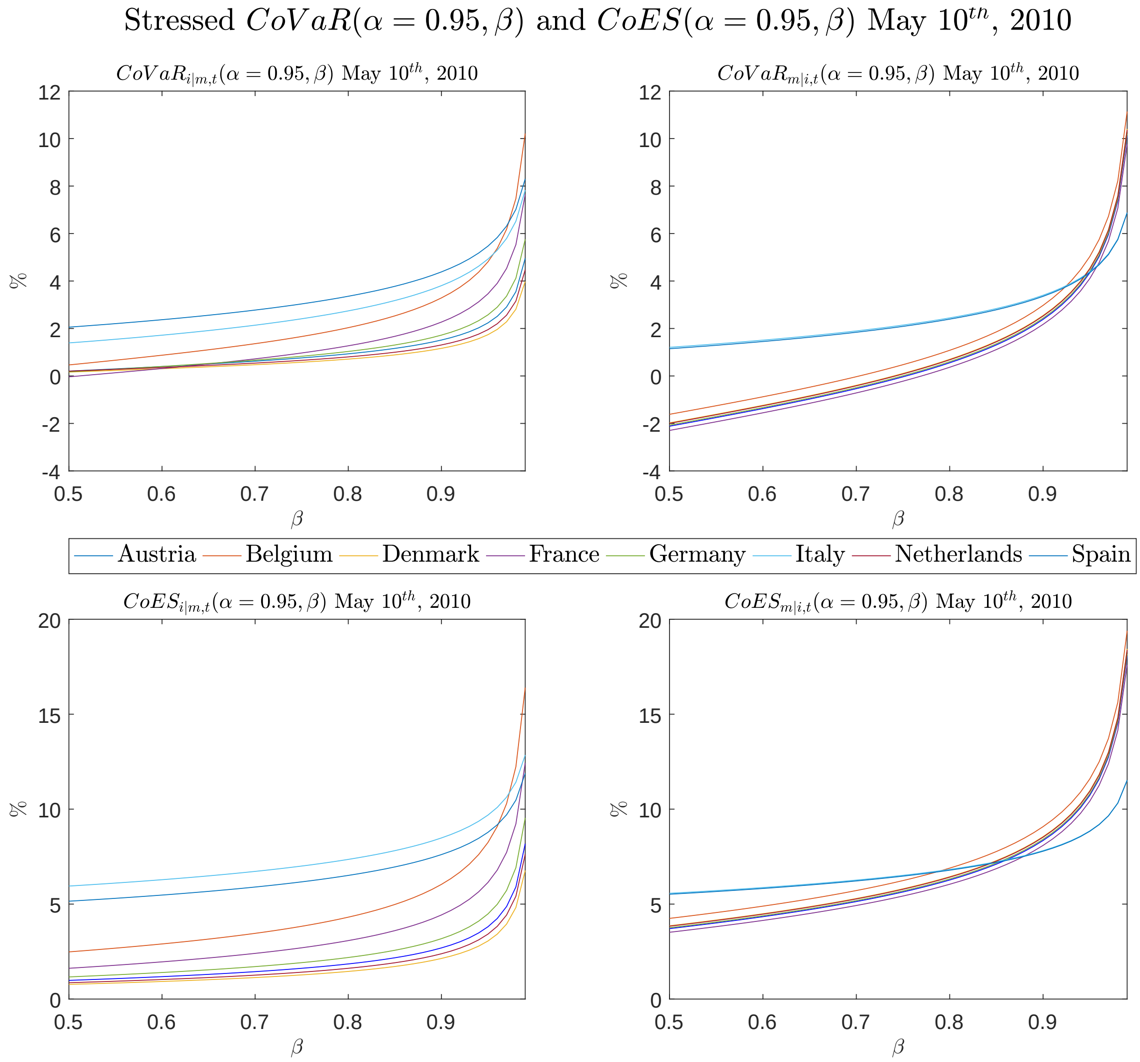

Figure 9: Stressed $CoVaR_{i|m,t}(\alpha = 0.95, \beta)$, $CoVaR_{m|i,t}(\alpha = 0.95, \beta)$, $CoES_{i|m,t}(\alpha = 0.95, \beta)$ and $CoES_{m|i,t}(\alpha = 0.95, \beta$ on May 10^{th}, 2010
A higher level of β means a more stressful scenario for the conditioned variable on May 10^{th}, 2010.

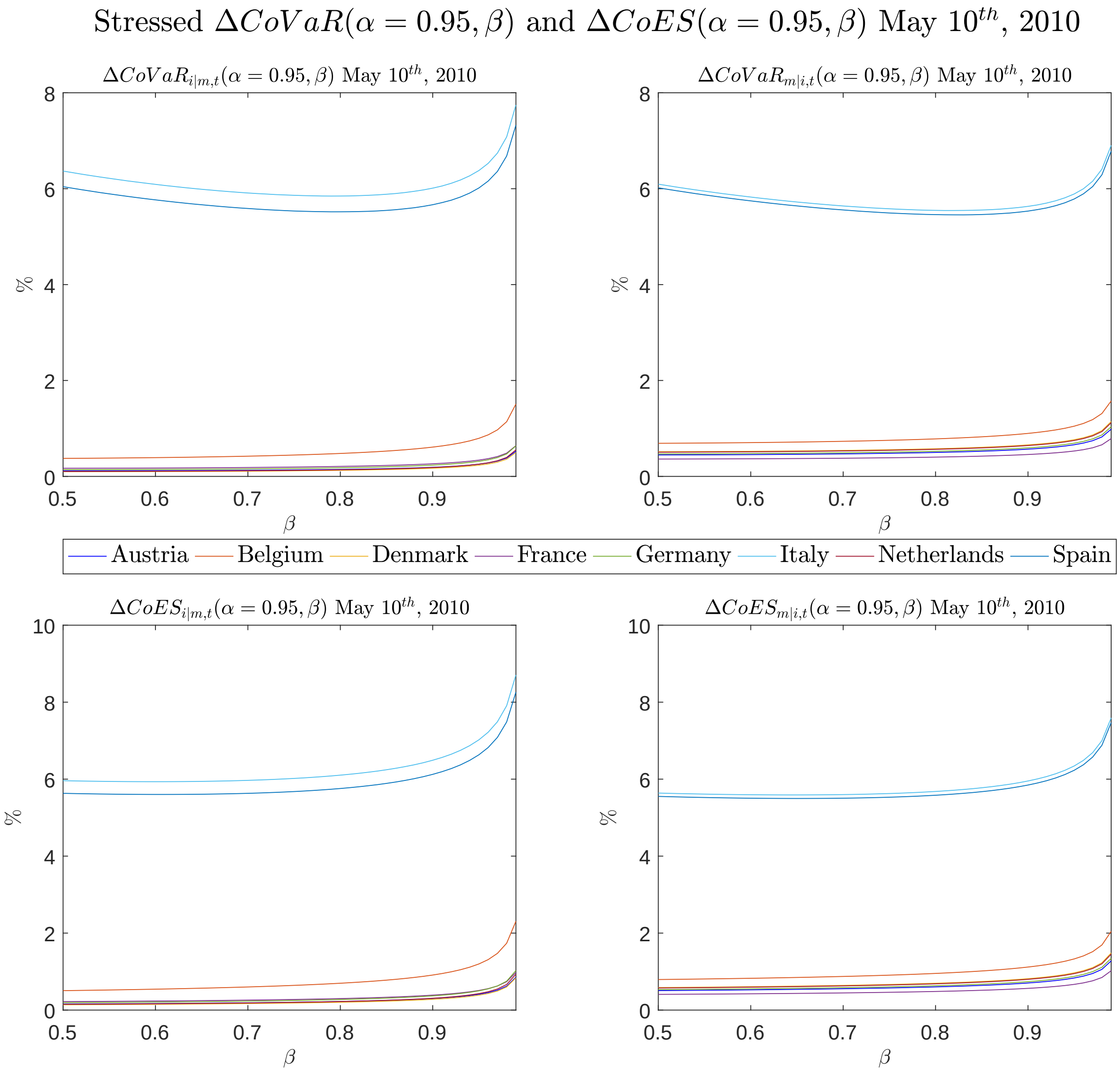

Figure 10: Stressed $\Delta CoVaR_{i|m,t}(\alpha = 0.95, \beta)$, $\Delta CoVaR_{m|i,t}(\alpha = 0.95, \beta)$, $\Delta CoES_{i|m,t}(\alpha = 0.95, \beta)$ and $\Delta CoES_{m|i,t}(\alpha = 0.95, \beta$ on May 10^{th}, 2010
A higher level of β means a more stressful scenario for the conditioned variable on May 10^{th}, 2010.

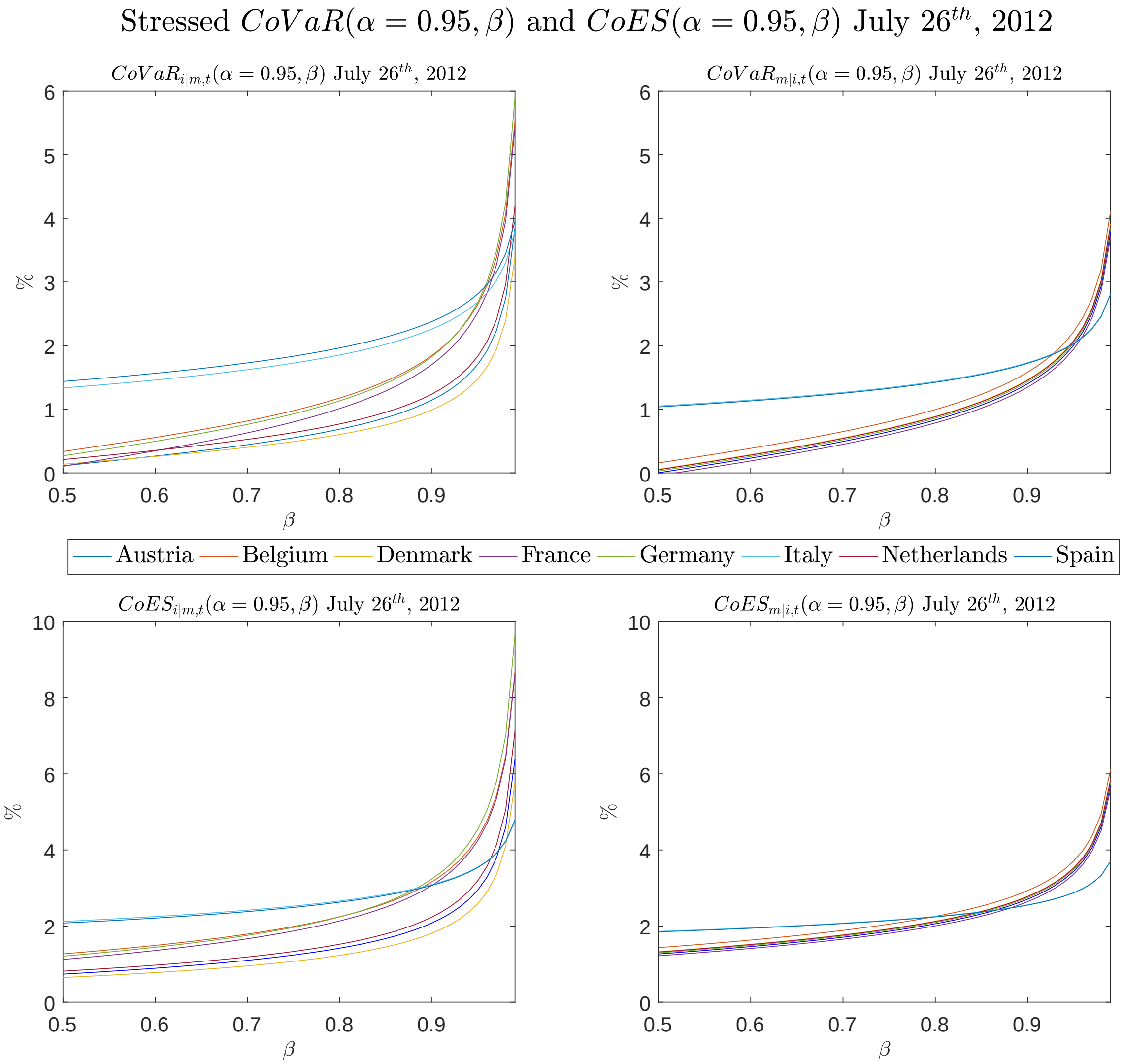

Figure 11: Stressed $CoVaR_{i|m,t}(\alpha = 0.95, \beta)$, $CoVaR_{m|i,t}(\alpha = 0.95, \beta)$, $CoES_{i|m,t}(\alpha = 0.95, \beta)$ and $CoES_{m|i,t}(\alpha = 0.95, \beta$ on July 26^{th}, 2012

A higher level of β means a more stressful scenario for the conditioned variable on July 26^{th}, 2012.

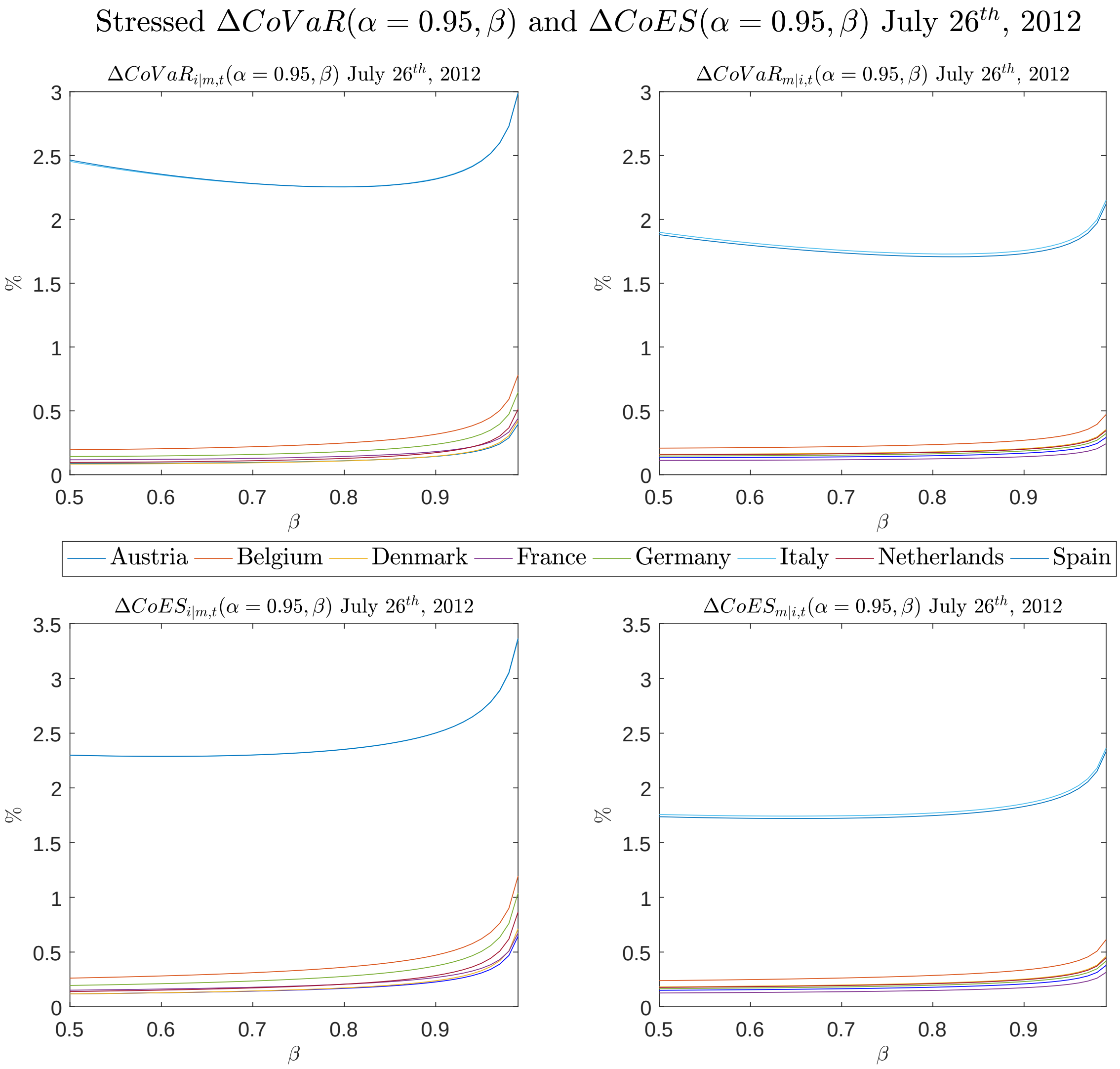

Figure 12: Stressed $\Delta CoVaR_{i|m,t}(\alpha = 0.95, \beta)$, $\Delta CoVaR_{m|i,t}(\alpha = 0.95, \beta)$, $\Delta CoES_{i|m,t}(\alpha = 0.95, \beta)$ and $\Delta CoES_{m|i,t}(\alpha = 0.95, \beta$ on July 26^{th}, 2012
A higher level of β means a more stressful scenario for the conditioned variable on July 26^{th}, 2012.