Abstract

This article focuses on the tail risk spillover (co-movement) effect between the sovereign and banking sector in the eurozone, using a novel multivariate quantile model (VAR for VaR method) and then the relative pseudo quantile impulse response functions. We analysed the causality risk transmission at different quantiles (up/downside), using daily credit default swap from 9 October 2008 to 29 May 2018. Our main findings confirm the two-way causality between these credit markets, highlight the presence of an asymmetry in the mechanisms of shock transmissions between core and no core bank/sovereign, respectively. Also, we measure the directional predictability in the quantiles using the cross-quantilogram approach. The results suggest that a high credit risk sovereign predicts high sovereign risk (and vice versa).

Keywords: Credit default spread, two-way feedback, risk spillover, VAR for VaR, cross-quantilogram, sovereign-bank nexus

JEL Codes: G01, G20, E44, C14

1 Introduction

The financial crisis has highlighted a critical aspect of European banks: their substantial exposure to the bonds of both their governments and other European countries. As a result, the risk of a collapse in government bond prices can lead to severe budgetary problems and make the banking system insolvent. The close interconnection between banks and sovereign debt has created a dangerous channel for the transmission and enhancement of shocks, namely "the diabolical loop", exposing eurozone governments to liquidity and solvency crises (Brunnermeier et al. (2011, 2016); Pisani-Ferry (2012); Shambaugh et al. (2012)).

The channel operates as follows: concerns about the solvency of sovereigns foment concerns about the solvency of banks, given their high exposure to government bonds. On the other hand, this financial stress reinforces concerns about sovereigns, given the increased likelihood of intervention to save the banking system. A speculative attack on the sovereign debt market (or a bank run) can, therefore, occur very quickly and at any time. This loop explains the rapid growth of yields first in Greece and Ireland and then in Portugal, Spain and Italy between 2010 and 2012. Figure 1 exhibits the time trend of the Eurozone sovereign (red), and bank (blue) CDS spreads. Its dynamic shows a spectacular co-movement between both credit risk (correlation = 0.95). These connections are related to the concept of contagion. Indeed, according to Pericoli and Sbracia (2003), the contagion can derive from a significant increase in co-movement of "prices and quantities across the market". This definition is also validated by Forbes and Rigobon (2002). For the authors, the contagion is a significant increase in cross-market correlation compared

to that measured in quiet times. On the other hand, a high co-movement during periods of tranquillity and stress should be referred to as interdependence.

[Figure 1 about here]

Nevertheless, what is the direction? Does sovereign credit risk spread to the banking sector? Or is the contrary? The literature is not clear about it. According to Acharya et al. (2014) model, the bank risk affects the sovereign risk due to the bail-out. The opposite view in the Gennaioli et al. (2014) framework. As well as for Alter and Schüler (2012) who investigate the relationship between sovereign and banks CDS for the European market. Their results suggest that before the bail-out, the contagion risk spreads from the banking sector to the sovereign CDS market, while the contrary effect spill over after the interventions (sovereigns to banks). The empirical application of Vergote (2016) shows how the contagion from the sovereign risk to the financial sector, is started in 2010. Moreover, the results of Avino and Cotter (2014) and Fratzscher and Rieth (2015) confirm that the sovereign-bank loop intensified during the sovereign debt crisis, without a predominant causality.

Hence, in this paper, we do not assume any a priori risk direction between sovereigns and banks. The aim is to examine the response effects between them. More specifically, we are interested in investigating how the banking market reacts to shocks in the sovereign market and vice versa, thus possible contagion risk effects. Therefore, an important question we effort to highlight is whether any heterogeneity exists across the response of the shock for this diabolical loop. The financial and sovereign debt crisis[1] have evidence how the dependencies in the extreme (event, crisis) risks are more relevant and implying attention to connections between tails risks. Measuring and monitoring tail risk have important implications for financial contagion and systemic risk, i.e. macroprudential policy.

Our article is related to several recent empirical investigations into the loop between sovereign credit risk and the banking sector credit risk. In recent years, several methods have been developed and applied. Many studies use time-series econometric tools, such as vector autoregressive (VAR) model (Alter and Schüler (2012); Bratis et al. (2018); Fratzscher and Rieth (2015); Kalbaska and Gatkowski (2012)), vector error correction (VEC) model (Alter and Schüler (2012); Avino and Cotter (2014); Yu (2017)), correlation analysis (De Bruyckere et al. (2013); Bratis et al. (2018)), conditional joint probability of default (Xu et al. (2017)), contingent claim analysis (Singh et al. (2016); Gomez-Puig et al. (2019)), STCC-GARCH model (Cifarelli and Paladino (2020)). This body of papers are able to highlight the bidirectional relationship but do not capture the cross-section dependence between them. To this, other works, in order to take into

[1]For a detailed understanding of sovereign risk during and after the sovereign debt crisis, please see Arakelian et al. (2019).

account the cross spillover effects, use the Diebold and Yilmaz (2009, 2012) methodology (Alter and Beyer (2014); Claeys and Vasicek (2015); Gomez-Puig et al. (2019)), the Global VAR (GVAR) model (Gross and Kok (2013); Bettendorf (2019)), the Panel VAR (Georgoutsos and Moratis (2017)), as well as the network analysis approach (Paltalidis et al. (2015); Betz et al. (2016); Vergote (2016)). However, these models allow to understand and estimate the extent of asymmetries, but not to deal with the measurement of different propagation mechanisms, during the bad and good conditions (equilibrium) and after a negative (positive) shock appears. Here, different to these works, we investigate the tail risk interdependence (co-movement) of the diabolical loop under extreme (downside/upside) conditions, by multivariate quantile model framework (MVMQ-CAViaR or VAR for Var) proposed by White et al. (2015). This model is a vector autoregressive approach of value-at-risk. There are three advantages to use the multivariate quantile model. First, parameter computes are robust. Therefore, it allows us to have estimates that take into account the extreme volatility of the financial markets. Second, it is not necessary to impose heavy restrictions on the data generation process, since the regression quantile is a semi-parametric technique. Third, the MVMQ-CAViaR framework measures the tail-dependency instead of modelling the time-varying first two moments (Wen et al. (2019)). Hence, the multivariate quantile model seems particularly appropriate to test if financial institutions/countries closer or further from their potential tend to influence each other in financial/country transmission, and then to capture the join dynamics of credit risk. Indeed, several research use this methodology to analyse the risk spillover between financial markets (Jian et al. (2018); Shen (2018)), sovereign risk and oil volatility (Bouri et al. (2018)) or between oil and stock markets (Wen et al. (2019)). Therefore, this multivariate method is useful to investigate the dynamic of inter-dependency structure across banking and sovereign markets, i.e. quantify how risk transmits between them. However, to taking into account also extreme events, we follow Jian et al. (2018), and we introduce the dummy variable of distress events into quantile dynamics. We also applied cross-quantilogram (Han et al. (2016)) to analyse the degree, direction and duration of inter-dependency. The main advantage of using these models is that they allow us to measure the different propagation mechanisms, both under favourable conditions (reduction of contagion) and after the appearance of a negative shock.

Our results confirm that defining positive and negative spillovers by pseudo quantile impulse function (QIRFs), is a crucial issue to have a complete picture of the transmission mechanism in a union characterised by a high level of heterogeneity. Through our findings, we can study, how a credit event in one banking sector/country spreads a credit event in another and which the banking sector/countries are more exposed to credit events than others. This suggests that the risk of default in one Eurozone banks can depend on perceived developments in other countries (banks).

The findings of VAR for VaR estimation, can be summarised as follows: i) the "perfect" two-way feedback is present in upside risk spillover for the Spain market as well

as for the Core sovereign links to the eurozone banking sectors; ii) at downside tail risk level, we find an asymmetry spillover phenomenons; iii) domestic and conditional extreme events are significant determinants of risk; iv) the diabolical relationship is more significant for the NoCore countries, corroborating the results of Fratzscher and Rieth (2015) and Acharya et al. (2014). Focusing on cross-quantilogram analysis, we show that when sovereign credit risk is in a higher quantile, the absolute value of the cross-quantilogram is higher, and it is significantly different from zero for longer delays. Our results show a complete relationship between banking stress and sovereign one, showing how the loop changes for different delays.

The contribution of the research is twofold. First, using the MVMQ-CAViaR framework, we are able to capture the positive and negative spillover effects between the two markets. Compared to the use of the classical version of VAR (e.g. Bratis et al. (2018)), this model allows the direct analysis of the degree of interdependence of the tail between the different random variables. Indeed, most studies focus on the average of distributions, which may underestimate the real effects of risk shocks. Thanks to this model, we can analyse some of the characteristics of shocks, such as their persistence, in different market scenarios (i.e., in lower, and upper quantiles). Second, by the cross-quantilogram methodology, we identify the difference in the impact of bank and sovereign credit risk spread at a different level of risk (quantiles) and different lag, not possible with the use the classical quantile regression model. Also, this technique allows us to measure the directional predictability in quantiles from (to) one credit market to (from) the other.

The paper is organized as follows. Section 2 describes the two models, while section 3 shows the data. In the section 4 we present the empirical results and the conclusion in section 5.

2 Empirical Strategy

2.1 VAR for Var approach

In order to quantify and identify the degree relationship between CDS markets, and then the risk spillover effects, we apply the multivariate multi-quantile conditional autoregressive (MVMQ-CAViaR) model, also known as VAR for VaR approach (White et al. (2015)). This model is a generalization of the CAViaR model, proposed by Engle and Manganelli (2004). The conception behind the method is that the distribution quantile of one time series is given by the lag of own lags (e.g. sovereigns CDS) and the lags of covariates (e.g. bank CDS). The MVMQ-CAViaR (1,1) allows us to capture the risk-transmission of tail interdependence between the two CDS markets. Hence,

$$q_{1t} = c_1(\theta) + a_{11}(\theta) r_{1(t-1)} + a_{12}(\theta) r_{2(t-1)} + b_{11}(\theta) q_{1(t-1)} + b_{12}(\theta) q_{2(t-1)} \tag{1}$$

$$q_{2t} = c_2(\theta) + a_{21}(\theta)r_{1(t-1)} + a_{22}(\theta)r_{2(t-1)} + b_{21}(\theta)q_{1(t-1)} + b_{22}(\theta)q_{2(t-1)} \tag{2}$$

where $r_{1(t-1)}$ and $r_{2(t-1)}$ consist the "return" of CDS spreads, while q_{1t} and q_{2t} represent the conditional quantiles. Therefore the quantiles of CDS return $(r_{1,t})q_{1t}$ at θ level, depends: on its CDS return (via a_{11}) at time $t-1$, on a lag CDS return of the other credit market (via a_{21}), on its own lag quantiles (via b_{12}) and on a lag of quantile of the other credit market. Therefore, the b_{12} and the b_{21} coefficients capture the risk spillover, i.e. how the risk in one credit market influences the risk in the other ones. However, the model fails to consider the influence of conditional distress events. To take into account extreme event (structural break), we follow Jian et al. (2018) and modified the model as follow (for $\theta = 0.05$)[2]:

$$\begin{aligned} q_{1t} &= c_1(\theta) + a_{11}(\theta)r_{1(t-1)} + a_{12}(\theta)r_{2(t-1)} + b_{11}(\theta)q_{1(t-1)} + b_{12}(\theta)q_{2(t-1)} + \\ & d_{11}1(\theta)(r_{1,t-1} \leq q_{1,t-1}) + d_{12}1(\theta)(r_{2,t-1} \leq q_{2,t-1}) \end{aligned} \tag{3}$$

$$\begin{aligned} q_{2t} &= c_2(\theta) + a_{21}(\theta)r_{1(t-1)} + a_{22}(\theta)r_{2(t-1)} + b_{21}(\theta)q_{1(t-1)} + b_{22}(\theta)q_{2(t-1)} + \\ & d_{21}1(\theta)(r_{1,t-1} \leq q_{1,t-1}) + d_{22}1(\theta)(r_{2,t-1} \leq q_{2,t-1}) \end{aligned} \tag{4}$$

where $I\{.\}$ is a dummy variable which equals 1 when an extreme event $\{.\}$ occurs. The coefficients d_{12} and d_{21}, capture the conditional extreme events. Hence, by using this modified model (Jian et al. (2018)), we are able to better seize the quantile patter, indeed now its dynamic is not only influenced by lagged "returns" and quantile but also affected by extreme risk events occurring in each market.

Following White et al. (2015), we define the quantiles $q_{1,t}$ and $q_{2,t}$ as follow:

$$q_{1,t} = -Q_0(r_{1,t}|F_{t-1}) = -inf\{q \in R|Pr(r_{1,t} \leq q|\mathcal{F}_{t-1}) \geq 0\} \tag{5}$$

$$q_{2,t} = -Q_0(r_{2,t}|F_{t-1}) = -inf\{q \in R|Pr(r_{2,t} \leq q|\mathcal{F}_{t-1}) \geq 0\} \tag{6}$$

where Q_0 is a quantile function at confidence level $\theta \in (0,1)$, while $\mathcal{F}_{t-1}$ is the information set available at time $t-1$.

Whit VAR for VaR model, we can analyse the degree impact of one shock of the sovereign market on tail risk bank CDS return (and vice versa). To this, the model permits us to estimate the pseudo quantile impulse response function (QIRFs). However, these impulse responses are quite differenced from the traditional one. In fact, they assume that the one-off intervention δ is assumed to the observable r_{it} at time t. This implies that there is no change in any other periods. The QIRF for r_{it} is given by $\Delta_{is}(\widetilde{r}_{1t})$ expressed as follows:

$$\Delta_{is}(\widetilde{r}_{1t}) = \widetilde{q}_{i,t+s} - q_{i,t+s} \ , \ s = 1, 2, 3... \tag{7}$$

[2]For $\theta = 0.95$, following Jian et al. (2018), we change the definition of extreme events from $r_{i,t-1} \leq q_{i,t-1}$ to $r_{i,t-1} \geq q_{i,t-1}$.

where $\widetilde{q}_{i,t+s}$ is the θth conditional quantile of treated variables ($\widetilde{r}_{1t}$), while $q_{i,t+s}$ stands for the θth conditional quantile of unaffected return $r_{i,t+s}$. We estimate the pseudo impulse response first with $i = 1$ and then for $i = 2$. Then, the QIRF is defined as follows:

$$\Delta_s(\widetilde{r}_{1t}) = \begin{bmatrix} \Delta_{1,s}(\widetilde{r}_{1t}) \\ \Delta_{2,s}(\widetilde{r}_{1t}) \end{bmatrix}, D_t = \widetilde{r}_{1t} - r_t \tag{8}$$

The generalization of the QIRF is as follows:

$$\Delta(\widetilde{r}_{1t}) = AD_t, \quad \text{for} \quad s = 1 \quad \text{and} \tag{9}$$

$$\Delta(\widetilde{r}_{1t}) = B^{s-1}AD_t \quad \text{for} \quad s > 1$$

QIRFs preserve the traditional interpretation of traditional impulse response functions. The advantage is that they allow us to directly model the tail-interdependency structure through financial series (Shen (2018)), then to examine how the credit risk is transmitted from one market to another, in a single framework.

2.2 A cross-quantilogram approach

To highlight these relationships and to measure the predictability of CDS spread sovereign through CDS spread bank and vice versa, we apply the cross-quantile (CQ) method of Han et al. (2016). This econometric model is useful to estimate the lead-lag relation and to capture the directional quantile dependence between two times series, at different lags and quantiles. For example, respect to the VAR methods, that can only measure a mean-to-mean dependence, the CQ approach can measure extreme-value dependence. Indeed, by CQ method - since it is a model-free measure - we can quantify extreme value dependence, and we can capture cross-quantile asymmetries in the dependence structure. Therefore, we are able to check if extremely high and low risks across banks (country) are symmetrically dependent. For these reasons, we use the bivariate CQ to corroborate the VAR for VaR analyses, as a complementary approach. According to Bouri et al. (2018), the quantile regression is given by:

$$q_{\alpha(\tau+1|\mathcal{F}_t)} = \beta_{0,\alpha} + \beta_{1,\alpha}x_t + \beta_{2,\alpha}x_t q_\alpha(\tau_t\mathcal{F}_{t-1}) + \beta_{3,\alpha}|\tau_t| \tag{10}$$

where τ_t is the sovereign CDS, while x_t is the CDS of bank, $q_\alpha(\tau_t\mathcal{F}_{t-1})$ is the conditional quantile of sovereign CDS with set of information $\mathcal{F}$ at time $t-1$. Also, we compute the "inverse" relationship, i.e. τ_t is the bank CDS while x_t is the CDS of the sovereign, and so on. The cross-quantilogram ($\hat{\rho}(k)$) and the portmanteau tests ($\hat{Q}^p_\alpha$)[3]of the Box-Ljung-Pierce modified, are used to explore the directional predictability ability between the two

[3]For an exhaustive understanding and derivation of the model, we refer to see Han et al. (2016).

credit risk markets. In particular, $\hat{Q}^p_\alpha$ test can be used to test the directional predictability of returns from one market to another for up/downside quantiles. Finally, Han et al. (2016) in order to compute the critical values for approximate the null distribution and to conduct inference, suggest to use the stationary bootstrap (SB) method proposed by Politis and Romano (1994). This SB approach is useful to take into account the serial dependence and to allow for random block lengths.

3 Data

Our empirical analysis focuses on risk spillover between sovereign bank nexus. Following Alter and Schüler (2012) and Bratis et al. (2018) we select the CDS spread contract based on 5-year senior bond as measure of sovereign and bank risks[4]. The daily CDS spreads are extracted from DataStream. The data span from 9 October 2008 to 29 May 2018 (2514 observations). We selected this period with the highest availability of data related to different unit analysis in order to minimise missing data. The Eurozone countries are: Austria, Germany, France (Core countries), Ireland, Italy, Portugal and Spain (NoCore countries). The banks are list in Table 2. The overall sample consists of 18 banks spread across seven countries. Following Bratis et al. (2018), we weighted the sovereign CDS spread on 2012 GDP (Table 1), while for the banks, we use the total assets in 2012 (Table 2). We choose the year 2012 as a transition period, from a high level of risk (December 2011) to the tranquil period (September 2012). Table 3 presents the summary statistics of the weighted portfolio.

[Table 1 about here]

The mean value for the banking sector (EZ Bank) is higher than the mean value of sovereign sector (EZ Sov), as well as for each sub-sample related (e.g. Core Bank Vs Core Sov). Concerning the country's differentiation (home country), the highest average value comes from NoCore, with a standard deviation that reflects the different dynamics in each CDS market. It is highest for the NoCore country, and it is smaller for the Core country for each market. These differences highlight how the peripheral countries are stressed respect the Core countries.

[Table 2 and Table 3 about here]

To perform the econometric analysis, we use the log first difference $\times$ 100 (daily "return") compute as:

$$r_{i,t} = \log \frac{CDS_{i,t}}{CDS_{i,t-1}} \times 100 \tag{11}$$

[4]We select the CDS spread contract based on five-year senior bond since these obligations are the most liquid (Meng and ap Gwilym (2008)).

where $CDS_{i,t}$ is the CDS spread at time t of country/bank i. Intuitively, an increase of "return" means an increase of risk and the contrary.

4 Empirical Findings

In this section, first, we employ the VAR for VaR model, namely the downside spillover ($\theta = 0.05$) and the upside spillover ($\theta = 0.95$), for each sub-market. Specially, we conduct the analysis considering three levels of portfolio weighted: i) at an aggregate level (EZ Sov and EZ Bank), ii) at a group of countries (Core, NoCore), and iii) at the selected country (Germany, France, Italy, Spain). Then, we compute the pseudo quantile impulse response function (QIRF). Finally, to explore the significant direction predictability from sovereign and bank markets (and vice versa), we employ the bivariate CQ method (Han et al. (2016)). It is important to clarify that, contrary to the stock market where $\theta = 0.95$ implies a positive impact, here in the context of credit risk is the opposite. For example, a downside risk spillover ($\theta = 0.05$) produces a "positive" effect or reduces risk[5]. Table 4 reports the results of VAR for VaR estimation, for the downside quantiles, while Table 5 reports the findings for the upside quantiles, for each weighted portfolio respectively.

[Table 4 about here]

[Table 5 about here]

These table show some interesting insights. The lag quantiles (upside and downside) are point out by a_{11} (a_{21}) and a_{12} (a_{22}) coefficients, while the spillover effects (tail dependence) between the two CDS markets are expressed by the b_{12} and b_{21} parameters. The parameter $a_{11}(a_{22})$ shows how a change in bank (sovereign) CDS spreads, has a positive or negative impact on the banking (sovereign) quantile depending on market conditions (θ). This result suggests that risk perception plays a key role in the transmission of shocks between two credit markets. In situations of extreme euphoria (in this case contagion), a change in the CDS causes higher risk (unlike in low uncertainty). In fact, worried investors begin to sell their bonds. The sale pushes interest rates to unsustainable levels, which in turn increases the risk of default and thus the CDS. From a financial point of view, investing in sovereign bonds or banks has no diversifying effect, which shows how the two markets crash and boom together in risk term. Focusing on the spillover effect, we can note the statistical significance of the coefficient a_{12} (a_{21}). This indicates that the quantile of the bank CDS market (sovereign CDS market) depends not only on its information at time $t-1$ but also on the information in sovereign (bank) markets. It is important to note that the two-way tail risk spillover is present at disaggregate level (e.g. EZ Bank link to Core Sov) especially for the upside spillover (mainly for Spain). These

[5]The lower quantiles show low uncertainty (risk), while the upper quantiles show high risk (Bouri et al. (2018)).

results are in line with the analysis of Gomez-Puig et al. (2019), Bratis et al. (2018) and Alter and Beyer (2014) that find the same evidence. The b_{21} parameter, that measures the impact of quantiles of sovereign risk on bank risk is significant with a negative sign for France, Spain and the EZ Bank in relationship with Core Sov, for the $\theta = 0.95$. Focusing on $\theta = 0.05$, we can see that the parameter is significant with a negative sign for Italy, as well as with a positive sign for NoCore Sov in relationship with EZ Bank. This means that an increase in EZ Bank CDS quantiles tail risk implies an increase in NoCore Sov quantile. All tail-dependence coefficients (b_{12} and b_{21}) have a negative sign when dealing with the upside risk ($\theta = 0.95$). The negative sign of these parameters concerning the impact of upside Bank/Sov tail "returns", indicates that Bank/Sov CDS may have a negative response to upward Bank/Sov credit risk behaviour. Finally, focusing on the impacts of extreme events (d_{11}, d_{12}, d_{21}, d_{22}), we can see how they are always significant, for each portfolio and both market conditions. Therefore, an extreme adverse event occurring in the banking credit market would result in a higher extreme risk in the sovereign credit market (and vice versa). This evidence shows that the effects of extreme events conditioned upward and downward between the two markets are perfectly symmetrical. Hence, the findings highlight the importance of considering extreme events when modelling quantile dynamics.

The findings can be summarised as follows: i) the "perfect" two-way feedback is present in upside risk spillover for the Spain market as well as for the Core sovereign links to the eurozone banking sectors; ii) the NoCore sovereign market depends for the EZ Bank, i.e. there is a univariate risk spillover from bank to NoCore countries; iii) a variation in risk is due to the spillovers of extreme events occurring in the other market. A very interesting result is the case of Italy markets. The risk of the banking sector influences the sovereign risk in the downside risk, while the sovereign risk influences the banking sector in the upside risk. These mean that the relationship depends on the type of risk movements. This suggests how this diabolical relationship is more significant for the NoCore countries, corroborate the results of Fratzscher and Rieth (2015) and Acharya et al. (2014). The latter provide empirical evidence of two-way feedback between financial and sovereign markets. They find evidence of widening sovereign spreads and narrowing bank spreads after a bail-out (in the short term), but significantly higher co-movement in the long term.

4.1 Impulse response analysis

To investigate how the banking sector either react negatively or positively to the downside and upside sovereign shocks and vice versa, we compute the pseudo quantile impulse response functions derived from the VAR for VaR regressions. The main advantage of these pseudo QIRFs respect to the standard is that we can separate the reaction to positive (right quantiles) and negative (left quantiles) shocks. To keep our analysis

easy to interpret, we consider 2 quantiles: the downside ($\theta = 0.05$) and the upside ($\theta = 0.95$) for selected weighted portfolios and selected countries (DE, FR, IT, SP). Figure 2 displays the impulse response for the aggregate credit risk markets, sovereign and bank.

[Figure 2 about here]

The x-axis is the time (50 days), while the y-axis is the value of the CDS spread's response to the Sov (left-side) or Bank (right-side) credit risk respectively. The pseudo QIRFs allows us to investigate the degree of impact and the time for sovereign/bank CDS spread to absorb the bank/sovereign changes. For each graph, the right-side plots the counterpart impulse response. This figure shows two important information. First, focusing on the response of EZ Bank on EZ Sov shock, we can note a homogeneity pattern for positive and negative tail risk shock. After 20 lag (days) the effect towards back to equilibrium at zero levels. A different pattern we can observe in the right panel. In this case, the effect is asymmetric for the response of EZ Sov on shock in EZ Bank. The positive effect (reduction of risk, $\theta = 0.05$) is persistent respect the negative that goes to zero after 25 days. Second, the response of EZ bank on EZ Sov differs from the contrary one: the response is live-short time (20 Vs more than 50; 20 Vs 30) and has a minor effect (-0.4 Vs -0.7; 0.7 Vs 0.9). An increase in one standard deviation for the sovereign (bank) risk, has a direct impact on bank (sovereign) risk of 0.7 (0.9) standard deviations. The results are consistent with Alter and Schüler (2012) that find a short-term impact of the banking sector on sovereign CDS spreads. In Figure 3 and 4, we report the QIRFs for the relationship between Core (bank/country) and NoCore (bank/country) respectively. In particular, we analyse the link among Core/NoCore Bank and EZ Sov and Core/NoCore Sov and EZ Bank, for the upside and downside risk. The investigation of plots reveals that the impulses follow a fairly homogeneous pattern for all weighted portfolios. Indeed, i) the upside/downside impulses exhibit similar sequences, ii) the response of EZ Sov on shocks in the banking sector takes more time (days) to return to zero, as well as iii) the response of EZ Bank on shocks in the sovereign markets (excepted for $\theta = 0.95$).

[Figure 3 and Figure 4 about here]

Significant differences are visible in the impact of the EZ Sov in Core (first and third plots in Figure 3) and NoCore banks and vice versa (the impact of the EZ Bank on Core and NoCore countries; first and third plots in Figure 4). In both cases, it can be seen that the impact of a sovereign (bank) shock lasts much longer for the core banks (countries) that return to equilibrium after 25 (15) days. Focusing on the magnitude of impact, we can see that it is more pronounced for the NoCore banks (about -0.9) than for the Core banks (about -0.4). These results suggest that, while NoCore banks are more advantaged by a shock (reduction) of the tail risk by the EZ Sov, Core countries are "affected" by shock (reduction) of the tail risk of the European banking system (both of impact degree

and time), due to "their perceived role as safe havens" (Asimakopoulos et al. (2018)). This finding accords with the empirical investigation worked recently by Fratzscher and Rieth (2015) and Bouri et al. (2018). The authors reach the same conclusion: i) bank risk is more relevant for Core countries then NoCore one, ii) in the latter sovereign risk plays a relatively more significant role. The results show the differences in reaction to shocks (positive and negative) of banks and Core/NoCore countries, highlighting the heterogeneity within the eurozone. Another aspect to consider is the different impact of an upside and downside spillover tail risk. The effect of an upside shock (EZ Bank) is much more persistent. This testifies to the predominant effect of the transmission of banking risk to the sovereign risk, implying that bank credit risk influences the sovereign risk more in cases of increased risk than a decrease in risk (heterogeneous effect). The plausible reason is the bail-out impact. Indeed, the government implements policies to reduce the negative effects (default risk) in the banking sector. This evidence reflects the analyses of the literature (Alter and Schüler (2012); Kalbaska and Gatkowski (2012); Gennaioli et al. (2014)) that shows how the bail-out effect spreads risk from the banking sector to the sovereign sector due to the diabolical loop. We further report the domestic pseudo QIRFs of 4 countries (Figures 5 and 6): two Core (Germany and France) and two NoCore (Italy and Spain).

[Figure 5 and Figure 6 about here]

In particular, the reaction of the Italian banking market to a sovereign shock shows a very different trend from the others. In effect, the shock (risk reduction) is absorbed very quickly (5 days). The risk co-movement is coherent with the analysis of Cifarelli and Paladino (2020), who find that "changes in the Italian riskiness perception seem to be a contained phenomenon". This result can be partly attributed to the fact that the Italian banking system did not receive official support compared to other countries. Indeed, as well evidenced by Alter and Schüler (2012), the lack of liability guarantees under the bail-out mechanism and the low use of the rescue funds offered, may have further contributed to the differences in performance for Italy. Moreover, spillover effects from Spanish Bank CDS to Spanish sovereign CDS become more similar in magnitude, as well as for the France markets. It is interesting to note the QIRFs for Germany markets. A reduction in the tail risk of German banks causes a slight reduction in sovereign risk, but the effect is persistent (lasting more than 50 days). Precisely the opposite if we focus on an upside risk spillover. In this case, an increase in banking tail risk has a major impact (the highest value compared to other countries), with a short duration (2 days). This result highlights the solidity of the Germany country risk in contrasts with fragility of the Germany banks (Paltalidis et al. (2015)). We document that the degree and the speed which responses are absorbed varies across national banking systems related for example, on the size and the degree of their interconnectedness (loop).

4.2 The asymmetries characteristic

As noted above, the different risk quantiles respond differently depending on the origin of the shock and the credit market of reference. Now, the aim is to show how market reactions vary depending on whether credit risk is reduced or increased. In this section, we examine this asymmetric property of risk transmission. Following Shen (2018) we calculate asymmetry as the absolute difference between risk reduction ($\theta = 0.05$) and increase ($\theta = 0.95$). This measure allows us to understand the asymmetric response given by external shocks. Table 6 reveals important asymmetric response patterns in the Bank responses to the Sov shock (left-column). We can note that the upside risks are easier to transmit between the credit market. Indeed, in a scenario of increased risk, sovereigns introduce greater risk. Different picture patterns in the Sov response to the Bank shook (right-column). In this case, asymmetric risks are transmitted in both scenarios. A particular case is Germany, which has the highest asymmetry with -3.52. One possible explanation is that Germany had more problems in the banking sector than in the solidity of the government (e.g. the Deutsche Bank crisis). Focusing on average, we document that the impact of risk transmitted is higher from Bank to Sov (-1.26 Vs -0.5 and 1.3 Vs 0.80), while concerns the asymmetries is the contrary (-0.17 Vs -0.30).

These results document how asymmetries are more dependent on the sovereign credit market, reflecting risk divergences across euro area countries. This means that under conditions of greater market euphoria (higher risk) there is more asymmetry in transmission between sovereign and bank. For example, an increase in sovereign risk has a more pronounced effect on bank risk. This suggests how sovereign risk can affect banks' credit conditions and thus, the real economy through lending to businesses and households. Therefore, the shock leads to constraints in the supply of credit by banks, which then hurt private investment[6], consumption and the economy in general. On the other hand, this financial instability (a negative shock on banks' balance sheets will affect their demand for sovereign bonds) worsens fiscal accounts (Dell'Ariccia et al. (2008)), as well as the monetary policy transmission (Peek and Rosengren (2010)). Our empirical findings contribute to a better understanding of how different kinds of information are transmitted between the sovereign bank nexus.

[Table 6 about here]

4.3 Results of directional predictability

Now, we study the directional predictability of the two-way relationship using the bivariate CQ method (Han et al. (2016)). This approach is useful to estimate the relation between time series at different lags and quantiles. For each aggregate weighted portfolio,

[6]For example, several works (Theobald and Tober (2020); Augustin et al. (2018)) show how an increases in government risk premia spillover to risk premia in the domestic private sector.

we plot (Figures 7–9) the cross-quantilogram $\hat{\rho}(k)$[7]. We compute the 95% bootstrap confidence intervals (blue line) based on 1000 replication and the cross-correlogram (red line), for low and high quantiles. Figure 7 reveals several interesting findings. Credit risk form EZ Sov to EZ bank is generally significant at different periods (1, 2, 3,..., 41). This result means that for an increase of risk ($\theta = 0.95$), the eurozone sovereign market forecasts the banking credit risk.

[Figure 7 about here]

We can find, the quite the same result, in plots 8 right side. Whether for EZ SOV to Core or NoCore Bank, we can see that the cross-quantilogram is significant for several delays. Moreover, also in the graph 9 the cross-quantilogram is significant for the relationship NoCore Sov to EZ Bank. This evidence is in line with Avino and Cotter (2014) that find the same results. For the authors, this dependence can be attributed to the factor that sovereign CDS spread "incorporate more timely information on the of the default probability of European banks".

[Figure 8 and Figure 9 about here]

In summary, when sovereign credit risk is in a higher quantile, the absolute value of the cross-quantilogram is higher, and it is significantly different from zero for longer delays. Our results show a complete relationship between banking stress and sovereign one, showing how the relationship changes for different lags. This framework improves the classical quantile regression model that cannot recognise the difference in the impact degree of the Bank/Sov CDS spread at a different level of risks. In particular, each market forecast the other in a short time, i.e. the lag = 1 is almost always significant. These findings confirm the existence of risk spillover between the two markets.

5 Discussions and Conclusion

The diabolical loop (sovereign/bank) is an amplification contagion risk mechanism; therefore, its management is crucial to the right and timely definition of macroprudential policies. As well evidenced by Eschenbach and Schuknecht (2002), the propagation mechanism works through several channels: i) direct bail-out costs; ii) direct revenue effects and iii) indirect effect *via* the impact on the real economy. In this work, we are not interested in studying the nature and economic/financial consequences of this loop-risk, nevertheless, we want to understand the reaction of one market to a shock of the other. To this purpose, we have studied the tail (co-movement) risk spillover between sovereign and banks credit risk markets by using two novel models: i) the VAR for VaR approach

[7]The plots for national markets are available upon request.

and ii) the cross-quantilogram function. We document the two-way feedback tail interdependence patterns between sovereigns and banks, suggesting how this loop is present during the two financial crisis and at the same time as in the last phase. In effect, the crisis has left a lot of debris on the ground, and the hug between banks and sovereigns remains at high levels (see Figure 2). Also, we show the asymmetric property of the risk-transmission channel. Indeed, the pseudo impulse response function highlight how the degree and the speed which responses are absorbed varies across national banking systems related for example, on the size and the degree of their interconnectedness (loop). Furthermore, we applied the predictive approach (Han et al. (2016)) to study the contemporaneous causality relationships, i.e. to compute the directional quantile dependence. Overall, the graphical results document the ability of each market to predict the other. We find that the diabolical loop is much more evident for NoCore countries/banks. In particular, this loop is very characteristic of Italy and Spain. Moreover, for the latter, the perfect loop is showed for the upside risk. This result is consistent with Fratzscher and Rieth (2015) and Singh et al. (2016). Especially, Singh et al. (2016) find two-way negative feedback between banks and sovereign risk. Two underlying features seem relevant for understanding these findings. First, the banking exposures to the government through State loans. In fact, according to the IMF (2017), the claims of Italian (first position) and Spanish (second position) banks on their sovereign bonds amounted to 16% and 11% of total assets at the end of 2016, respectively. This can evidence the presence of the "moral suasion" and the "carry trade" hypotheses for the Eurozone periphery banks (Battistini et al. (2013)). Second, the liabilities value in the financial sector. Indeed, the Spanish government provided guarantees on some bank liabilities during the crisis. Besides, a third reason concerns the economic size of the two countries (sector). As far as Spain is concerned, the size of its banking sector has grown internationally, strengthening the transmission of internal tax problems to the rest of Europe. As regards Italy, the size of its economy and the poor state of public finances (higher level of public debt within Europe) have made risk transmission particularly strong.

In this research, we pay special focus in comprehending the asymmetric tail risk spillover effects between these markets at the upside and downside quantiles. When assessing macroprudential policy, it is important to know these dynamics in order to avoid a complete understanding of the tail risk spillover effect. In this respect, the research is of practical use to figure out the asymmetric risk transmission between the countries/banks.

Beyond our approach, it might be interesting to incorporate more factors into the VAR for VaR framework. For example, the macro variables (e.g. industrial production), to capture the consequences of this doom-loop on the real economy. This new model could highlight the dynamics of contagion by distinguishing the financial risk and the macro context risks.

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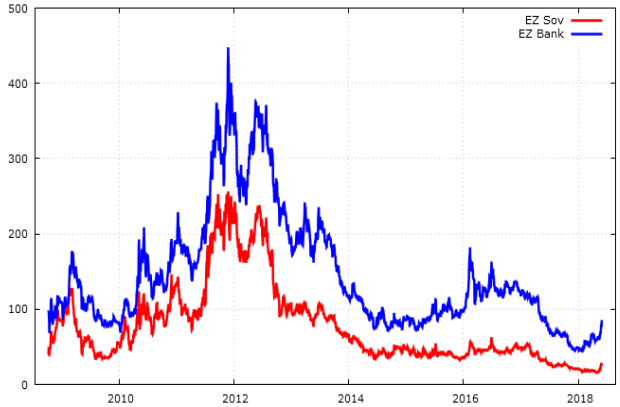
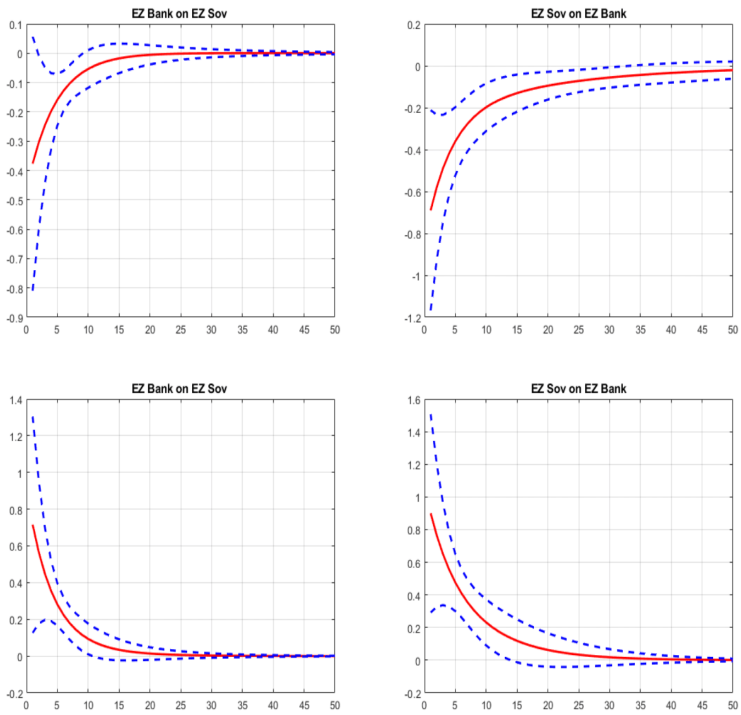
Figures

Figure 1. Sovereign and Banks CDS Spread



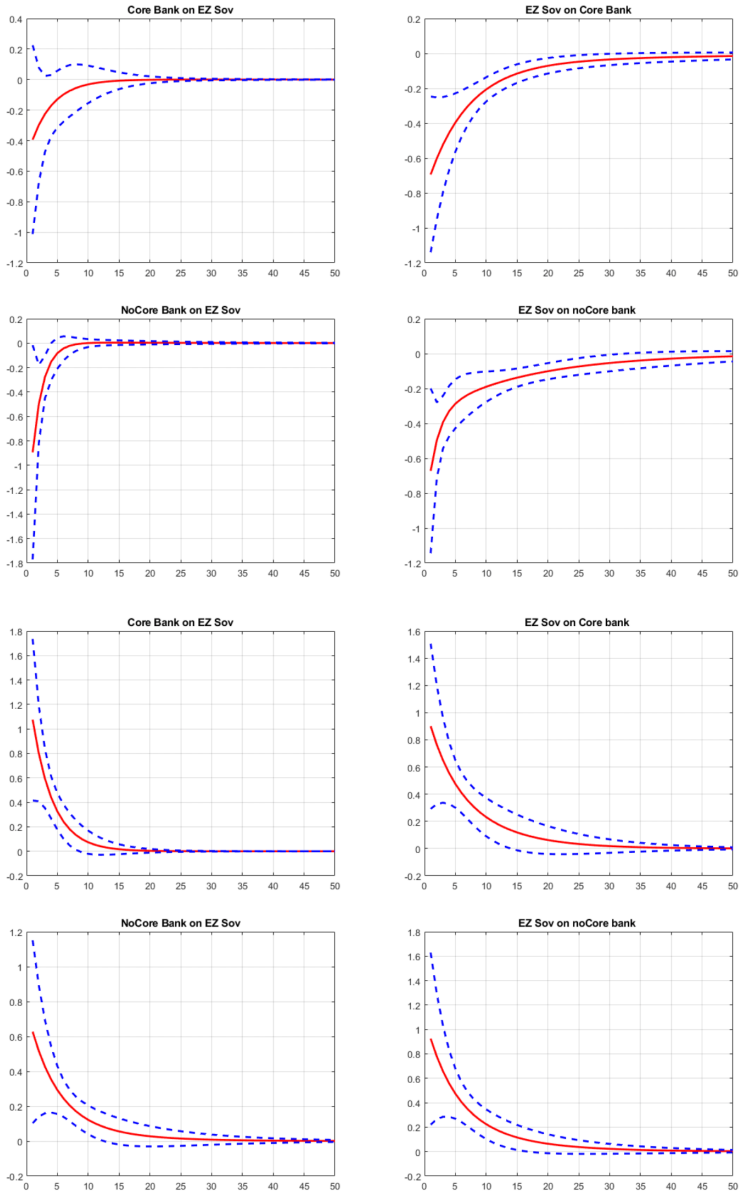
Notes: Ez Sov is the weighted (GDP 2012) average of the Eurozone countries selected, while EZ Bank is the weighted (asset size 2012) average of the Eurozone banks selected. For details, see section Data.

Figure 2. EZ Bank and EZ Sov



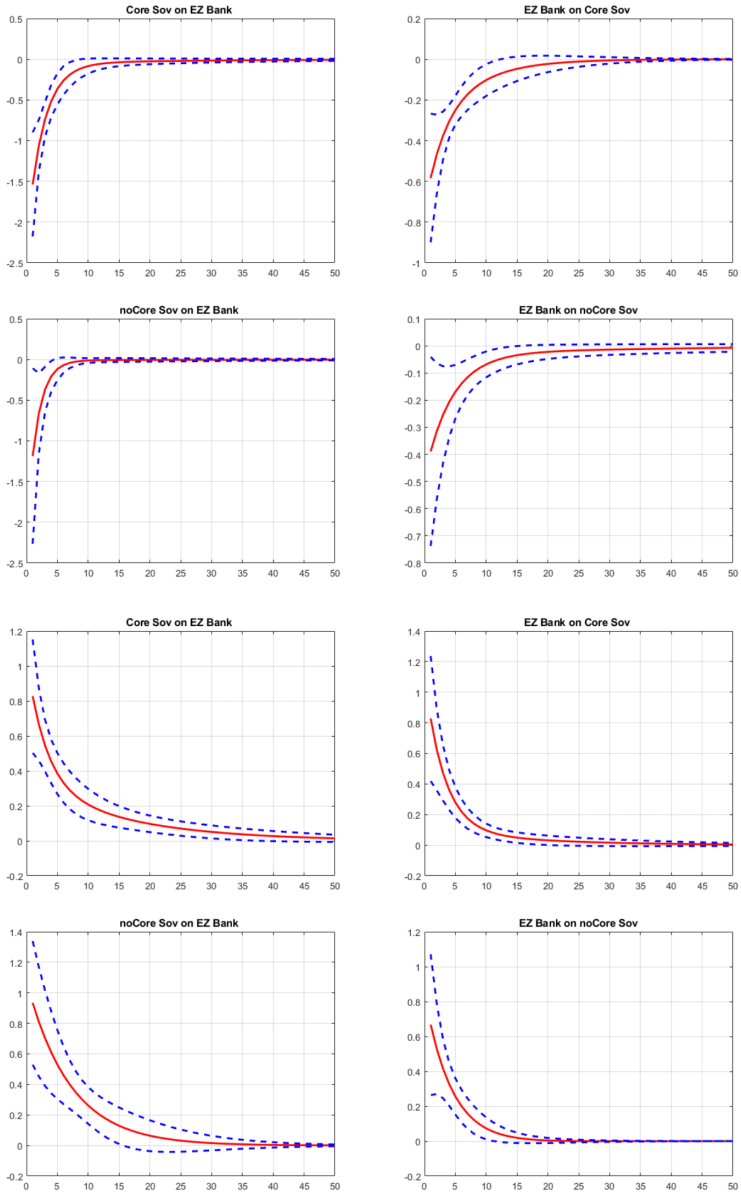
Notes: The impulse response functions to a one-standard deviation shock. In the upper for $\theta = 0.05$, while in the lower for $\theta = 0.95$.

Figure 3. Core/NoCore Bank and EZ Sov



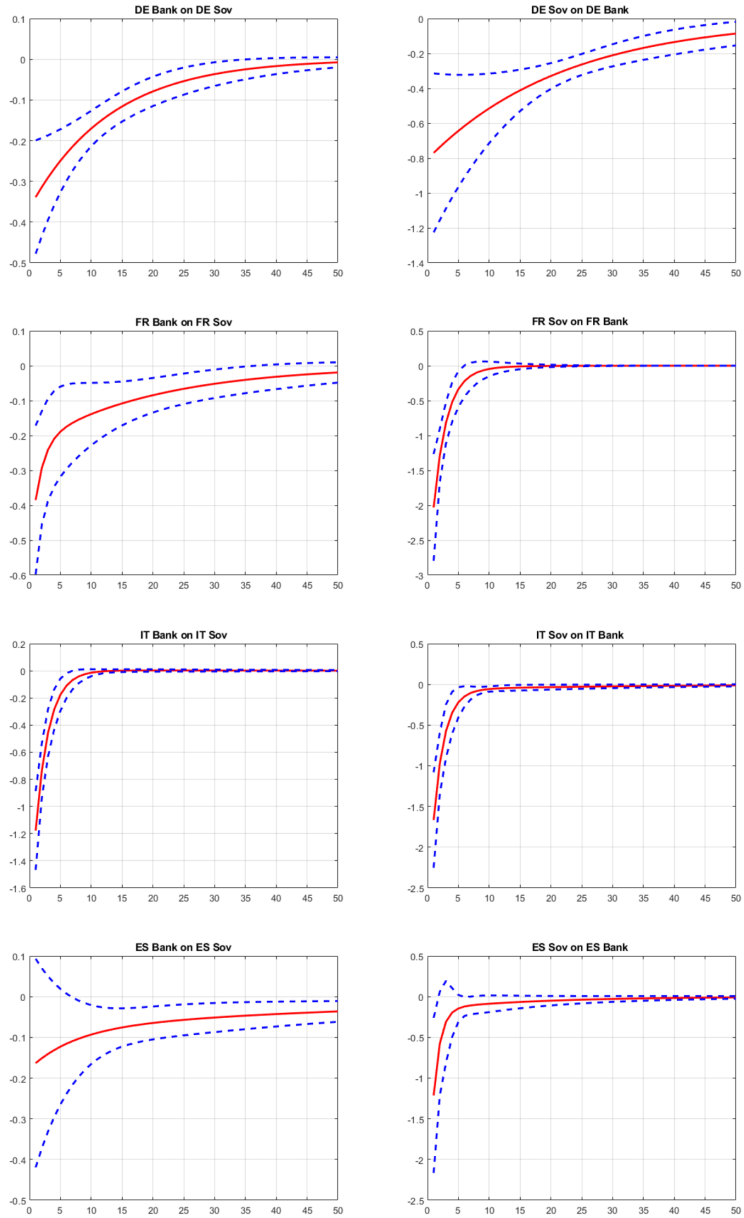
Notes: The impulse response functions to a one-standard deviation shock. In the upper for $\theta = 0.05$, while in the lower for $\theta = 0.95$.

Figure 4. Core/NoCore Sov and EZ Bank



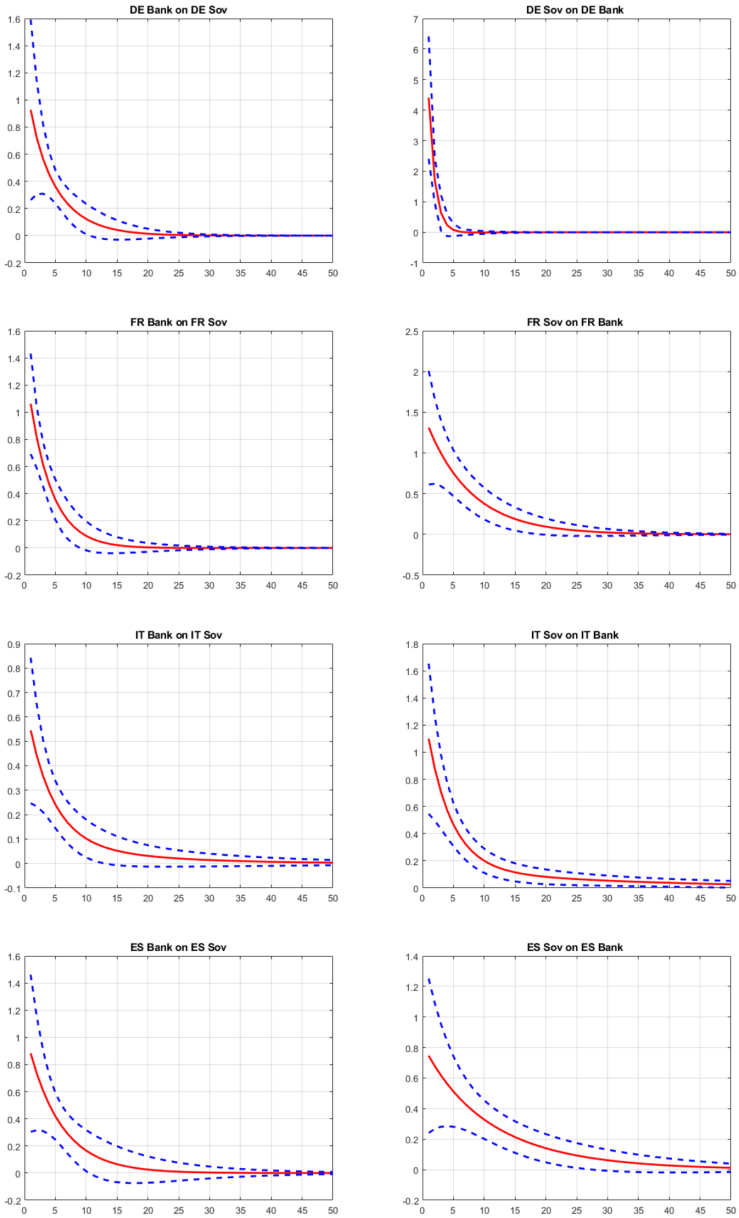
Notes: The impulse response functions to a one-standard deviation shock. In the upper for $\theta = 0.05$, while in the lower for $\theta = 0.95$.

Figure 5. Country Bank and EZ Country (A)



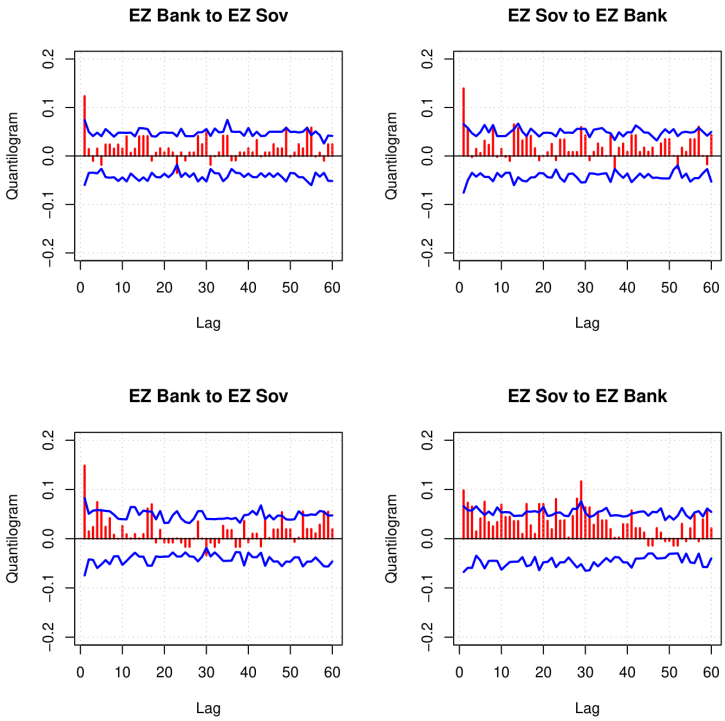
Notes: The impulse response functions to a one-standard deviation shock. $\theta = 0.05$.

Figure 6. Country Bank and EZ Country (B)



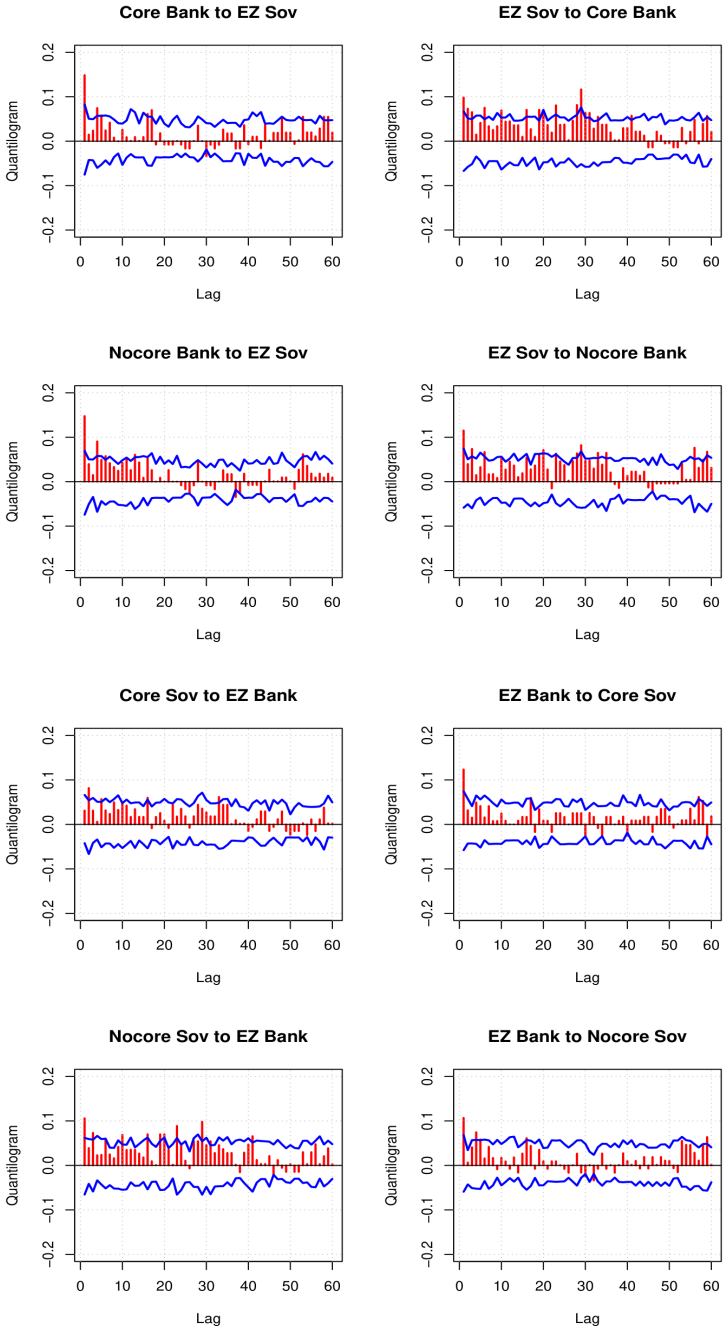
Notes: The impulse response functions to a one-standard deviation shock. $\theta = 0.95$.

Figure 7. Cross-quantilogram plot (A)



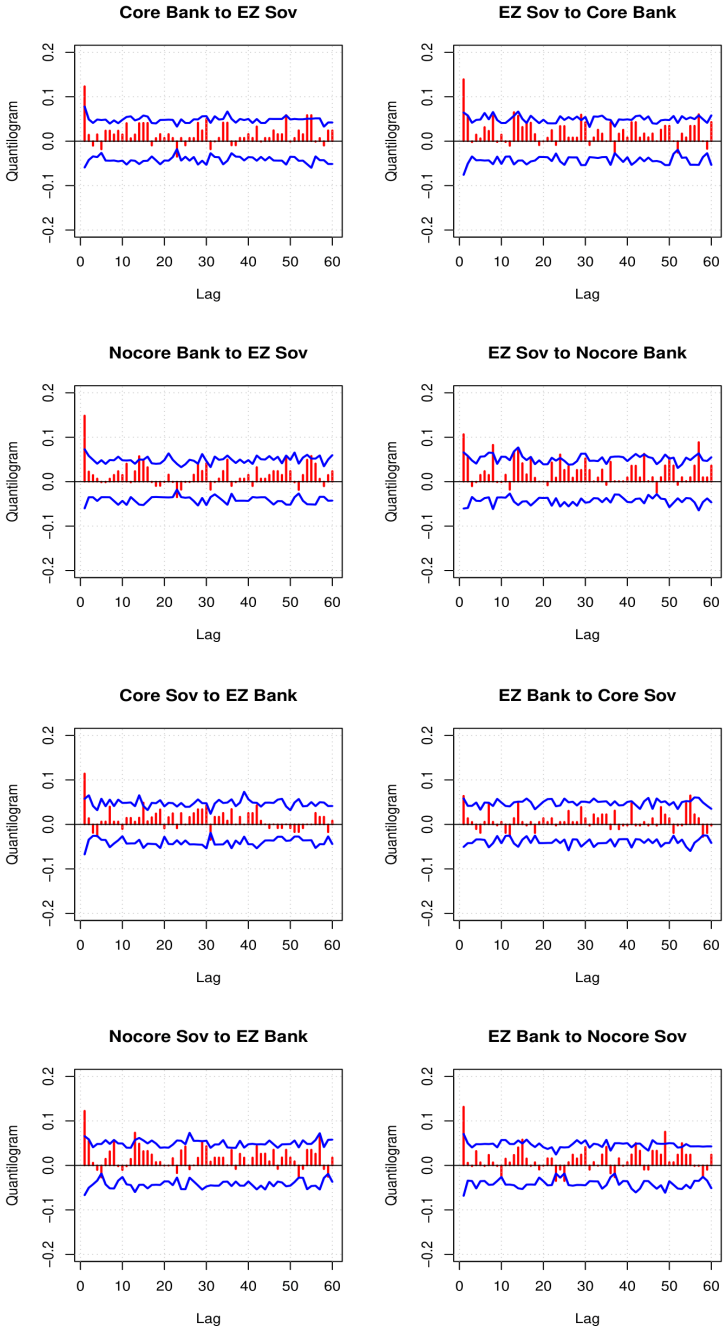
Notes: In the upper the Cross-quantilogram plot for $\theta = 0.05$, while in the lower for $\theta = 0.95$.

Figure 8. Cross-quantilogram plot (B)



Notes: Cross-quantilogram plot for $\theta = 0.95$.

Figure 9. Cross-quantilogram plot (C)



Notes: Cross-quantilogram plot for $\theta = 0.05$.

Tables

Table 1. CDS Sovereign

CDS Sovereign	Country	Weights
EZ Sov	Austria	0.04
	France	0.26
	Germany	0.34
	Ireland	0.02
	Italy	0.19
	Portugal	0.02
	Spain	0.13
Core Sov	Austria	0.06
	France	0.40
	Germany	0.54
NoCore Sov	Ireland	0.06
	Italy	0.54
	Portugal	0.05
	Spain	0.35

Notes: The first column reports the variables name; the second column reports the countries concerned; the last column reports the weight. GDP (2012) weighted.

Table 2. CDS Bank

CDS Bank	Country	Banks	Weights
EZ Bank	Austria	Erste Group Bank	0.017
		Raif Zentralbank	0.011
	Germany	Commerzbank	0.052
		Deutsche Bank	0.165
		Lb Baden-Wuerttemberg	0.027
	France	BNP Paribas	0.155
		Societe Generale	0.093
		Credit Agricole	0.132
	Ireland	Allied Irish Banks	0.009
		Bank Of Ireland	0.009
	Italy	Banca Monte Paschi	0.017
		Intesa Sanpaolo	0.055
		Unicredit	0.075
	Portugal	Espirito Santo	0.006
		Banco Com Portugues	0.007
	Spain	Bbv Argentaria	0.052
		Banco Santander	0.103
		Banco Pop Espanol	0.008
Core Bank	Austria	Erste Group Bank	0.026
		Raif Zentralbank	0.017
	Germany	Commerzbank	0.079
		Deutsche Bank	0.252
		Lb Baden-Wuerttemberg	0.042
	France	BNP Paribas	0.238
		Societe Generale	0.142
		Credit Agricole	0.202
NoCore Bank	Ireland	Allied Irish Banks	0.028
		Bank Of Ireland	0.026
	Italy	Banca Monte Paschi	0.052
		Intesa Sanpaolo	0.159
		Unicredit	0.219
	Portugal	Espirito Santo	0.018
		Banco Com Portugues	0.021
	Spain	Bbv Argentaria	0.151
		Banco Santander	0.300
		Banco Pop Espanol	0.024
Country Bank	Austria	Erste Group Bank	0.612
		Raif Zentralbank	0.388
	Germany	Commerzbank	0.212
		Deutsche Bank	0.675
		Lb Baden-Wuerttemberg	0.112
	France	BNP Paribas	0.409
		Societe Generale	0.244
		Credit Agricole	0.347
	Ireland	Allied Irish Banks	0.521
		Bank Of Ireland	0.478
	Italy	Banca Monte Paschi	0.120
		Intesa Sanpaolo	0.370
		Unicredit	0.509
	Portugal	Espirito Santo	0.454
		Banco Com Portugues	0.546
	Spain	Bbv Argentaria	0.317
		Banco Santander	0.631
		Banco Pop Espanol	0.051

Notes: The first column reports the variables name; the second column reports the countries concerned; the third column the bank concerned; the last column reports the weight. Total asset (2012) weighted.

Table 3. Summary Statistics

Variable	Mean	Median	S.D.	Min	Max
EZ Sov	77.4	54.8	53.7	15.8	256.
EZ Bank	145.	119.	78.1	44.7	448.
Core Sov	32.0	22.8	23.1	6.06	118.
NoCore Sov	156.	105.	111.	31.7	514.
Core Bank	116.	102.	58.4	32.0	365.
NoCore Bank	199.	156.	119.	66.0	605.

Table 4. Estimation results. Downside quantiles

	Downside quantiles $\theta = 0.05$						
EZ Bank	c_1	a_{11}	a_{12}	b_{11}	b_{12}	d_{11}	d_{12}
	−0.39***	−0.12*	−0.09**	0.89***	−0.00	−0.04***	−0.05***
	(0.18)	(0.07)	(0.04)	(0.09)	(0.03)	(0.01)	(0.01)
EZ Sov	c_2	a_{21}	a_{22}	b_{21}	b_{22}	d_{21}	d_{22}
	−0.22	−0.01	−0.13**	0.94***	−0.01	−0.03***	−0.03***
	(0.15)	(0.05)	(0.05)	(0.01)	(0.03)	(0.00)	(0.00)
Core Bank	c_1	a_{11}	a_{12}	b_{11}	b_{12}	d_{11}	d_{12}
	−0.57	−0.11	−0.08	0.91***	0.000	−0.05***	−0.06***
	(0.45)	(0.09)	(0.06)	(0.02)	(0.06)	(0.01)	(0.01)
EZ Sov	c_2	a_{21}	a_{22}	b_{21}	b_{22}	d_{21}	d_{22}
	0	0.03	−0.11*	0.04	0.92***	−0.00***	−0.01***
	(0.14)	(0.03)	(0.02)	(0.06)	(0.02)	(0.00)	(0.00)
NoCore Bank	c_1	a_{11}	a_{12}	b_{11}	b_{12}	d_{11}	d_{12}
	−0.74**	−0.29**	−0.18	0.59***	0.13	−0.11***	−0.12***
	(0.35)	(0.13)	(0.13)	(0.18)	(0.12)	(0.02)	(0.02)
EZ Sov	c_2	a_{21}	a_{22}	b_{21}	b_{22}	d_{21}	d_{22}
	−0.38	−0.12	−0.17**	−0.19	0.97***	−0.05***	−0.06***
	(0.28)	(0.12)	(0.08)	(0.17)	(0.05)	(0.01)	(0.01)
EZ Bank	c_1	a_{11}	a_{12}	b_{11}	b_{12}	d_{11}	d_{12}
	−0.61***	−0.19***	−0.09**	0.81***	−0.06*	−0.05***	−0.12***
	(0.18)	(0.05)	(0.04)	(0.06)	(0.03)	(0.02)	(0.01)
Core Sov	c_2	a_{21}	a_{22}	b_{21}	b_{22}	d_{21}	d_{22}
	−0.96***	−0.03	−0.29***	−0.08	0.78***	−0.09***	−0.17***
	(0.39)	(0.09)	(0.09)	(0.08)	(0.07)	(0.02)	(0.02)
EZ Bank	c_1	a_{11}	a_{12}	b_{11}	b_{12}	d_{11}	d_{12}
	−0.44***	−0.13**	−0.09***	0.84***	−0.04	−0.05***	−0.04***
	(0.14)	(0.06)	(0.04)	(0.06)	(0.03)	(0.01)	(0.01)
NoCore Sov	c_2	a_{21}	a_{22}	b_{21}	b_{22}	d_{21}	d_{22}
	−0.51***	−0.11	−0.15***	−0.15**	0.92***	−0.07 ***	−0.05***
	(0.18)	(0.07)	(0.04)	(0.08)	(0.03)	(0.01)	(0.02)
AT Bank	c_1	a_{11}	a_{12}	b_{11}	b_{12}	d_{11}	d_{12}
	−0.07	−0.04***	−0.01	0.98***	−0.01	−0.01***	−0.00***
	(0.05)	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)
AT Sov	c_2	a_{21}	a_{22}	b_{21}	b_{22}	d_{21}	d_{22}
	−1.04***	0.11	−0.44***	0.00	0.73***	−0.17***	−0.11***
	(0.23)	(0.09)	(0.05)	(0.05)	(0.05)	(0.03)	(0.03)

Table 4 continued from previous page

DE Bank	c_1	a_{11}	a_{12}	b_{11}	b_{12}	d_{11}	d_{12}
	−0.14**	−0.10***	0.00	0.95***	0.00	−0.01***	−0.01***
	(0.06)	(0.02)	(0.01)	(0.02)	(0.00)	(0.00)	(0.01)
DE Sov	c_2	a_{21}	a_{22}	b_{21}	b_{22}	d_{21}	d_{22}
	−0.14	0.04*	−0.12***	0.00	0.96***	−0.01***	−0.01***
	(0.13)	(0.02)	(0.02)	(0.02)	(0.01)	(0.00)	(0.01)
FR Bank	c_1	a_{11}	a_{12}	b_{11}	b_{12}	d_{11}	d_{12}
	−0.22	−0.10***	−0.11**	1.02***	−0.10***	−0.02***	−0.01***
	(0.15)	(0.03)	(0.04)	(0.06)	(0.05)	(0.00)	(0.00)
FR Sov	c_2	a_{21}	a_{22}	b_{21}	b_{22}	d_{21}	d_{22}
	−0.73	−0.20***	−0.42***	0.25	0.56***	−0.06***	−0.05**
	(0.61)	(0.07)	(0.05)	(0.18)	(0.17)	(0.01)	(0.02)
IE Bank	c_1	a_{11}	a_{12}	b_{11}	b_{12}	d_{11}	d_{12}
	−0.65***	−0.28***	−0.02	0.81***	−0.05	−0.16***	−0.16***
	(0.28)	(0.06)	(0.06)	(0.07)	(0.03)	(0.02)	(0.02)
IE Sov	c_2	a_{21}	a_{22}	b_{21}	b_{22}	d_{21}	d_{22}
	−0.59***	0.03*	−0.37***	−0.03	0.80***	−0.14***	−0.15***
	(0.11)	(0.01)	(0.03)	(0.02)	(0.05)	(0.02)	(0.02)
IT Bank	c_1	a_{11}	a_{12}	b_{11}	b_{12}	d_{11}	d_{12}
	−0.54**	−0.35***	−0.13***	0.61***	0.04	−0.06***	−0.10***
	(0.23)	(0.04)	(0.05)	(0.06)	(0.05)	(0.02)	(0.02)
IT Sov	c_2	a_{21}	a_{22}	b_{21}	b_{22}	d_{21}	d_{22}
	−0.28*	−0.16*	−0.10**	−0.18*	0.99***	−0.03***	−0.05***
	(0.17)	(0.10)	(0.05)	(0.11)	(0.03)	(0.01)	(0.01)
PT Bank	c_1	a_{11}	a_{12}	b_{11}	b_{12}	d_{11}	d_{12}
	−0.78**	−0.41*	−0.07	0.82***	−0.14*	−0.13***	−0.16***
	(0.34)	(0.24)	(0.09)	(0.12)	(0.08)	(0.03)	(0.03)
PT Sov	c_2	a_{21}	a_{22}	b_{21}	b_{22}	d_{21}	d_{22}
	−0.95***	−0.21	−0.23***	−0.03	0.72***	−0.16***	−0.20***
	(0.24)	(0.15)	(0.08)	(0.09)	(0.08)	(0.03)	(0.03)
ES Bank	c_1	a_{11}	a_{12}	b_{11}	b_{12}	d_{11}	d_{12}
	−0.65**	−0.38***	−0.03	0.55***	0.25	−0.02***	−0.04***
	(0.27)	(0.07)	(0.07)	(0.11)	(0.15)	(0.00)	(0.00)
ES Sov	c_2	a_{21}	a_{22}	b_{21}	b_{22}	d_{21}	d_{22}
	−0.06	−0.05	−0.03**	−0.03	0.98***	−0.03***	−0.06***
	(0.07)	(0.04)	(0.01)	(0.05)	(0.04)	(0.01)	(0.01)

Notes: Table reports the estimation results of the MVQM-CAViaR (1,1) for each weighted-portfolio, respectively. Estimated coefficients are in the first row. Numbers in parentheses are standard errors of the corresponding estimated coefficients. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

Table 5. Estimation results. Upside quantiles

	Downside quantiles $\theta = 0.95$						
EZ Bank	c1	a11	a12	b11	b12	d11	d12
	0.47***	0.23**	0.07	0.92***	−0.06	0.06***	0.01
	(0.14)	(0.10)	(0.10)	(0.01)	(0.06)	(0.01)	(0.01)
EZ Sov	c2	a21	a22	b21	b22	d21	d22
	0.29	0.1	0.25***	−0.07	0.85***	0.04***	0.01
	(0.18)	(0.08)	(0.10)	(0.08)	(0.06)	(0.00)	(0.01)
Core Bank	c1	a11	a12	b11	b12	d11	d12
	0.53***	0.31***	0.03	0.84***	−0.01	0.06***	0.02
	(0.15)	(0.10)	(0.06)	(0.09)	(0.04)	(0.01)	(0.01)
EZ Sov	c2	a21	a22	b21	b22	d21	d22
	0.24	0.1	0.26***	−0.01	0.86***	0.02***	0.01
	(0.16)	(0.06)	(0.06)	(0.07)	(0.05)	(0.00)	(0.01)
NoCore Bank	c1	a11	a12	b11	b12	d11	d12
	0.31***	0.21**	0.1	0.84***	−0.04	0.06***	0.02*
	(0.11)	(0.09)	(0.08)	(0.07)	(0.05)	(0.01)	(0.01)
EZ Sov	c2	a21	a22	b21	b22	d21	d22
	0.27	0.08	0.26***	−0.07	0.87***	0.05***	0.02*
	(0.24)	(0.07)	(0.09)	(0.09)	(0.05)	(0.01)	(0.01)
EZ Bank	c1	a11	a12	b11	b12	d11	d12
	0.58***	0.27***	0.06	0.80***	−0.06*	0.08***	0.07***
	(0.17)	(0.07)	(0.04)	(0.04)	(0.04)	(0.01)	(0.01)
Core Sov	c2	a21	a22	b21	b22	d21	d22
	0.70***	0.24***	0.20***	−0.18***	0.86***	0.11***	0.08***
	(0.23)	(0.10)	(0.03)	(0.06)	(0.03)	(0.02)	(0.02)
EZ Bank	c1	a11	a12	b11	b12	d11	d12
	0.53***	0.22***	0.14*	0.78***	−0.05	0.06***	0.07***
	(0.12)	(0.07)	(0.07)	(0.06)	(0.03)	(0.01)	(0.02)
NoCore Sov	c2	a21	a22	b21	b22	d21	d22
	0.18	−0.03	0.26***	0.06	0.85***	0.02***	0.02***
	(0.18)	(0.12)	(0.06)	(0.07)	(0.03)	(0.00)	(0.00)
AT Bank	c1	a11	a12	b11	b12	d11	d12
	0.17***	0.33***	0.05**	0.87***	−0.03***	0.04***	0.03***
	(0.06)	(0.04)	(0.03)	(0.02)	(0.00)	(0.00)	(0.00)
AT Sov	c2	a21	a22	b21	b22	d21	d22
	0.53***	0.03	0.53***	0.00	0.73***	0.14***	0.12***
	(0.19)	(0.11)	(0.08)	(0.05)	(0.04)	(0.02)	(0.03)

Table 5 continued from previous page

DE Bank	c1	a11	a12	b11	b12	d11	d12
	0.62*	0.27***	0.02	0.90***	−0.03	0.08***	0.04*
	(0.29)	(0.10)	(0.02)	(0.10)	(0.03)	(0.01)	(0.02)
DE Sov	c2	a21	a22	b21	b22	d21	d22
	2.34	0.30**	0.66***	0.01	0.44**	0.31***	0.17**
	(1.79)	(0.13)	(0.11)	(0.46)	(0.19)	(0.07)	(0.07)
FR Bank	c1	a11	a12	b11	b12	d11	d12
	0.69***	0.20***	0.00	0.90***	0.00	0.08***	0.06***
	(0.24)	(0.06)	(0.03)	(0.10)	(0.02)	(0.02)	(0.02)
FR Sov	c2	a21	a22	b21	b22	d21	d22
	0.99**	0.23*	0.25***	−0.23*	0.88***	0.12***	0.08***
	(0.40)	(0.13)	(0.07)	(0.14)	(0.04)	(0.02)	(0.03)
IE Bank	c1	a11	a12	b11	b12	d11	d12
	−0.19	0.89***	0.10***	0.45***	0.19*	0.04***	0.06***
	(0.14)	(0.13)	(0.04)	(0.14)	(0.11)	(0.01)	(0.01)
IE Sov	c2	a21	a22	b21	b22	d21	d22
	0.02	−0.01	0.13***	0.02	0.93***	0.00***	0.00**
	(0.03)	(0.05)	(0.02)	(0.04)	(0.02)	(0.00)	(0.00)
IT Bank	c1	a11	a12	b11	b12	d11	d12
	0.36***	0.16***	0.15***	0.85***	−0.05*	0.07***	0.04***
	(0.11)	(0.04)	(0.05)	(0.06)	(0.03)	(0.01)	(0.01)
IT Sov	c2	a21	a22	b21	b22	d21	d22
	0.43***	0.13*	0.28***	−0.12	0.87***	0.08***	0.05*
	(0.13)	(0.07)	(0.07)	(0.07)	(0.05)	(0.02)	(0.03)
PT Bank	c1	a11	a12	b11	b12	d11	d12
	0.15	0.24***	0.08*	0.89***	−0.04	0.02***	0.03***
	(0.10)	(0.05)	(0.04)	(0.02)	(0.03)	(0.00)	(0.00)
PT Sov	c2	a21	a22	b21	b22	d21	d22
	0.33***	0.07*	0.23***	−0.02	0.89***	0.05***	0.08***
	(0.13)	(0.04)	(0.06)	(0.02)	(0.05)	(0.01)	(0.01)
ES Bank	c1	a11	a12	b11	b12	d11	d12
	0.45***	0.25***	0.17***	0.89***	−0.16*	0.05***	0.05***
	(0.14)	(0.06)	(0.06)	(0.04)	(0.07)	(0.01)	(0.01)
ES Sov	c2	a21	a22	b21	b22	d21	d22
	0.36***	0.14**	0.16***	−0.06*	0.85***	0.06***	0.06***
	(0.11)	(0.05)	(0.04)	(0.03)	(0.05)	(0.01)	(0.01)

Notes: Table reports the estimation results of the MVQM-CAViaR (1,1) for each weighted-portfolio, respectively. Estimated coefficients are in the first row. Numbers in parentheses are standard errors of the corresponding estimated coefficients. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

Table 6. Asymmetric attribute

Bank on Sov	**0.05**	**0.95**	**Asymmetric**	**Sov on Bank**	**0.05**	**0.95**	**Asymmetric**
EZ bank on EZ Sov	-0.38	0.75	-0.37	EZ Sov on EZ Bank	-0.65	0.9	-0.25
Core Bank on EZ Sov	-0.4	1.1	-0.7	EZ Sov on Core Bank	-0.65	0.9	-0.25
NoCore Bank on EZ Sov	-0.9	0.6	0.3	EZ Sov on NoCore Bank	-0.63	0.9	-0.27
EZ Bank on Core Sov	-0.58	0.82	-0.24	Core Sov on EZ Bank	-1.5	0.82	0.68
EZ Bank on NoCore Sov	-0.38	0.65	-0.27	NoCore Sov on EZ Bank	-1.2	0.95	0.25
DE Bank on DE Sov	-0.33	0.9	-0.57	DE Sov on DE Bank	-0.78	4.3	-3.52
FR Bank on FR Sov	-0.39	1.1	-0.71	FR Sov on FR Bank	-2	1.4	0.6
IT Bank on IT Sov	-1.1	0.55	0.55	IT Sov on IT Bank	-1.53	1.1	0.43
ES Bank on ES Sov	-0.15	0.9	-0.75	ES Sov on ES Bank	-1.12	0.78	0.34
Average	-0.50	0.80	-0.30	Average	-1.13	1.30	-0.17

Notes: The left-side columns report the impact and the asymmetric attribute for the response of Bank on Sov shock; the right-side column columns report the impact and the asymmetric attribute for the response of Sov on Bank shock.