How important are GSI banks for the financial distress in the Eurozone? An analysis based on MIDAS VAR

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Abstract

In this paper, we examine the role of the Globally Systemic Important Banks, GSIB, located in Europe as a possible source of financial distress in eurozone. For this purpose we fit a MIDAS VAR to daily observation of individual bank CDS spread changes (a proxy of individual bank distress) and to the weekly observations of the CISS index constructed by ECB to proxy financial distress in the eurozone. Our findings show that, overall, GSIBs' distress shocks account for 8.5% of the EZ financial stress variation at 4-week horizon, by averaging across different regimes, and, during the financial turmoil period, their impact raises above 10%. Moreover, the shocks in MIDAS VAR model explain a much larger part of the FEVD than those obtained by a traditional VAR model.

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1. INTRODUCTION

The instability in banking sector has been one of the major threats for the European financial system in the last decade. Firstly, this instability has originated after the collapse of the US investment bank Lehman Brothers. In the following years, several eurozone member states were facing the possibility of default since the significant amounts of euro-area sovereign debt were held in the European banks. As the result, the default risk in the majority of the European banks reached the peak in the end of 2011. In that time, the financial regulatory authorities have introduced new regulations in order to prevent the failure of so-called *global systemically important banks (GSIBs)*. In November 2011, Financial Stability Board (FSB) published a list of GSIBs, which failure due to their notable size, interconnectedness, substitutability, complexity, cross jurisdictional activities would be significantly harmful for the all financial system and economic activity (FSB, 2016). Nevertheless, in the end of 2016, the fears of a European banking crisis have been still on the rise, with the particular attention to Germany's Deutsche Bank.

In this paper we seek to examine the role of the European GSIBs as a possible source of financial distress in euro-area. Our empirical analysis concentrates on 12 GSI banks located in Europe. In line with recent literature, we use daily CDS spreads with 5-year maturity as an indicator of G-SIB distress.[1] To proxy financial distress of the eurozone we select a weekly composite indicator of systemic stress (CISS) for EZ, developed by Hollo (2012). The collected data covers the period starting before the global financial crisis and ending in 28/10/2016. In particular, our analysis is carried out for three periods: (i) before the global financial crisis (GFC), (ii) during the GFC and European sovereign debt crisis (SDC), and (iii) after the SDC. Unlike many studies, we do not impose the start and the end day of each period exogenously. Instead, we infer the break dates from our data. For this, we use Qu and Perron (2007) methodology applied to a reduced-form VAR(1) model fitted to the changes in CDS spread and the CISS index.

This paper contributes to the literature in several ways. First, to analyse the importance of GSIBs to EZ financial distress we use a recently developed structural MIDAS-VAR model, suggested by Ghysels (2016), which allows to deal with mismatch of the data frequency. In particular, we estimate forecast error variance decomposition and impulse response analysis by using mixed frequency data: daily CDS spreads and weekly CISS index. By using MIDAS-VAR we can evaluate the effect of European GSIBs distress shocks depending on the day of the week they occur. We also compare the results obtained by MIDAS-VAR model and the common-frequency (traditional) SVAR model.

[1] Even if CDS spreads have a number of advantages in proxing for credit and default risk, the use of CDS spreads data for financial institutions is relatively recent (Ballester et al., 2016; Alter and Schüler, 2012; Alter and Beyer, 2014, among others).

Second, our paper contributes to the literature on financial stability monitoring and on global systemically important European banks supervision. In particular, our paper relates to a literature seeking to measure the contribution of financial institutions to a whole financial system. Several authors have proposed measures to identify the systemic contribution of a bank or other financial institution to the all financial system. Among others, Adrian and Brunnermeier (2016) proposed the Conditional Value-at-Risk (CoVaR) to evaluate the system loss conditional on each institution being in distress. Other alternative measures of expected loss of an institution when the system is in distress are: Marginal Expected Shortfall (MES) by Acharya et al. (2017), the Systemic Risk Measure (SRISK) by Brownlees and Engle (2016) and the Distress Insurance Premium (DIP) by Huang, Zhou, Zhu (2012).

Since our sample period includes a number of key events affecting the eurozone financial market, like: global financial crisis, eurozone crisis, the changes in the banking supervision regarding the GSIBs, few questions have arisen. How important are European GSIBs for eurozone financial stability? How the impact has changed during the years? What is the role of non-EZ GSIBs for the EZ financial distress? Which European GSIBs were the most important for EZ financial distress before and after the global financial crisis?

The main findings of our paper are the following. First, EZ financial stability is vulnerable to European GSI banks distress shocks and the contribution has been increasing in period 2002 – 2016. In the period before the global financial crisis, only distress shocks of two analyzed banks explained more than 10% of the EZ financial stress variation at 4-week horizon. While in the later period (July 2007 – October 2016) 8 out of the 12 analysed GSI banks accounted for more than 10% of the EZ financial distress. Overall, we find that the major contribution of GSIBs distress shocks to CISS fluctuations occurred in the last regime. Second, MIDAS-SVAR results suggest that a shock observed at the beginning of the week, especially Monday, has a stronger effect than the shocks occurring in the other days of the week. In addition, we observe that the main results in MIDAS SVAR model are supported by the traditional SVAR. However, the shocks in MIDAS-SVAR model explain a much larger part of the FEVD than in traditional SVAR model.

Third, we find that in the recent years the 4 biggest contributors to EZ financial distress were UBS, DB, Barclays bank and HSBC bank. In contrast, we find that UniCredit bank and Société Générale bank were the least important for EZ financial fluctuations in 2002–2016. Moreover, the rankings suggest that the contribution of non-eurozone GSIBs is not less important as the contribution of EZ-GSIBs. In addition, the systemic importance of non-eurozone GSIBs has increased since September 2007. Finally, the biggest contributors to the EZ financial distress not often coincide with the banks with the highest CDS spreads.

The rest of the paper is organized as follows. In Section 2 we present the methodology. Section 3 describes the data. Section 4 discusses our results. Finally, Section 5 concludes.

2. METHODOLOGY

2.1 Structural Change Points in VAR Models

We use Qu and Perron (2007) methodology to test for structural change points in a VAR model when the dates and the number of points in the parameters are unknown. Following the authors' notation, we denote *m* as total number of structural changes in the system and *m+1* as the number of unknown regimes. The total number of observations is indicated by T and the unknown break dates by vector$(T_1, \dots, \mathrm{T_m})$, where $T_0 = 1$ and $T_{m+1} = T$. Consequently, each regime $j = (1, \dots, m+1)$ has a sub-period of length $T_{j-1} + 1 \le t \le T_j$. Consider the following reduced-form vector autoregressive model with two variables and 1 lag, as in the application in Section 4:

$$\mathrm{y_t} = \mu + \Gamma \mathrm{y_{t-1}} + \mathrm{u_t}, \tag{1}$$

where $y_t = (\Delta CISS_t, \Delta cds_t)'$ is a vector of weekly endogenous variables observed at week *t*, $\mu_j = (\mu_j^1, \mu_j^2)'$ is a constant term, $\Gamma_{j1} = (\gamma_{j1}^{11}, \gamma_{j1}^{12}, \gamma_{j1}^{21}, \gamma_{j1}^{22})$ is a (2×2) coefficient matrix of the model and an error term u_t has a mean zero and a covariance matrix $E(u_t u_t') = \sum_j$. When testing for structural breaks, we allow only a covariance matrix $\sum$ of residuals to change.

In order to determine the number of break points in the model, we rely on tests suggested by Qu and Perron (2007). Firstly, we use a *double maximum test* to see if at least one structural break is present in our model. More precisely, we test the null hypothesis of no structural break versus an unknown number of breaks given some upper bound M. If the test rejects the null hypothesis, we use a *SEQ(l+1|l)* test. The test uses the sequential testing procedure considering the null hypothesis of *l* breaks against an alternative hypothesis of *l+1* structural breaks.

2.2 From Traditional to Mixed Frequency VAR Models

2.2.1 VAR Analysis: Traditional Approach

In a *traditional* VAR model it is common to use the time series sampled at the same frequency. If the data have a different frequency the usual solution is to aggregate the higher-frequency variable to the frequency of the lowest-frequency variable. In our case, a CISS has a weekly frequency and all CDS spread variables are published daily. Thus, for our *traditional* VAR model estimation we simply take an average of a daily CDS spread within one week. In addition, we test for unit roots in all the variables, using the Augmented Dickey-fuller test (ADF, Dickey and Fuller, 1981). The results show that all the variables are integrated of order one (i.e. stationary in first differences). Thus, for the analysis we transform the data in the first-differences.

Consider a traditional structural representation of VAR *(p)* model is as follows:

$$Ay_t = c + \sum_{i=1}^{p} C_i y_{t-i} + B\varepsilon_t, \quad \varepsilon_t \sim N(0, I_n) \tag{2}$$

where y_t is a (2×1) vector of endogenous variables, containing a weekly change of CDS spread(Δcds) and a weekly change in eurozone's financial distress ($\Delta CISS$), A is a (2×2) coefficient matrix of contemporaneous relations among the endogenous variables, B is a (2×2) coefficient matrix of standard deviations restricted to be diagonal and ε_t is a (2×1) vector of orthogonalized structural shocks with covariance matrix Σ_ε. The structural shocks ε_t include a GSI bank distress shock (ε_t^b) and a EZ financial distress shock (ε_t^f). In order to estimate the structural model we need to express it in a reduced-form. We can do it by pre-multiplying the structural model by A^{-1}. A reduced-form vector autoregressive model with p-lag order:

$$y_t = \mu + \sum_{i=1}^{p} \Gamma_i y_{t-i} + u_t, \qquad u_t \sim N(0, \Sigma_u), \tag{3}$$

where $y_t = (\Delta cds_t, \Delta CISS_t)'$ is a vector of an endogenous variables observed at week t, $\mu_j = (\mu^1, \mu^2)'$ is a constant term, $\Gamma_i = (\gamma_i^{11}, \gamma_i^{12}, \gamma_i^{21}, \gamma_i^{22})$ is a (2 × 2) coefficient matrix of the model and an error term u_t has a mean zero and a covariance matrix $E(u_t u_t') = \sum_u$. In the first step, the residuals (u_t) of the reduced-VAR model (3) are obtained by using OLS estimation.[2] Then, in the second step, we identify the structural shocks by using exactly identified Cholesky decomposition. Considering that we are interested in analysing the impact of GSI bank distress shock on EZ financial distress, we put a variable of CDS spread before the CISS. Therefore, we assume that a GSIB's distress shocks affect contemporaneously (within a week) a EZ financial distress, but not vice versa. Thus, we consider matrix $A = \begin{pmatrix} 1 & 0 \\ a & 1 \end{pmatrix}$ to be a lower triangular matrix with 1's on the diagonal and the matrix $B = \begin{pmatrix} b_1 & 0 \\ 0 & b_2 \end{pmatrix}$ to be simply diagonal, with b_1 and b_2 being the standard deviations. Finally, the structural shocks can be estimated from the reduced-form errors by using this relationship:

$$u_t = A^{-1}Be_t \qquad e_t \sim N(0, I_2), \tag{4}$$

Then, we estimate the impulse responses from the structural Vector Moving Average representation:

$$y_t = \Phi_0 \varepsilon_t + \Phi_1 \varepsilon_{t-1} + \cdots, \tag{5}$$

where Φ_i matrix contains the structural impulse responses, which can be estimated from $\Phi_i = \Psi_i A^{-1} B$, $\Psi_i = \sum_{i=1}^{s} \Psi_{s-i}\Gamma_i$ $\ for\ i = 1,2 \ldots$.[3]

[2] An optimal lag length p was chosen using a *Bayesian information criterion*.

[3] We consider a reduced-form VAR(p) model Vector Moving average representation to be: $y_t = \Psi_0 u_t + \Psi_1 u_{t-1} + \cdots$, with $\Psi_0 = I_2$.

2.2.2 VAR Analysis: MIDAS Approach

In a recent literature, it has become more popular to use a mixed-frequency data directly, without a need to aggregate the data the same sampling frequency (see Ghysels, 2016; Clements and Galvão, 2008; Foroni et al., 2015; Götz at al., 2016; among others). In this section, we present a VAR model for mixed frequency data proposed by Ghysels (2016).

Let us firstly consider a common notation in a mixed-frequency literature. We denote a low-frequency variable by y_L and a high frequency variable by y_H. A high-frequency variable is observed m times during a low-frequency period t. Ghysels (2016) distinguish the situation where (i) m is fixed e.g. the case where series have quarterly/annual, monthly/quarterly, weekly/daily observations; and (ii) a situation where m is pre-determined by a certain time path e.g. daily/monthly, weekly/quarterly observations. In this paper, we consider a weekly/daily observation case when the high-frequency variable – CDS spread, is observed 5 days during a week, i.e. *m=5.* An index *j =(1,2,3,4,5)* indicates a specific high-frequency observation in a week t. More precisely, we indicate a CDS spread on Monday by $y_H(t,1)$, Tuesday by $y_H(t,2)$, Wednesday by $y_H(t,3)$, Thursday by $y_H(t,4)$ and Friday by $y_H(t,5)$. Next, we compose a vector of endogenous variables following Ghysels (2016) *stacked vector* approach. Thus, we append a low-frequency and high-frequency variables into the column vector of six endogenous variables.[4]

Consider a basic reduced-form MIDAS-VAR(p) model:

$$Z_t = \mu + \sum_{i=1}^{p} \Gamma_i Z_{t-i} + u_t^{MF}, \tag{6}$$

where Z_t is a vector of endogenous variables, Γ_i is a coefficient matrix and u_t^{MF} is independent and identically distributed (i.i.d.) error term with $\mathrm{E}(u_t^{MF}) = 0$ and $E\left(u_t^{MF} u_t^{MF'}\right) = \Sigma_u^{MF}$. In lag operator notation, the MIDAS-VAR(p) can be written as:

$$\Gamma(L) Z_t = \mu + u_t^{MF}, \tag{7}$$

where L denotes a low-frequency lag operator and $\Gamma(L) = 1 - \sum_{i=1}^{p} \Gamma_i L^i$. Z_t is generated by the MIDAS-VAR(p) model, for which it holds that that (i) the roots of the matrix polynomial $\Gamma(L)$ all lie outside the unit root circle; (ii) u_t^{MF} is independent and identically distributed (i.i.d.) with $\mathrm{E}(u_t^{MF}) = 0$, $E\left(u_t^{MF} u_t^{MF'}\right) = \Sigma_u^{MF}$. The assumption (i) ensures that the MIDAS-VAR is I(0) and (ii) is a standard assumption to ensure validity of the bootstrap for VAR models (see Götz at al. 2016, Assumption 2). A reduced-form MIDAS-VAR model can be treated as a *traditional* VAR model. The parameters in Γ_p and

[4] For more details on stacked vector see Ghysels (2016).

residuals (u_t^{MF}) of the model can be estimated by using an OLS estimator and an optimal lag length can be obtained using a standard approach.[5]

Consider $Z_t = \big(y_H(t,1), y_H(t,2), y_H(t,3), y_H(t,4), y_H(t,5), y_L(t)\big)'$ to be a vector of endogenous variables. Then a reduced-form MIDAS-VAR(p) model in a matrix notation has the following form:

$$\begin{pmatrix} y_H(t,1) \\ y_H(t,2) \\ y_H(t,3) \\ y_H(t,4) \\ y_H(t,5) \\ y_L(t) \end{pmatrix} = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \\ \mu_4 \\ \mu_5 \\ \mu_L \end{pmatrix} + \sum_{i=1}^{p} \begin{pmatrix} \gamma_{11}^i & \gamma_{12}^i & \gamma_{13}^i & \gamma_{14}^i & \gamma_{15}^i & \gamma_1^i \\ \gamma_{21}^i & \gamma_{22}^i & \gamma_{23}^i & \gamma_{24}^i & \gamma_{25}^i & \gamma_2^i \\ \gamma_{31}^i & \gamma_{32}^i & \gamma_{33}^i & \gamma_{34}^i & \gamma_{35}^i & \gamma_3^i \\ \gamma_{41}^i & \gamma_{42}^i & \gamma_{43}^i & \gamma_{44}^i & \gamma_{45}^i & \gamma_4^i \\ \gamma_{51}^i & \gamma_{52}^i & \gamma_{53}^i & \gamma_{54}^i & \gamma_{55}^i & \gamma_5^i \\ \gamma_{L1}^i & \gamma_{L2}^i & \gamma_{L3}^i & \gamma_{L4}^i & \gamma_{L5}^i & \gamma_L^i \end{pmatrix} \begin{pmatrix} y_H(t-i,1) \\ y_H(t-i,2) \\ y_H(t-i,3) \\ y_H(t-i,4) \\ y_H(t-i,5) \\ y_L(t-i) \end{pmatrix} + \begin{pmatrix} u_H(t,1) \\ u_H(t,2) \\ u_H(t,3) \\ u_H(t,4) \\ u_H(t,5) \\ u_L(t) \end{pmatrix}, \quad (8)$$

where a time index t remains a week, as in a *traditional VAR* model (3). Parameters to be estimated in each Γ_i are *(m+1)*[2] with $i = (1, \dots, p)$ being a lag order and a covariance matrix of error term being symmetric:

$$\Sigma_u^{MF} = \begin{pmatrix} \sigma_{11} & \cdots & \cdots & \sigma_{1L} \\ \vdots & \sigma_{22} & \cdots & \vdots \\ \sigma_{51} & \vdots & \ddots & \vdots \\ \sigma_{L1} & \sigma_{L2} & \cdots & \sigma_L \end{pmatrix}. \quad (9)$$

In MIDAS-VAR model a matrix Γ_i includes the dynamics of the high-frequency variables naturally missing in the formulation of the *traditional* reduced-form specification.[6] Moreover, the covariance matrix of error terms contains contemporaneous relations between the high frequency variables ($\sigma_{11}, \dots, \sigma_{15}, \sigma_{21}, \dots, \sigma_{25}, \dots, \sigma_{51}, \dots, \sigma_{55}$) and between the low- and high-frequency variables ($\sigma_{L1}, \dots, \sigma_{L5}, \sigma_{1L}, \dots, \sigma_{5L}$) (see Bacchiocchi et al. 2016, Götz et al. 2016).

Now, consider a structural MIDAS-VAR model:

$$A \begin{pmatrix} y_H(t,1) \\ y_H(t,2) \\ y_H(t,3) \\ y_H(t,4) \\ y_H(t,5) \\ y_L(t) \end{pmatrix} = c + \sum_{i=1}^{p} \mathrm{C}_i \times \begin{pmatrix} y_H(t-i,1) \\ y_H(t-i,2) \\ y_H(t-i,3) \\ y_H(t-i,4) \\ y_H(t-i,5) \\ y_L(t-i) \end{pmatrix} + B \begin{pmatrix} \varepsilon_H(t,1) \\ \varepsilon_H(t,2) \\ \varepsilon_H(t,3) \\ \varepsilon_H(t,4) \\ \varepsilon_H(t,5) \\ \varepsilon_L(t) \end{pmatrix}, \quad (10)$$

where A is a coefficient matrix containing contemporaneous relations within a week, C_i is a matrix containing structural-form VAR coefficients and $\varepsilon_t^{MF} = (\varepsilon_H(t,j)', \varepsilon_L(t)')$ is a vector of structural shocks, with a covariance matrix $\varepsilon_t^{MF} \sim \mathrm{N}(0, \mathrm{I}_6)$. Structural shocks can be recovered from reduced-form

[5] We choose an optimal lag length p (in weeks) by using a *Bayesian information criterion*.

[6] In MIDAS-VAR approach, a high-frequency variable does not depend on its own natural lag. For instance, the observation of Tuesday of week t does not depend on observation of Monday of the same week t, i.e. $y_H(t,2)$ does not depend on its first natural lag $y_H(t,1)$.

errors u_t^{MF} by $u_t^{MF} = A^{-1}B\varepsilon_t^{MF}$ and its variance-covariance matrix is $\Sigma_u^{MF} = A^{-1}BB'A^{-1\prime}$. For estimation we use a ML estimator, generally used also in a traditional SVAR literature.

We analyse dynamic interactions between the endogenous variables in MIDAS-VAR model by using the impulse response analysis. Since the ordering of the variables in the stacked vector (Z_t) in MIDAS-VAR models is no longer arbitrary, Ghysels (2016) consider the Cholesky decomposition to be a natural tool for an impulse response analysis.[7] Thus, we identify the structural shocks by using Cholesky decomposition and ordering a CISS after the CDS spread.[8] Likewise in a traditional SVAR model, we estimate the impulse responses from the structural form of vector moving average representation in eq. (5), by considering the following relationship:

$$\begin{pmatrix} u_H^{cds}(t,1) \\ u_H^{cds}(t,2) \\ u_H^{cds}(t,3) \\ u_H^{cds}(t,4) \\ u_H^{cds}(t,5) \\ u_L^{CISS}(t) \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ a_1 & 1 & 0 & 0 & 0 & 0 \\ a_2 & a_3 & 1 & 0 & 0 & 0 \\ a_4 & a_5 & a_6 & 1 & 0 & 0 \\ a_7 & a_8 & a_9 & a_{10} & 1 & 0 \\ a_{11} & a_{12} & a_{13} & a_{14} & a_{15} & 1 \end{pmatrix} \begin{pmatrix} b_{11} & 0 & 0 & 0 & 0 & 0 \\ 0 & b_{22} & 0 & 0 & 0 & 0 \\ 0 & 0 & b_{33} & 0 & 0 & 0 \\ 0 & 0 & 0 & b_{44} & 0 & 0 \\ 0 & 0 & 0 & 0 & b_{55} & 0 \\ 0 & 0 & 0 & 0 & 0 & b_{66} \end{pmatrix} \begin{pmatrix} \varepsilon_H^{br}(t,1) \\ \varepsilon_H^{br}(t,2) \\ \varepsilon_H^{br}(t,3) \\ \varepsilon_H^{br}(t,4) \\ \varepsilon_H^{br}(t,5) \\ \varepsilon_L^{f}(t) \end{pmatrix}, \quad (11)$$

where $u_H^{cds}(t,j)$, $u_L^{CISS}(t)$ are the error terms of reduced-form model, $\varepsilon_H^{br}(t,j)$ represent a bank distress shock in a *j'th* day in a week *t* and a $\varepsilon_L^{f}(t)$ is a financial distress shock in euro area in a week *t.* Therefore, we assume that the high-frequency structural shocks ($\varepsilon_H^{br}(t,j)$) hit a low frequency variable 5 times within the same week ($a_{11}, a_{12}, a_{13}, a_{14}, a_{15}$), but not vice versa. In addition, we assume that a bank risk shocks on Monday $\varepsilon_H^{br}(t,1)$ affects a CDS spread of the following days of the week *t* (a_1, a_2, a_4, a_7).

3. DATA

To identify the impact of Global systemically important banks' distress on the overall EZ financial system we rely on two proxies: credit default swap (CDS) spreads and composite indicator of systemic stress (CISS) in EZ.

Our analysis concentrate on 12 banks located in Europe: *BNP Paribas (FR), Banco Santander S.A. (ES), Barclays Bank PLC (UK), Groupe Crédit Agricole (FR), Deutsche Bank AG (DE), HSBC Bank PLC (UK), ING Bank NV (NL), Royal Bank of Scotland (UK),* Société Générale S.A. *(FR), Standard Chartered Bank (UK), UBS AG (CH) and UniCredit SpA (IT).* All the selected banks, according to FSB, were considered as the Global Systemically Important Banks in 2016. In line with recent literature, we use the CDS

[7] See also Ghysels (2016), Foroni et al. (2015).
[8] See section 2.2.1 for the explanation of the variable order.

spreads as an indicator of G-SIB distress.[9] In particular, we collect the senior CDS spreads with 5-year maturity since these contacts are generally considered the most liquid and constitute the majority of the entire CDS market.[10] The data is from Bloomberg. All CDS spreads are free of units and are usually denominated in basis points. For our analysis we transform CDS spreads in percentages, where 1 basis point = 0.01%.

As a measure of financial distress in eurozone we use a Composite Indicator of Systemic Stress (CISS), proposed by Hollò et al. (2012). CISS index is based on 15 raw indicators of financial stress representing the movements in five important financial sectors of euro area: money market, foreign exchange market, the bank and non-bank financial intermediaries sector, equity market and bond market. The construction of the index consists in: firstly, the raw indicators have to be transformed by cumulative distribution function (CDF). Secondly, the separate sub-indexes are computed for each of the five markets and finally, the five sub-indexes are aggregated by taking into account the time-varying correlation between five sub-indexes. We collect CISS data from ECB database. By the construction, the value of CISS varies between 0 and 1. The higher CISS indicates the higher stress level in eurozone.

Table 1. Dataset: description and sources

Name of the variable	Symbol	Country	Frequency	Time span: From	Time span: To	Source
Composite indicator of systemic stress	CISS	EZ	Weekly	21/09/2001	28/10/2016	ECB
CDS spreads of:						
BNP Paribas SA	BNP	FR	Daily	13/05/2002	28/10/2016	Bloomberg
Banco Santander SA	SANTAN	ES	Daily	24/06/2002	28/10/2016	Bloomberg
Barclays Bank PLC	BACR	GB	Daily	27/01/2003	28/10/2016	Bloomberg
Credit Agricole SA	ACAFP	FR	Daily	10/09/2007	28/10/2016	Bloomberg
Deutsche Bank AG	DB	DE	Daily	25/03/2002	28/10/2016	Bloomberg
HSBC Bank PLC	HSBC	GB	Daily	10/03/2003	28/10/2016	Bloomberg
ING Bank NV	INTNED	NL	Daily	27/01/2003	28/10/2016	Bloomberg
Royal Bank of Scotland	RBS	GB	Daily	13/05/2002	28/10/2016	Bloomberg
Societe Generale SA	SOCGEN	FR	Daily	13/05/2002	28/10/2016	Bloomberg
Standard Chartered Bank	STANLN	GB	Daily	23/06/2008	28/10/2016	Bloomberg
UBS AG	UBS	CH	Daily	13/05/2002	28/10/2016	Bloomberg
UniCredit SpA	UCGIM	IT	Daily	17/09/2001	28/10/2016	Bloomberg

Note: for CDS spreads we consider 5 daily observations per week (from Monday to Friday). The CISS variable is released on Friday.

[9] More precisely, the CDS spread is an insurance premium paid by CDS buyer to CDS seller in order to be insured/protected in case the credit event. Thus, the more the holder of a security thinks its issuer is likely to default, the more desirable is a CDS. Consequently, the higher premium or CDS spread is.

[10] Ballester et al. (2016), Acharya et al. (2015), Cetina et al. (2016), Alter & Beyer (2014), among others.

For the empirical analysis, the collected dataset is grouped into 12 subsets. Each of the subset contains weekly CISS variable and daily CDS spread variable for one of the previously selected GSIBs'. The staring date of the each sample varies because of the CDS spread data availability (even though CISS starts earlier), and ends on 28/10/2016. See Table1 for more details. For CDS spread we use 5 observations per week (from Monday to Friday). Thus, we exclude weekends. Moreover, we choose Monday to be the first observation of CDS spread variable (i.e. we eliminate all the observations previous to the first available Monday). Descriptive statistics are presented in Table 4 (see Appendix A).

4. RESULTS

4.1 Structural Change Points

In this section, we apply Qu and Perron (2007) methodology to investigate whether there has been a change in the impact of a European GSI banks on the EZ financial stability over the time.[11] Since our sample period covers 2002-2016, we expect the impact to change due to the global financial crisis and/or the European debt crisis. In particular, we search for shifts in a variance-covariance matrix of a *traditional* reduced-form VAR(1) model, containing two endogenous variables – weekly CISS index and daily CDS spread variable for one of the 12 GSIBs.[12] The choice of *traditional* VAR model, instead of mixed-frequency framework is motivated by the following arguments. The covariance matrix of residuals of MIDAS-VAR model contains both the contemporaneous relations between the CISS and CDS spreads and the contemporaneous relations between the CDS spread variables (see eq. (9)). Thus, the Qu and Perron (2007) algorithm applied to MIDAS-VAR model also capture the shifts in the latter relationships. Since for our analysis we are interested only in the change of the impact of a European GSI banks on the EZ financial stability, we consider the *traditional* VAR model to be more appropriate.

Table 2 and Figure 1 show the results, regarding the identified number of structural breaks and the break dates in the 12 models. In addition, table 2 presents a *SEQ(l+1|1)* test statistic and critical values. Note that the results are reported after the tests described in section 2.1 were implemented. Following Qu and Perron (2007), we need to introduce restrictions on the possible number of break points (*m)* and the minimal length of the regime (ε). For the datasets having more than 700 weekly observations we allow maximum three break points (*m=3)* and only one break (*m=1)* for those having

[11] To perform the estimation procedure we use a GAUSS code of Qu and Perron (2007), which is available on the authors' web sites.

[12] We test for unit roots in all the variables, using the Augmented Dickey-fuller test (ADF, Dickey and Fuller, 1981). The results show that all the variables are integrated of order one (i.e. stationary in first differences). Thus, for the further analysis we transform the data in the first-differences.

less than 500 observations.[13] The trimming parameter is set the same for all datasets $\varepsilon = 0.2$, thus, each regime has a length of $h = T * 0.2$.

Table 2. Structural break dates and *SEQ_T (l+1|l)* test results

CDS spread variable	Number of breaks	Break dates	SEQ_T (l+1|l) test statistics (critical values at the 5% level)
BNP Paribas	2	13/07/2007 12/10/2012	The Seq(2 | 1) test is : 158.253 (15.458) The Seq(3 | 2) test is : 0.000 (16.337)
Banco Santander	2	14/12/2007 12/10/2012	The Seq(2 | 1) test is : 121.149 (15.458) The Seq(3 | 2) test is : 0.000 (16.337)
Barclays Bank	2	06/07/2007 12/10/2012	The Seq(2 | 1) test is : 142.645 (15.458) The Seq(3 | 2) test is : 0.000 (16.337)
Credit Agricole*	1	28/06/2013	
Deutsche Bank	2	13/07/2007 10/08/2012	The Seq(2 | 1) test is : 104.634 (15.458) The Seq(3 | 2) test is : 0.000 (16.337)
HSBC Bank	3	06/07/2007 26/03/2010 28/12/2012	The Seq(3 | 2) test is : 67.670 (16.337)
ING Bank	2	13/07/2007 28/09/2012	The Seq(2 | 1) test is : 168.804 (15.458) The Seq(3 | 2) test is : 0.000 (16.337)
Royal Bank of Scotland	2	13/07/2007 12/10/2012	The Seq(2 | 1) test is : 197.305 (15.458) The Seq(3 | 2) test is : 0.000 (16.337)
Societe Generale	2	13/07/2007 07/09/2012	The Seq(2 | 1) test is : 154.560 (15.458) The Seq(3 | 2) test is : 0.000 (16.337)
Standard Chartered Bank*	1	05/03/2010	
UBS	3	13/07/2007 11/06/2010 03/05/2013	The Seq(3 | 2) test is : 53.177 (15.458)
UniCredit	2	13/07/2007 12/10/2012	The Seq(2 | 1) test is : 109.226 (15.458) The Seq(3 | 2) test is : 0.000 (16.337)

Note: The * marks the models with the maximum one number of break changes allowed in the model *(m=1*). For all other models we consider *m=3*. *Number of breaks* corresponds to the number of breaks identified in the model. Each of the 12 VAR models include CISS and one of the CDS spread variable indicated in the table. The number and the dates of the break points are estimated using the code in GAUSS of Qu and Perron (2007). For SEQ (l+1|l) test the test statistics are reported, the critical values are in the brackets.

Let us firstly consider the models with *m=3*. The *SEQ(3|2)* test allows us to reject the null hypothesis of two structural break points against the alternative of three break points in two VAR models: the one including a HSBC Bank CDS spread variable and the other including a CDS spread of UBS bank. However, for other models with *m* set to 3 we cannot reject the null hypothesis of SEQ (3|2) test. Hence, we accept two structural break points. Next, for VAR models with *m=1,* i.e. for the models

[13] We impose *m=3* for the following banks: BNP Paribas SA, Banco Santander SA, Barclays Bank PLC, , Deutsche Bank AG, HSBC Bank PLC, ING Bank NV, Royal Bank of Scotland, Societe Generale SA,UBS AG and UniCredit; we impose *m=1* for the following banks: Credit Agricole SA and Standard Chartered Bank.

with CDS spread of Credit Agricole and Standard Chartered Bank we find one structural break. Note that we do not report the results on double maximum tests (*WDmax*) as we always reject the null hypothesis of no break vs. existence of at least one breakpoint.

The results in this section suggest that the identified structural break points can be related to the important systemic changes. The break dates occurring in *July 2007* and in the *second half of the 2012* are common for almost all the models. The first breakpoint can be related to the beginning of the global financial crisis, caused by the US subprime mortgage market. Indeed, at that time the banks faced serious liquidity problems. In addition, the perceived risk in the financial markets grew up and triggered the financial stress in euro area. On the contrary, the break points of the *second half of the 2012* as well as the ones of *May and June 2013* denote a return to a more tranquil period. An additional structural change point was found for models including CDS spread of HSBC bank and UBS bank in *March 2010* and *June 2010,* respectively. This break point can be associated with the shift from the financial crisis to a sovereign debt crisis.

4.2 The Importance of GSI Banks Distress to EZ Financial Stability

4.2.1 FEVD: Importance of G-SIB Shocks

We analyze the contribution of the GSI banks distress shocks to the fluctuations of EZ financial distress by estimating forecast error variance decomposition (FEVD). The results of FEVD are in Tables 5 - 17. The reported results indicate the percentage of the forecast error variance in the CISS variable that can be attributed to innovations in GSI banks distress at different forecast horizons: 1, 2, 3, 4 weeks ahead for each of regime. Moreover, when the focus is on the MIDAS-SVAR we present results for each day of the week and, separately, we add them up to compare the aggregate results with the ones associated with the traditional SVAR.

We first consider the FEVD for the CISS in MIDAS-SVAR model. We can observe that the role played by a bank distress shock in explaining the fluctuations of the EZ financial stress index increases when we move from 1-week to a 1 month horizon. In particular, as shown by Table 17 which provides a summary of results, GSIBs' distress shocks account for 8.5% of the EZ financial stress variation at 4-week horizon, by averaging across different regimes. Therefore, the focus on the whole sample period leads to the conclusion that GSI banks distress shocks are important for the dynamics of financial stress in the eurozone within one month period.

In addition, we find that the contribution of GSI banks distress shocks to EZ financial stress variation increased over the years. More precisely, we find that in the period before the global financial crisis (i.e. before the July 2007) just Santander bank and RBS bank distress shocks explained more than 10% of the EZ financial stress variation at 4-week horizon. While in the later period (July 2007 – October 2016), the distress shocks to Barclays, Crédit Agricole, Deutsche Bank, HSBC, ING, Royal Bank of Scotland, Standard Chartered and UBS banks, that is shocks to 8 out of the 12 analysed GSI banks, accounted for more than 10% of the CISS forecast error variance at 4-week horizon. Furthermore, we find that the major contribution of GSIBs distress shocks to CISS fluctuations at 4-week horizon occurred in the last regime. More specifically, shocks to Barclays, Crédit Agricole, Deutsche Bank, HSBC, ING, Royal Bank of Scotland and UBS banks, that is shocks to 7 out of 12 GSIBs, explained more than 10% of EZ financial stress variance at 4-week horizon in the last regime.

The other interesting finding is that, at 1-week horizon, the major contribution of the Global systemically important banks distress shocks to EZ financial stress variation occurred in the crisis period. More precisely, during the global financial crisis, the major contributors at 1-week horizon were HSBC (06/07/2007 – 25/03/2010) and Standard Chartered (23/06/2008 – 04/03/2010) which explained 8.5% and 10.1% of the CISS fluctuations, respectively. During the period of the sovereign debt crisis, the major contributors at 1-week horizon, were shocks to UBS (11/06/2010 – 02/05/2013) bank and HSBC (26/03/2010 – 27/12/2012) bank, 7.2% and 11.5% respectively.

If we focus on the last column of Tables 5-17, we can observe that the main results in MIDAS SVAR model are supported by the traditional SVAR. In particular, the traditional SVAR confirms that in the period 2002-2016, the contribution of the GSI banks distress shock to the fluctuation of EZ financial stress has been increasing, and the major contribution at 1-week horizon occurred over the crisis period. Moreover, it is important to notice that the shocks in MIDAS-SVAR model explain a much larger part of the FEVD than in traditional SVAR model.[14]

4.2.2 Impulse Response to Structural Shocks

To illustrate the importance of GSI banks distress shocks to the dynamics of EZ financial distress we estimate the cumulative impulse response analysis based on MIDAS-SVAR model. The cumulative IRFs of CISS to average standard deviation increase in a GSIB's distress (CDS spread) are presented in Figures 2–7. The maximum of the time horizon is set to 12 weeks. The results are presented for each regime: on the left column are presented results for the first regime and on the right one for the last regime. The main results can be summarized as follows.

Firstly, we find that the impact effect on EZ financial distress to an increase in a GSI banks distress is much lower before the global financial crisis (July 2007), than in the period after. The strongest effect to EZ financial stress in the period before the global financial crisis came from Santander Bank. An unexpected increase in Santander Bank distress i.e. increase in CDS spread, had a positive and significant effect on EZ financial stress when it took place at the end of the week (Thursday and Friday). In addition, before the mid-2007, the effect on EZ financial distress was slightly

[14] These findings are similar to those obtained by Bacchiocchi et al. (2016). The authors find that the moderate impact of monetary policy, economic and policy uncertainty shocks on capital inflows suggested by traditional SVAR is then magnified when using the MIDAS-SVAR.

positive and significant only to shocks in Barclays bank, Deutsche Bank, ING bank and Royal Bank of Scotland distress. On the other hand, a distress shock in the BNP Paribas bank, HSBC bank, UBS bank, Societe Generale bank and UniCredit bank have caused no or almost no impact on EZ financial system conditions.

Secondly, in the crisis period we find that an unexpected increase in all GSI banks distress caused a statistically significant increase in the EZ financial stress.[15] The strongest impact on EZ financial distress in the period of crisis comes from an increase in the distress of Barclays bank, ING bank, Royal Bank of Scotland, HSBC bank and UBS bank. More precisely, the impulse response of CISS is strongly positive and statistically significant when a distress shock of Barclays bank, ING bank and Royal bank of Scotland occurs on Monday, Tuesday and Friday; and positive but statistically significant only within two weeks when distress shock of UBS occurs on Tuesday and Friday (13/07/2007 – 10/06/2010). In addition, we find the effect of HSBC bank distress shock had impact causing the increase in EZ financial distress in the period of global financial crisis (06/07/2007 – 24/03/2010) and in the period on European sovereign crisis (25/03/2010 – 26/12/2012), while the distress shock in UBS bank had no significant impact on EZ financial during the period 11/06/2010 – 03/05/2013. Furthermore, we find that Santander bank distress shocks in all five days of the week increased the CISS.

Finally, we find that in the recent years (the last regime) the strongest effect on EZ financial stress was caused by the unexpected increase in CDS spread of BNP Paribas bank, Barclays bank, Deutsch Bank and ING Bank. The impact was positive and immediate for all banks except Barclays bank, which effect was positive but significant only within two weeks.

The other interesting finding is that a shock observed at the beginning of the week, especially Monday, has a stronger effect than the shocks occurring in the other days of the week. In addition, two thirds of the GSI banks distress shocks hitting the EZ financial system on Monday has an immediate effect, while the shocks striking on Tuesday-Friday takes more time to reach its strongest effect.[16]

4.2.3 Ranking: the most Important Banks for EZ Financial Distress

In this section, we provide the raking of the European GSIBs sorted by their contribution to the EZ financial distress. The banks have been ranked according to the FEVD results at 4-week horizon, obtained by using MIDAS-VAR approach. Table 3 shows the ranking for 3 periods separately: (i) before the global financial crisis (GFC), (ii) during the GFC and European sovereign debt crisis (SDC), and (iii) after the SDC. The contribution of GSIBs distress shocks to CISS fluctuations at 4-week horizon are reported in the brackets.

[15] We consider the crisis period, the regimes starting after the mid-2007 and ending before the mid-2013.
[16] We consider only the positive and statistically significant impulse responses.

Table 3. Ranking of the GSIBs to EZ financial distress

I regime			II regime			III regime		
1.	Santander	(13.76)	1.	UBS	(13.12)	1.	UBS	(13.82)
2.	RBS	(11.19)	2.	HSBC	(12.32)	2.	DB	(13.14)
3.	BNP Paribas	(7.13)	3.	Standard Ch.	(11.30)	3.	Barclays	(12.86)
4.	Barclays	(6.70)	4.	Santander	(9.98)	4.	HSBC	(12.49)
5.	ING	(5.74)	5.	ING	(9.28)	5.	Crédit Agricole	(11.67)
6.	UBS	(5.50)	6.	RBS	(8.88)	6.	RBS	(11.41)
7.	DB	(4.99)	7.	Barclays	(8.14)	7.	ING	(10.32)
8.	Société Générale	(4.75)	8.	BNP Paribas	(7.59)	8.	BNP Paribas	(9.39)
9.	HSBC	(4.64)	9.	Société Générale	(7.55)	9.	Santander	(5.70)
10.	UniCredit	(3.88)	10.	UniCredit	(6.06)	10.	Standard Chart.	(5.63)
			11.	DB	(5.77)	11.	Société Générale	(5.57)
			12.	Crédit Agricole	(5.68)	12.	UniCredit	(5.46)

Before the global financial crisis, Banco Santander (13.76%) and RBS (11.19%) were the top contributors to the fluctuations of EZ financial distress. The distress shocks of both banks explained more than 10% of CISS fluctuations, while the impact of other banks was less important. Going into the crisis period, the contribution of European GSIBs to EZ financial distress increased, with the exception of Banco Santander and RBS. On the other hand, Banco Santander remained among the 4 highest ranked banks. Another bank ranked as a top 4 during the GFC (23/06/2008-02/03/2010) was Standard Chartered Bank. However, its impact noticeably diminished since March 2010. From the beginning of the global financial crisis (September 2007), also the UBS and HSBC moved to the top 4 contributors of EZ financial distress fluctuations. Moreover, these two banks remained the most systemically important banks for EZ also in the recent years. More precisely, the four highest contributors for EZ in 2012-2016, were UBS (13.82%), DB (13.14%), Barclays (12.86%) and HSBC (12.49%). In contrast, we find that UniCredit bank and Société Générale bank are the least important for EZ financial fluctuations in all the three periods.

We now consider the importance of GSIBs to EZ financial distress relative to their respective countries. Firstly, the rankings suggest that the contribution of non-eurozone GSIBs is not less important as the contribution of EZ-GSIBs. In fact, Swiss UBS bank and the UK banks (Barclays, Standard Chartered, HSBC and RBS) are listed among the top 4 contributors to EZ financial distress at least in one of the regimes. Secondly, the systemic importance of non-eurozone GSIBs appears to have been increasing since September 2007. For example, in the first regime just one non-EZ bank (RBS) explains more than 10% of the EZ financial distress fluctuations while in the second regime all the top contributors are non-EZ banks.

We also find that the biggest contributors to the EZ financial distress not often coincide with the banks with the highest CDS spreads. For instance, the CDS spread of highest ranked bank – HSBC, is relatively low during the crisis. And on the other hand, the lowest ranked banks like Crédit Agricole, UniCredit and Société Générale have higher CDS spread.

Finally, we examine how similar our rankings are to the ones provided by other authors. The considered alternative rakings are the following: (i) SRISK measure from the Volatility Institute of NYU Stern by Brownlees and Engle (2017)[17], (ii) the list of European GSIB provided by Financial Stability board, published each year since November 2011, and (iii) the DIP by Black et al. (2016).

We compare the rankings for each of the regimes separately. In the first regime, the top 2 ranked banks in our list (Banco Santander and RBS) are not considered among the most systemically important banks for Europe according to SRISK measure. On the other hand, the bottom 3 banks in the rankings are the same. For the crisis period, we find our results to be more similar to the FSB list than the rankings provided by SRISK and DIP measures. In contrast to SRISK and DIP lists, we rank the HSBC bank as the highest contributor to EZ financial distress during the crisis. However, also the FSB list the HSBC bank as the most systemically important European bank (the 4th bucket) in the period 2012-2015.[18] The FSB list the UBS bank in the 2nd bucket for the period 2012-2013.

5. CONCLUSIONS

In this paper we have evaluated the importance of 12 European GSI banks on the EZ financial stability. Our empirical findings suggest that the contribution of the European GSIBs to EZ financial fluctuations has increased in the period 2002-2016. On average, the GSIBs' distress shocks accounted for 8.5% of the EZ financial stress variation. In the recent years, the 4 biggest contributors to EZ financial distress were UBS, DB, Barclays bank and HSBC bank. On the other hand, the least important were UniCredit bank and Société Générale. In addition, the biggest contributors to the EZ financial distress not often coincide with the banks with the highest CDS spreads. Finally, the non-EZ GSIBs have played an important role for EZ financial stability, especially since September 2007.

For our empirical analysis we have used recently developed structural MIDAS-VAR model, suggested by Ghysels (2016). The findings show that the GSIBs shocks observed at the beginning of the week, especially Monday, has a stronger effect than the shocks occurring in the other days of the week. In fact, two thirds of the GSI banks distress shocks hitting the EZ financial system on Monday has an immediate effect, while the shocks striking on Tuesday-Friday takes more time to reach its strongest effect.[19] We find that the main results in MIDAS SVAR model are supported by the traditional SVAR. However, the shocks in MIDAS-SVAR model explain a much larger part of the FEVD than in traditional SVAR model.

[17] Since the SRISK ranking is available on daily basis, we make a simple average of the daily SRISK values for the considered period.

[18] Higher bucket corresponds to the higher risk.

[19] We consider only the positive and statistically significant impulse responses.

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Appendix A. Data

Table 4. Descriptive Statistics of CDS spread

	Mean	Median	MAX	MIN	St.dev	Observations daily	
BNP Paribas SA	1.25	1.08	6.21	0.09	1.20	3775	%
Banco Santander SA	1.85	1.48	7.32	0.12	1.67	3745	%
Barclays Bank PLC	1.49	1.38	5.42	0.08	1.24	3590	%
Credit Agricole SA	2.23	1.65	7.25	0.23	1.41	2385	%
Deutsche Bank AG	1.38	1.32	5.24	0.14	1.10	3810	%
HSBC Bank PLC	0.99	1.03	3.14	0.08	0.68	3560	%
ING Bank NV	1.26	1.28	4.68	0.07	1.00	3590	%
Royal Bank of Scotland	1.97	1.52	8.78	0.07	1.88	3775	%
Societe Generale SA	1.53	1.29	7.96	0.09	1.51	3775	%
Standard Chartered Bank	1.98	1.77	5.55	0.88	0.81	2180	%
UBS AG	1.15	1.25	5.38	0.07	0.94	3775	%
UniCredit SpA	2.14	1.52	11.53	0.12	2.21	3945	%

Appendix B: Structural Breaks

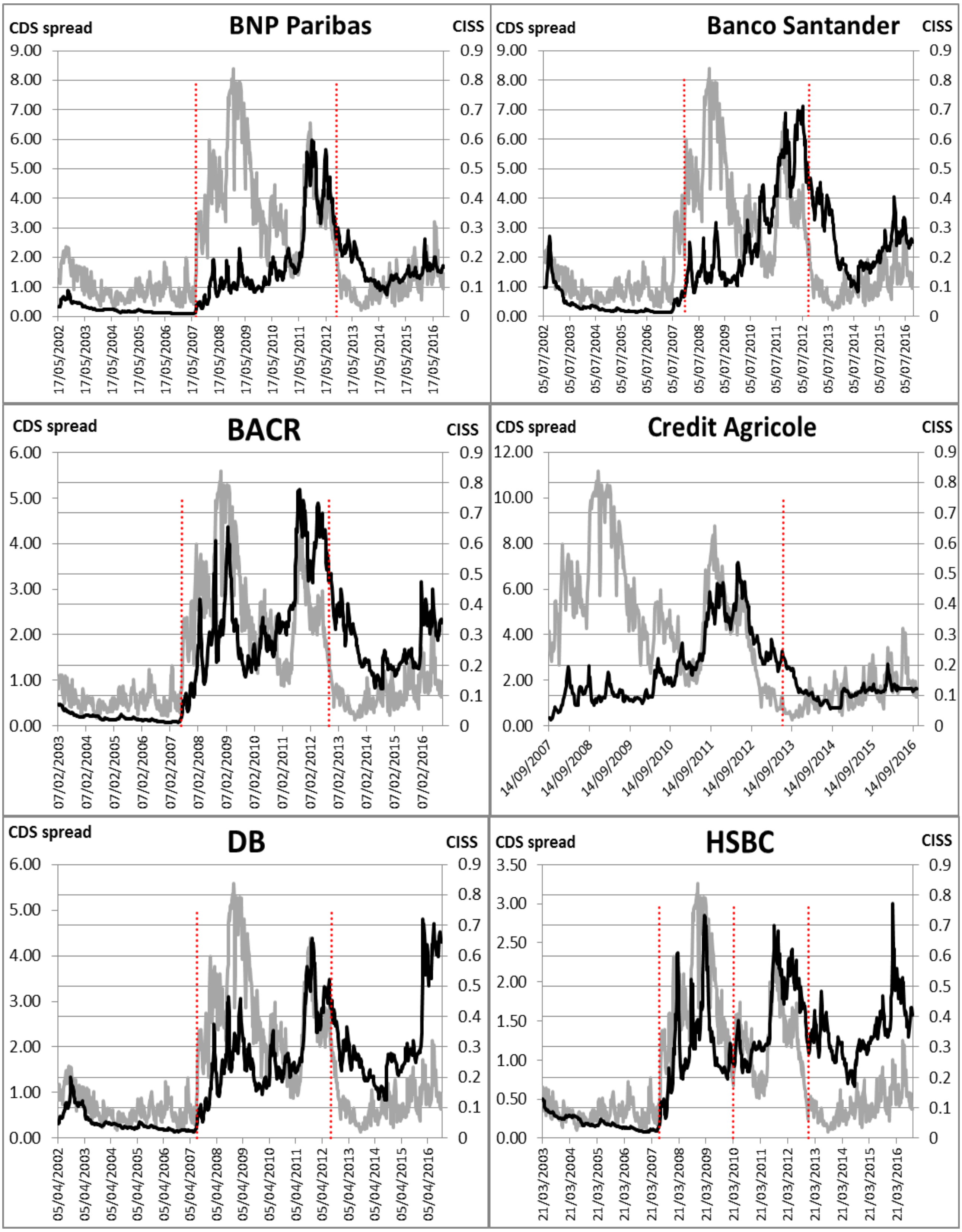

Figure 1. Structural break points

Note: the CISS index is presented in grey colour, CDS spreads - in black and structural change points in red.

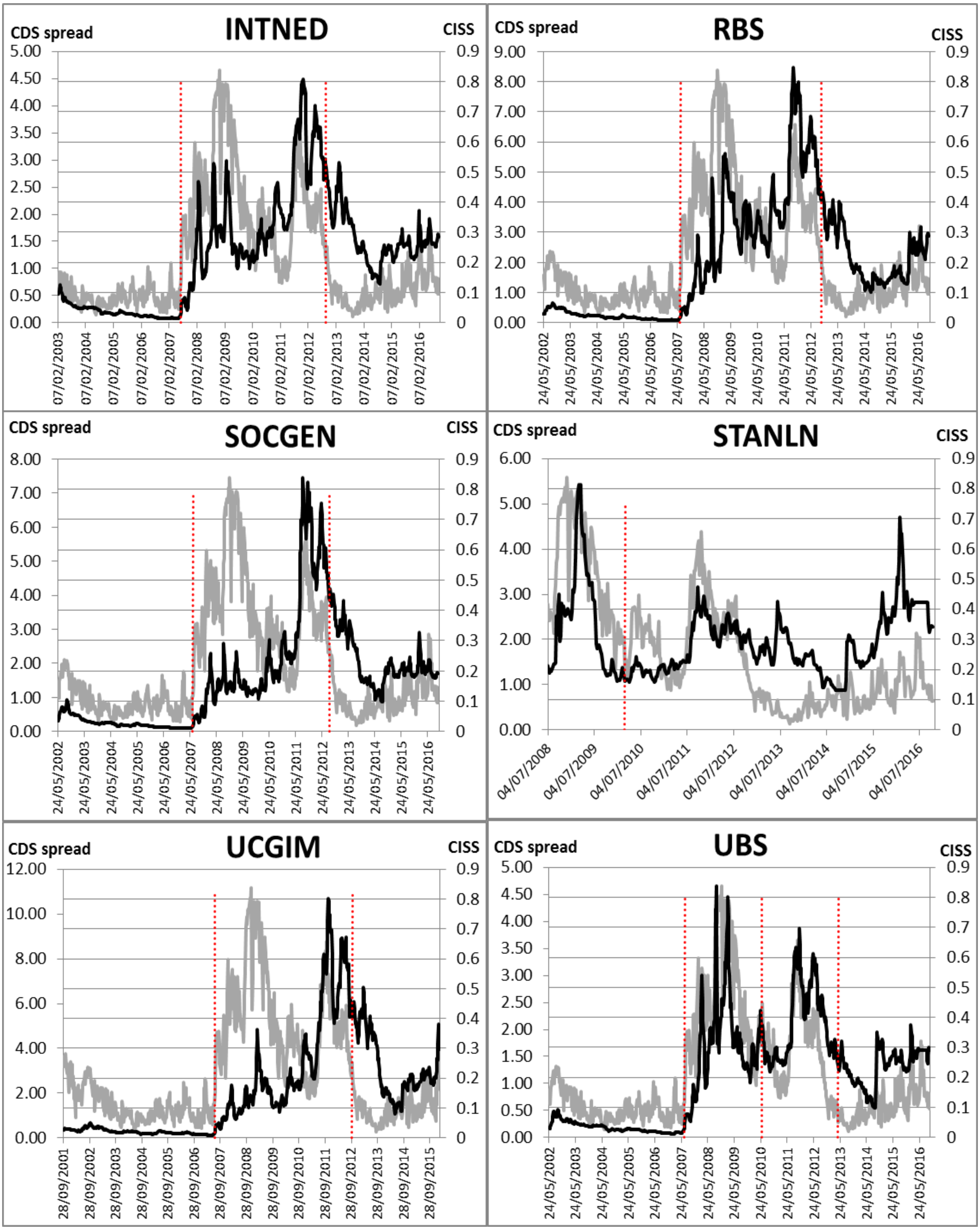

Figure 1. (Continued)

Note: the CISS index is presented in grey colour, CDS spreads - in black and structural change points in red.

Appendix C: FEVD Results

Table 5. FEVD for EZ financial distress subject to BNP Paribas bank distress shocks.

	MIDAS-SVAR							Traditional-SVAR	
I regime: 13/05/2002 - 12/07/2007									
h	**CISS**	BNP5	BNP4	BNP3	BNP2	BNP1	**SUM (BNP)**	CISS	BNP
1	**97.32**	0.02	0.00	0.53	1.64	0.49	**2.68**	98.85	1.15
2	**97.40**	0.05	0.13	0.52	1.42	0.48	**2.60**	98.63	1.37
3	**94.57**	2.45	0.17	0.66	1.64	0.52	**5.43**	98.63	1.37
4	**92.87**	3.19	0.51	0.95	1.74	0.74	**7.13**	98.63	1.37
II regime: 13/07/2007 - 11/10/2012									
h	**CISS**	BNP5	BNP4	BNP3	BNP2	BNP1			
1	**94.30**	0.03	0.01	0.09	0.00	5.57	**5.70**	96.45	3.55
2	**93.15**	0.39	0.02	0.49	0.64	5.31	**6.85**	96.53	3.47
3	**92.53**	0.51	0.02	0.72	0.88	5.34	**7.47**	96.53	3.47
4	**92.41**	0.52	0.02	0.77	0.92	5.36	**7.59**	96.53	3.47
III regime 12/10/2012 - 28/10/2016									
h	**CISS**	BNP5	BNP4	BNP3	BNP2	BNP1			
1	**95.47**	0.33	0.25	0.00	0.58	3.37	**4.53**	96.86	3.14
2	**92.05**	2.03	0.70	0.03	1.35	3.83	**7.95**	95.97	4.03
3	**91.21**	2.13	1.37	0.06	1.39	3.84	**8.79**	95.95	4.05
4	**90.61**	2.28	1.49	0.32	1.51	3.79	**9.39**	95.95	4.05

Notes: 1 stands for Monday, 2 – Tuesday, 3 – Wednesday, 4 – Thursday, 5 – Friday, h – forecast horizon.

Table 6. FEVD for EZ financial distress subject to Santander bank distress shocks.

	MIDAS-SVAR							Traditional-SVAR	
I regime: 24/06/2002 - 13/12/2007							**SUM**		
h	**CISS**	SANT5	SANT4	SANT3	SANT2	SANT1	**(SANTAN)**	CISS	SANTAN
1	**96.56**	0.00	2.66	0.36	0.15	0.27	**3.44**	100	0.00
2	**93.47**	2.05	2.51	0.32	1.26	0.40	**6.53**	97.91	2.09
3	**88.97**	5.66	3.21	0.48	1.26	0.42	**11.03**	97.70	2.30
4	**86.24**	5.78	3.71	2.59	1.27	0.41	**13.76**	97.49	2.51
II regime: 14/12/2007 - 11/10/2012									
h	**CISS**	SANT5	SANT4	SANT3	SANT2	SANT1			
1	**97.92**	0.27	0.30	0.55	0.01	0.93	**2.08**	96.68	3.32
2	**93.58**	1.70	0.29	0.52	2.64	1.28	**6.42**	96.83	3.17
3	**91.89**	1.75	0.31	0.84	3.42	1.79	**8.11**	96.83	3.17
4	**90.02**	1.75	0.52	2.51	3.41	1.79	**9.98**	96.83	3.17
III regime: 12/10/2012 - 28/10/2016									
h	**CISS**	SANT5	SANT4	SANT3	SANT2	SANT1			
1	**97.51**	0.27	0.02	0.60	1.15	0.45	**2.49**	98.16	1.84
2	**94.43**	1.06	0.68	0.98	1.86	0.99	**5.57**	96.80	3.20
3	**94.34**	1.14	0.68	0.98	1.84	1.00	**5.66**	96.81	3.19
4	**94.30**	1.16	0.71	0.98	1.85	1.00	**5.70**	96.81	3.19

Notes: 1 stands for Monday, 2 – Tuesday, 3 – Wednesday, 4 – Thursday, 5 – Friday, h – forecast horizon.

Table 7. FEVD for EZ financial distress subject to Barclays bank distress shocks.

	MIDAS-SVAR							Traditional -SVAR	
I regime: 27/01/2003 - 05/07/2007									
h	CISS	BACR5	BACR4	BACR3	BACR2	BACR1	**SUM (BACR)**	CISS	BACR
1	94.76	0.11	0.74	1.00	0.40	3.00	**5.24**	96.46	3.54
2	94.40	0.79	0.67	0.88	0.38	2.89	**5.60**	96.63	3.37
3	93.68	1.45	0.69	0.92	0.37	2.89	**6.32**	96.63	3.37
4	93.30	1.73	0.72	1.01	0.37	2.88	**6.70**	96.63	3.37
II regime: 06/07/2007 - 11/10/2012									
h	CISS	BACR5	BACR4	BACR3	BACR2	BACR1			
1	96.70	0.15	0.17	0.02	0.19	2.77	**3.30**	97.37	2.63
2	94.33	0.35	0.16	0.18	1.85	3.13	**5.67**	97.46	2.54
3	93.37	0.40	0.41	0.34	1.87	3.61	**6.63**	97.47	2.53
4	91.86	0.55	0.44	1.71	1.88	3.55	**8.14**	97.47	2.53
III regime: 12/10/2012 - 28/10/2016									
h	CISS	BACR5	BACR4	BACR3	BACR2	BACR1			
1	98.22	0.31	0.03	0.01	0.18	1.26	**1.78**	98.23	1.77
2	90.24	3.76	2.04	0.50	0.75	2.70	**9.76**	96.32	3.68
3	89.09	3.83	2.20	0.59	1.48	2.81	**10.91**	96.29	3.71
4	87.14	4.11	2.51	0.94	2.58	2.72	**12.86**	96.28	3.72

Notes: 1 stands for Monday, 2 – Tuesday, 3 – Wednesday, 4 – Thursday, 5 – Friday, h – forecast horizon.

Table 8. FEVD for EZ financial distress subject to Deutsche bank distress shocks.

	MIDAS-SVAR							Traditional -SVAR	
I regime: 25/03/2002 - 12/07/2007									
h	CISS	DB5	DB4	DB3	DB2	DB1	**SUM (DB)**	CISS	DB
1	96.50	0.00	0.36	0.02	3.00	0.12	**3.50**	99.77	0.23
2	96.46	0.25	0.51	0.19	2.50	0.10	**3.54**	99.67	0.33
3	95.54	0.94	0.65	0.27	2.49	0.11	**4.46**	99.67	0.33
4	95.01	1.00	1.08	0.27	2.48	0.16	**4.99**	99.67	0.33
II regime: 13/07/2007 - 09/08/2012									
h	CISS	DB5	DB4	DB3	DB2	DB1			
1	95.55	0.93	0.21	0.68	0.01	2.62	**4.45**	95.54	4.46
2	94.98	1.25	0.26	0.76	0.13	2.62	**5.02**	95.61	4.39
3	94.39	1.61	0.29	0.90	0.20	2.61	**5.61**	95.62	4.38
4	94.23	1.71	0.29	0.94	0.22	2.60	**5.77**	95.62	4.38
III regime: 10/08/2012 - 28/10/2016									
h	CISS	DB5	DB4	DB3	DB2	DB1			
1	95.09	0.14	0.23	0.01	0.01	4.51	**4.91**	96.27	3.73
2	88.88	3.67	1.46	0.75	1.06	4.19	**11.12**	94.37	5.63
3	88.24	3.68	1.80	1.06	1.04	4.18	**11.76**	94.39	5.61
4	86.86	4.18	1.98	1.60	1.28	4.10	**13.14**	94.39	5.61

Notes: 1 stands for Monday, 2 – Tuesday, 3 – Wednesday, 4 – Thursday, 5 – Friday, h – forecast horizon.

Table 9. FEVD for EZ financial distress subject to Credit Agricole bank distress shocks.

	MIDAS-SVAR							Traditional-SVAR	
I regime: 10/09/2007 - 27/06/2013									
h	CISS	ACAFP5	ACAFP4	ACAFP3	ACAFP2	ACAFP1	**SUM (ACAFP)**	CISS	ACAFP
1	96.65	0.14	0.19	0.03	0.59	2.40	**3.35**	97.34	2.66
2	95.43	0.26	0.21	0.53	1.28	2.29	**4.57**	97.42	2.58
3	94.52	0.31	0.21	0.85	1.77	2.33	**5.48**	97.42	2.58
4	94.32	0.31	0.21	0.93	1.88	2.36	**5.68**	97.42	2.58
II regime: 28/06/2013 - 28/10/2016									
h	CISS	ACAFP5	ACAFP4	ACAFP3	ACAFP2	ACAFP1			
1	92.03	0.22	1.69	0.24	0.00	5.81	**7.97**	99.36	0.64
2	90.22	0.48	3.01	0.66	0.21	5.42	**9.78**	98.61	1.39
3	88.71	1.54	3.03	0.65	0.73	5.34	**11.29**	98.61	1.39
4	88.33	1.76	3.03	0.72	0.84	5.32	**11.67**	98.61	1.39

Notes: 1 stands for Monday, 2 – Tuesday, 3 – Wednesday, 4 – Thursday, 5 – Friday, h – forecast horizon.

Table 10. FEVD for EZ financial distress subject to HSBC bank distress shocks.

	MIDAS-SVAR							Traditional-SVAR	
I regime: 10/03/2003 - 05/07/2007									
Period	CISS	HSBC5	HSBC4	HSBC3	HSBC2	HSBC1	**SUM (HSBC)**	CISS	HSBC
1	96.85	1.19	0.13	1.58	0.18	0.08	**3.15**	99.96	0.04
2	96.09	1.48	0.38	1.47	0.49	0.09	**3.91**	99.96	0.04
3	95.58	1.68	0.59	1.44	0.62	0.09	**4.42**	99.96	0.04
4	95.36	1.76	0.70	1.44	0.65	0.09	**4.64**	99.96	0.04
II regime: 06/07/2007 - 25/03/2010									
h	CISS	HSBC5	HSBC4	HSBC3	HSBC2	HSBC1			
1	91.45	0.05	0.01	0.34	2.02	6.13	**8.55**	96.93	3.07
2	89.64	0.89	0.81	0.74	2.10	5.81	**10.36**	96.51	3.49
3	89.54	0.89	0.81	0.74	2.16	5.85	**10.46**	96.52	3.48
4	89.53	0.89	0.82	0.74	2.16	5.86	**10.47**	96.52	3.48
III regime: 26/03/2010 - 27/12/2012									
h	CISS	HSBC5	HSBC4	HSBC3	HSBC2	HSBC1			
1	88.55	0.42	2.87	0.10	2.15	5.91	**11.45**	94.65	5.35
2	87.35	0.41	3.16	0.31	3.03	5.73	**12.65**	94.82	5.18
3	86.26	0.40	3.23	0.38	4.07	5.66	**13.74**	94.83	5.17
4	85.82	0.44	3.23	0.38	4.49	5.64	**14.18**	94.83	5.17
IV regime: 28/12/2012 - 28/10/2016									
h	CISS	HSBC5	HSBC4	HSBC3	HSBC2	HSBC1			
1	96.96	0.30	0.07	0.02	0.01	2.65	**3.04**	95.98	4.02
2	89.99	4.39	1.50	0.32	0.88	2.92	**10.01**	95.19	4.81
3	88.87	4.57	1.77	0.48	1.36	2.95	**11.13**	95.19	4.81
4	87.51	4.67	1.87	1.10	1.96	2.89	**12.49**	95.19	4.81

Notes: 1 stands for Monday, 2 – Tuesday, 3 – Wednesday, 4 – Thursday, 5 – Friday, h – forecast horizon.

Table 11. FEVD for EZ financial distress subject to ING bank distress shocks.

	MIDAS-SVAR							TRADITIONAL-SVAR	
I regime: 27/01/2003 - 12/07/2007									
h	CISS	INT5	INT4	INT3	INT2	INT1	**SUM (INTNED)**	CISS	INTNED
1	97.58	0.00	0.02	0.17	2.10	0.13	**2.42**	97.73	2.27
2	95.30	0.11	0.58	0.97	1.97	1.08	**4.70**	97.98	2.02
3	94.39	0.12	0.79	1.04	2.09	1.57	**5.61**	97.94	2.06
4	94.26	0.13	0.82	1.06	2.09	1.64	**5.74**	97.94	2.06
II regime: 13/07/2007 - 27/09/2012									
h	CISS	INT5	INT4	INT3	INT2	INT1			
1	95.28	0.12	0.03	0.00	0.29	4.27	**4.72**	95.60	4.40
2	92.76	1.17	0.28	0.23	1.59	3.97	**7.24**	95.71	4.29
3	91.77	1.49	0.85	0.24	1.56	4.10	**8.23**	95.70	4.30
4	90.72	2.03	0.85	0.84	1.53	4.04	**9.28**	95.70	4.30
III regime: 28/09/2012 - 28/10/2016									
h	CISS	INT5	INT4	INT3	INT2	INT1			
1	96.26	0.11	0.02	0.02	1.11	2.49	**3.74**	93.93	6.07
2	91.00	3.12	1.80	0.02	1.08	2.98	**9.00**	93.94	6.06
3	90.81	3.17	1.77	0.17	1.15	2.93	**9.19**	93.97	6.03
4	89.68	3.23	1.78	0.21	2.22	2.88	**10.32**	93.97	6.03

Notes: 1 stands for Monday, 2 – Tuesday, 3 – Wednesday, 4 – Thursday, 5 – Friday, h – forecast horizon.

Table 12. FEVD for EZ financial distress subject to Royal Bank of Scotland distress shocks.

	MIDAS-SVAR							TRADITIONAL-SVAR	
I regime: 13/05/2002 - 12/07/2007									
h	CISS	RBS5	RBS4	RBS3	RBS2	RBS1	**SUM (RBS)**	CISS	RBS
1	94.48	0.29	1.91	2.92	0.02	0.38	**5.52**	98.64	1.36
2	94.61	0.44	1.69	2.92	0.02	0.33	**5.39**	98.71	1.29
3	91.20	2.71	2.26	3.30	0.20	0.33	**8.80**	98.72	1.28
4	88.81	4.04	2.20	3.22	1.36	0.37	**11.19**	98.72	1.28
II regime: 13/07/2007 - 11/10/2012									
h	CISS	RBS5	RBS4	RBS3	RBS2	RBS1			
1	95.93	0.20	0.10	0.05	0.04	3.69	**4.07**	97.86	2.14
2	93.90	0.68	0.15	0.06	1.68	3.52	**6.10**	97.89	2.11
3	92.57	0.68	0.56	0.19	2.47	3.53	**7.43**	97.89	2.11
4	91.12	0.81	0.55	1.30	2.68	3.54	**8.88**	97.89	2.11
III regime: 12/10/2012 - 28/10/2016									
h	CISS	RBS5	RBS4	RBS3	RBS2	RBS1			
1	97.86	0.52	0.00	0.58	0.01	1.03	**2.14**	98.58	1.42
2	92.04	2.01	2.72	0.56	1.00	1.67	**7.96**	97.40	2.60
3	90.70	2.14	2.82	0.56	2.14	1.64	**9.30**	97.41	2.59
4	88.59	2.66	3.41	0.89	2.85	1.60	**11.41**	97.41	2.59

Notes: 1 stands for Monday, 2 – Tuesday, 3 – Wednesday, 4 – Thursday, 5 – Friday, h – forecast horizon.

Table 13. FEVD for EZ financial distress subject to Societe Generale bank distress shocks.

	MIDAS-SVAR							TRADITIONAL-SVAR	
I regime: 13/05/2002 - 12/07/2007									
h	CISS	SOCG5	SOCG4	SOCG3	SOCG2	SOCG1	**SUM (SOCGEN)**	CISS	SOCGEN
1	98.34	0.24	0.85	0.28	0.01	0.27	**1.66**	99.79	0.21
2	97.47	0.53	0.95	0.24	0.02	0.80	**2.53**	99.10	0.90
3	96.41	1.40	0.95	0.25	0.17	0.82	**3.59**	99.10	0.90
4	95.25	2.50	1.02	0.24	0.18	0.81	**4.75**	99.08	0.92
II regime: 13/07/2007 - 06/09/2012									
h	CISS	SOCG5	SOCG4	SOCG3	SOCG2	SOCG1			
1	94.26	0.35	0.02	0.10	0.03	5.24	**5.74**	96.13	3.87
2	93.40	0.45	0.06	0.22	0.81	5.05	**6.60**	96.26	3.74
3	92.65	0.53	0.07	0.38	1.31	5.05	**7.35**	96.26	3.74
4	92.45	0.54	0.08	0.44	1.44	5.06	**7.55**	96.26	3.74
III regime: 07/09/2012 - 28/10/2016									
h	CISS	SOCG5	SOCG4	SOCG3	SOCG2	SOCG1			
1	97.14	0.29	0.27	0.11	0.71	1.48	**2.86**	96.39	3.61
2	94.74	0.93	1.52	0.17	1.09	1.55	**5.26**	96.15	3.85
3	94.57	1.03	1.51	0.24	1.10	1.55	**5.43**	96.16	3.84
4	94.43	1.04	1.55	0.27	1.15	1.56	**5.57**	96.16	3.84

Notes: 1 stands for Monday, 2 – Tuesday, 3 – Wednesday, 4 – Thursday, 5 – Friday, h – forecast horizon.

Table 14. FEVD for EZ financial distress subject to UniCredit bank distress shocks.

	MIDAS-SVAR							TRADITIONAL-SVAR	
I regime: 17/09/2001 - 12/07/2007									
h	CISS	UCGI5	UCGI4	UCGI3	UCGI2	UCGI1	**SUM (UCGIM)**	CISS	UCGIM
1	97.56	0.18	0.06	1.14	0.61	0.45	**2.44**	99.46	0.54
2	97.42	0.21	0.34	0.99	0.62	0.42	**2.58**	99.35	0.65
3	96.48	0.81	0.62	1.01	0.61	0.47	**3.52**	99.37	0.63
4	96.12	0.89	0.62	1.01	0.87	0.49	**3.88**	99.37	0.63
II regime: 13/07/2007 - 11/10/2012									
h	CISS	UCGI5	UCGI4	UCGI3	UCGI2	UCGI1			
1	96.86	0.29	0.01	0.03	0.21	2.60	**3.14**	97.39	2.61
2	94.82	0.98	0.22	0.34	1.16	2.47	**5.18**	97.23	2.77
3	94.13	1.01	0.51	0.37	1.50	2.47	**5.87**	97.22	2.78
4	93.94	1.01	0.56	0.37	1.63	2.48	**6.06**	97.21	2.79
III regime: 12/10/2012 - 28/10/2016									
h	CISS	UCGI5	UCGI4	UCGI3	UCGI2	UCGI1			
1	97.46	0.73	0.00	0.11	0.97	0.73	**2.54**	97.56	2.44
2	95.04	1.46	0.22	0.40	1.73	1.15	**4.96**	96.51	3.49
3	94.70	1.55	0.38	0.46	1.76	1.16	**5.30**	96.52	3.48
4	94.54	1.56	0.49	0.49	1.76	1.16	**5.46**	96.52	3.48

Notes: 1 stands for Monday, 2 – Tuesday, 3 – Wednesday, 4 – Thursday, 5 – Friday, h – forecast horizon.

Table 15. FEVD for EZ financial distress subject to Standard Chartered Bank distress shocks.

	MIDAS-SVAR							TRADITIONAL-SVAR	
I regime: 23/06/2008 - 04/03/2010									
h	CISS	STAN5	STAN4	STAN3	STAN2	STAN1	**SUM (STANLN)**	CISS	STANLN
1	89.89	2.83	0.38	0.02	0.11	6.78	**10.11**	95.14	4.86
2	89.03	2.98	0.37	0.02	0.43	7.17	**10.97**	94.87	5.13
3	88.73	3.23	0.37	0.03	0.50	7.15	**11.27**	94.86	5.14
4	88.70	3.26	0.37	0.03	0.50	7.15	**11.30**	94.86	5.14
II regime: 05/03/2010 - 28/10/2016									
h	CISS	STAN5	STAN4	STAN3	STAN2	STAN1			
1	95.32	0.33	0.51	0.05	0.94	2.85	**4.68**	97.66	2.34
2	95.21	0.35	0.47	0.17	1.16	2.63	**4.79**	97.58	2.42
3	94.75	0.45	0.56	0.19	1.47	2.58	**5.25**	97.59	2.41
4	94.37	0.45	0.63	0.32	1.63	2.59	**5.63**	97.59	2.41

Notes: 1 stands for Monday, 2 – Tuesday, 3 – Wednesday, 4 – Thursday, 5 – Friday, h – forecast horizon.

Table 16. FEVD for EZ financial distress subject to UBS bank distress shocks.

	MIDAS-SVAR							TRADITIONAL-SVAR	
I regime: 13/05/2002 - 12/07/2007									
h	CISS	UBS5	UBS4	UBS3	UBS2	UBS1	**SUM (UBS)**	CISS	UBS
1	98.43	0.83	0.00	0.02	0.00	0.71	**1.57**	99.24	0.76
2	95.75	1.35	0.05	0.49	1.73	0.63	**4.25**	99.00	1.00
3	94.89	1.34	0.44	0.62	1.90	0.81	**5.11**	99.00	1.00
4	94.50	1.37	0.49	0.63	1.95	1.06	**5.50**	98.99	1.01
II regime: 13/07/2007 - 10/06/2010									
h	CISS	UBS5	UBS4	UBS3	UBS2	UBS1			
1	98.62	0.19	0.21	0.14	0.04	0.80	**1.38**	97.34	2.66
2	93.15	1.45	0.31	0.32	2.55	2.22	**6.85**	97.35	2.65
3	90.80	1.51	0.46	0.30	2.80	4.12	**9.20**	97.35	2.65
4	87.93	1.46	1.51	2.20	2.89	4.00	**12.07**	97.35	2.65
III regime: 11/06/2010 - 02/05/2013									
h	CISS	UBS5	UBS4	UBS3	UBS2	UBS1			
1	92.76	0.80	0.00	3.00	2.05	1.38	**7.24**	96.07	3.93
2	92.19	0.94	0.89	2.77	1.92	1.29	**7.81**	96.23	3.77
3	91.09	1.09	1.65	2.88	2.02	1.28	**8.91**	96.23	3.77
4	90.49	1.16	1.92	3.04	2.11	1.28	**9.51**	96.23	3.77
IV regime: 03/05/2013 - 28/10/2016									
h	CISS	UBS5	UBS4	UBS3	UBS2	UBS1			
1	89.58	1.99	3.16	0.42	2.05	2.79	**10.42**	97.39	2.61
2	87.30	3.18	3.40	1.09	2.41	2.62	**12.70**	97.49	2.51
3	86.34	3.15	3.87	1.17	2.86	2.62	**13.66**	97.49	2.51
4	86.18	3.14	3.94	1.17	2.95	2.62	**13.82**	97.49	2.51

Notes: 1 stands for Monday, 2 – Tuesday, 3 – Wednesday, 4 – Thursday, 5 – Friday, h – forecast horizon.

Table 17. Descriptive statistics of FEVD for EZ financial stress subject to GSI banks distress shocks

	MIDAS-SVAR					Traditional-SVAR			
Period I									
n. ahead	*1-4*	*1*	*2*	*3*	*4*	*1-4*	*1*	*2*	*3*
Max	13.76	5.52	6.53	11.03	13.76	3.54	3.54	3.37	3.37
Min	1.57	1.57	2.53	3.52	3.88	0.00	0.00	0.04	0.04
Mean	5.00	3.16	4.16	5.83	6.83	1.25	1.01	1.31	1.33
sd.dev	2.57	1.34	1.40	2.38	3.18	1.01	1.14	0.98	1.00
Period II									
n. ahead	*1-4*	*1*	*2*	*3*	*4*	*1-4*	*1*	*2*	*3*
max	14.18	11.45	12.65	13.74	14.18	5.35	5.35	5.18	5.17
min	1.38	1.38	4.57	5.48	5.68	2.11	2.14	2.11	2.11
mean	7.50	5.38	7.31	8.27	9.03	3.52	3.53	3.52	3.52
sd.dev	2.85	2.99	2.40	2.33	2.48	0.94	0.97	0.96	0.96
Period III									
n. ahead	*1-4*	*1*	*2*	*3*	*4*	*1-4*	*1*	*2*	*3*
max	13.82	10.42	12.70	13.66	13.82	6.07	6.07	6.06	6.03
min	1.78	1.78	4.79	5.25	5.46	0.64	0.64	1.39	1.39
mean	7.81	4.26	8.24	8.58	9.79	3.43	2.80	3.64	3.64
sd.dev	3.52	2.57	2.62	2.93	3.32	1.38	1.44	1.37	1.36

Note: The label *Period I* refers to a first regime for all banks except Credit Agricole, Standard Chartered. The label Period III refers to the last regime of all the banks. Period II refers to the remaining regimes.

Appendix D. IRF Results

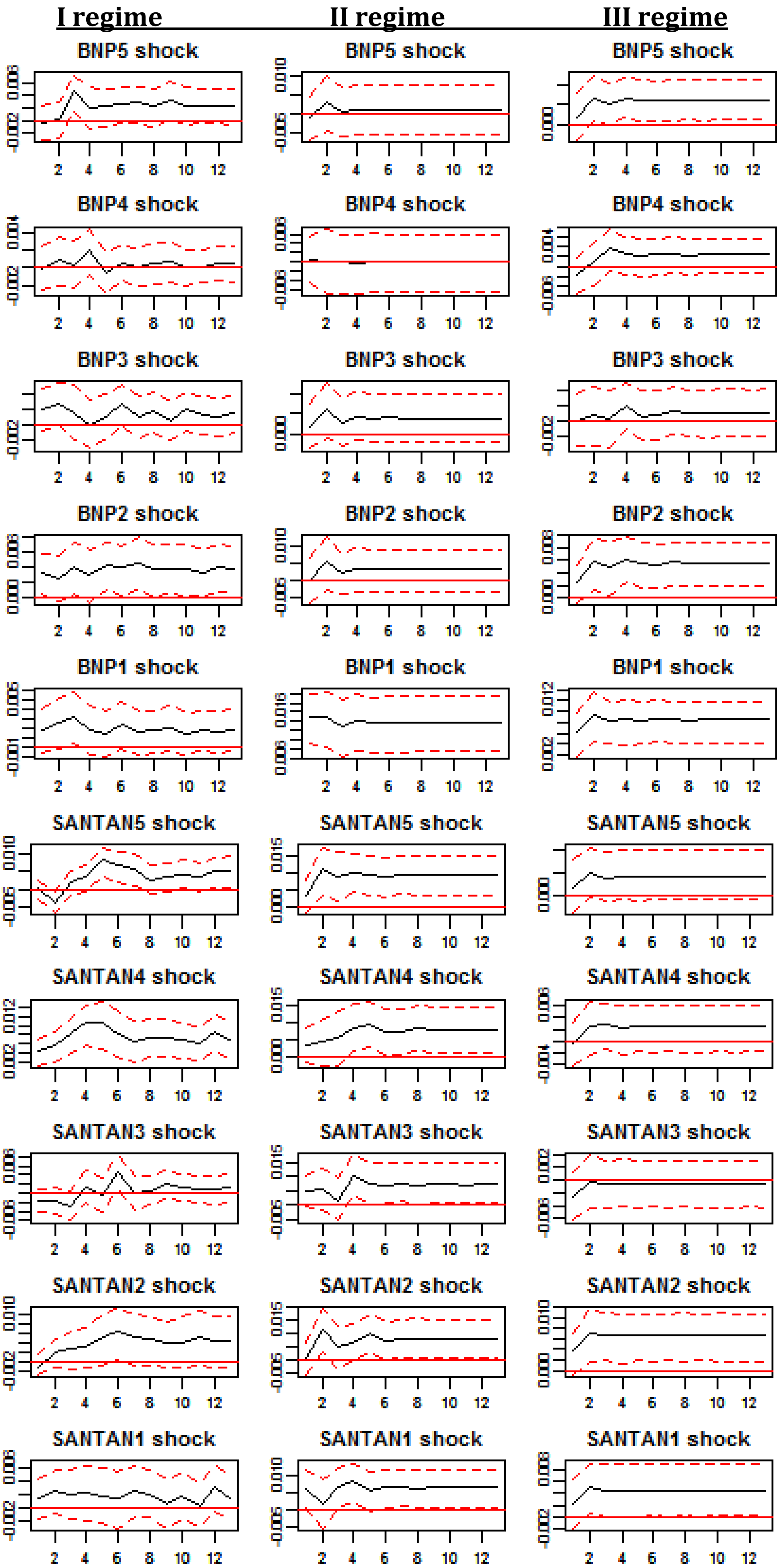

Figure 2. Cumulated IRFs of CISS to a BNP Paribas and Santander bank distress shocks

Notes: BNP indicates a BNP Paribas bank, SANTAN denotes a Santander bank. 1 stands for a shock hitting the eurozone financial system on Monday, 2 – Tuesday, 3 – Wednesday, 4 – Thursday, 5 – Friday. The x-axis represent weeks after the shock. The responses are presented with 90% probability bands (red dashed lines).

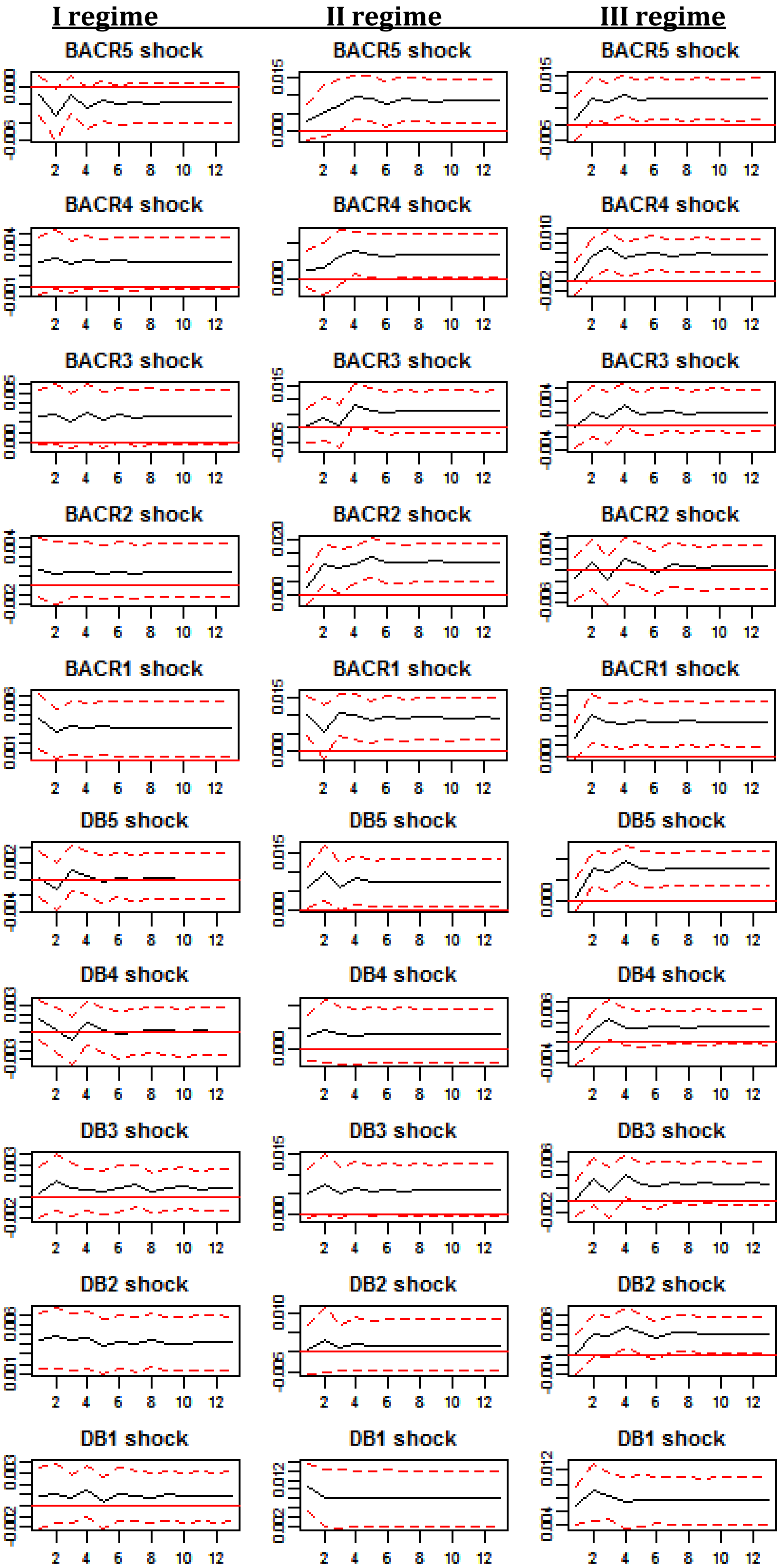

Figure 3. Cumulated IRFs of CISS to a Barclays bank and Deutsche Bank distress shocks

Notes: BACR indicates a Barclays bank, DB – a Deutsche bank. 1 stands for a shock hitting the eurozone financial system on Monday, 2 – Tuesday, 3 – Wednesday, 4 – Thursday, 5 – Friday. The x-axis represent weeks after the shock. The responses are presented with 90% probability bands (red dashed lines).

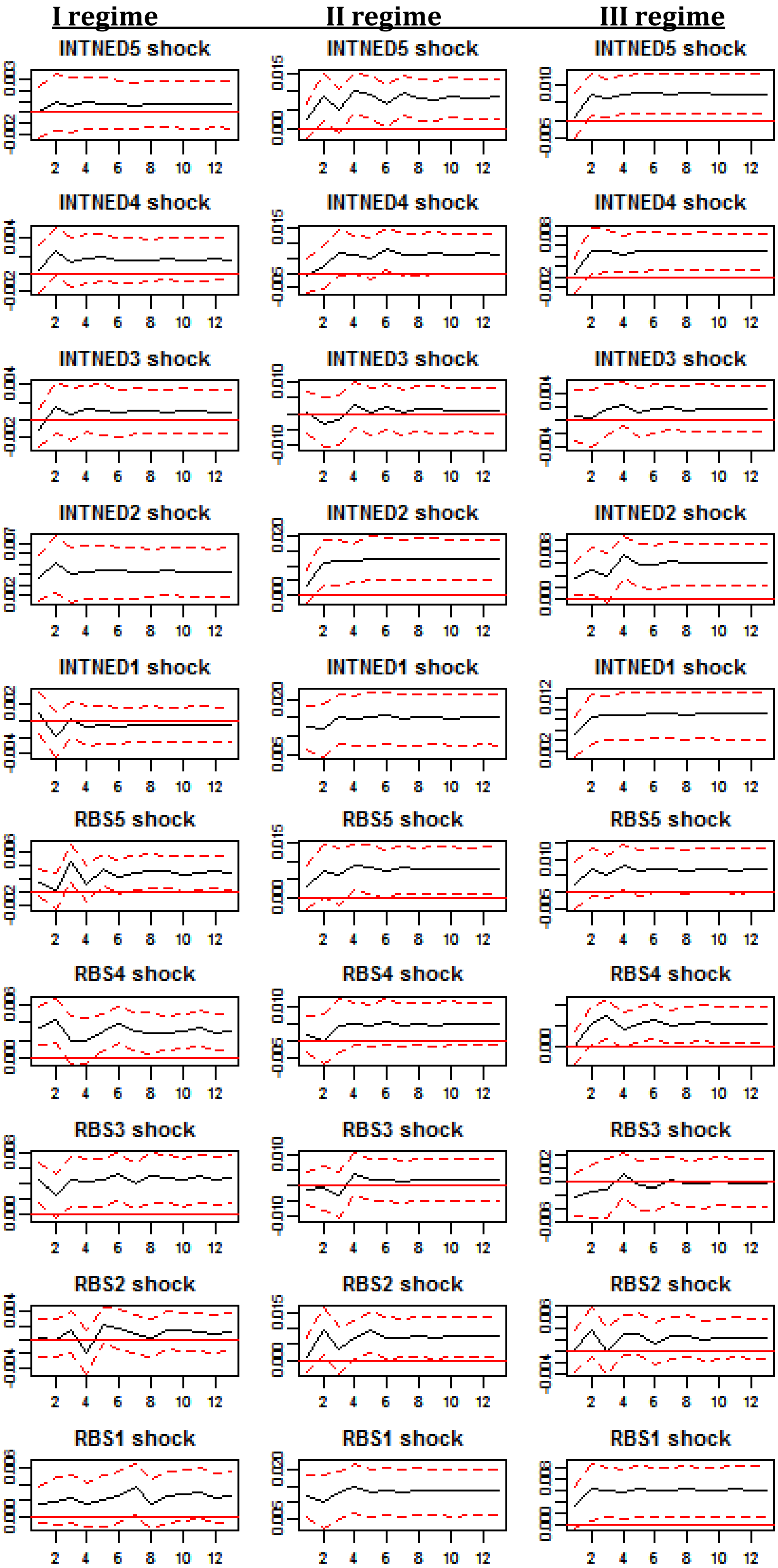

Figure 4. Cumulated IRFs of CISS to a ING Bank and Royal Bank of Scotland distress shocks

Notes: INTNED indicates a ING Bank, RBS denotes a Royal Bank of Scotland1 stands for a shock hitting the eurozone financial system on Monday, 2 – Tuesday, 3 – Wednesday, 4 – Thursday, 5 – Friday. The x-axis represent weeks after the shock. The responses are presented with 90% probability bands (red dashed lines).

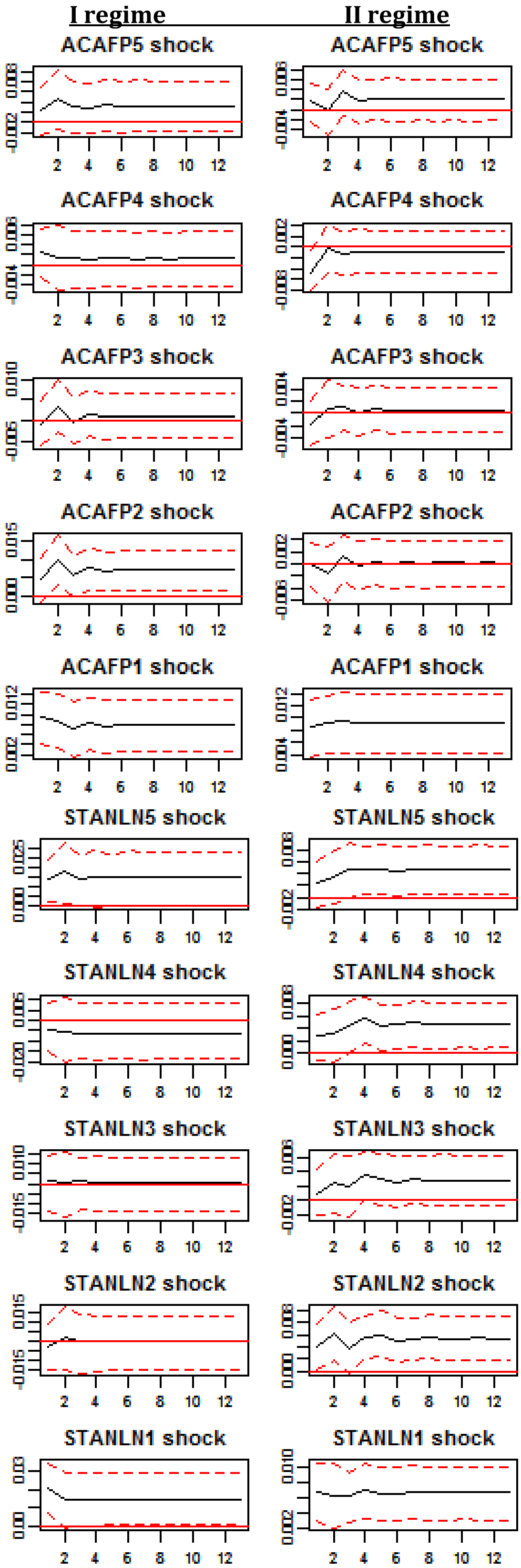

Figure 5. Cumulated IRFs of CISS to a Credit Agricole and Standard Chartered banks distress shocks

Notes: ACAFP denotes a Credit Agricole bank, STANLN a Standard Chartered Bank. 1 stands for a shock hitting the eurozone financial system on Monday, 2 – Tuesday, 3 – Wednesday, 4 – Thursday, 5 – Friday. The x-axis represent weeks after the shock. The responses are presented with 90% probability bands (red dashed lines).

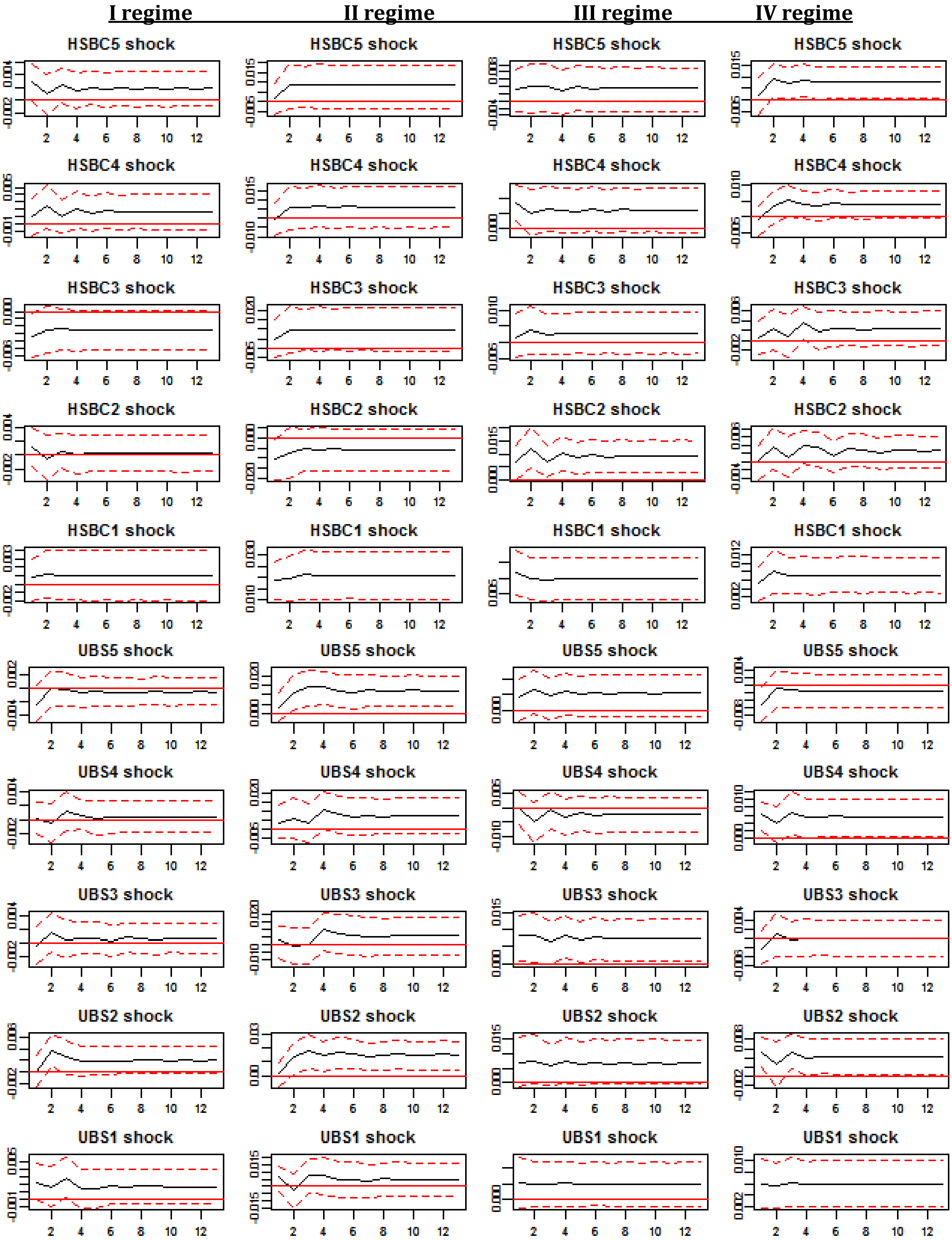

Figure 6. Cumulated IRFs of CISS to a HSBC Bank and UBS Bank distress shocks

Notes: HSBC denotes a HSBC Bank, UBS a UBS Bank. 1 stands for a shock hitting the eurozone financial system on Monday, 2 – Tuesday, 3 – Wednesday, 4 – Thursday, 5 – Friday. The x-axis represent weeks after the shock. The responses are presented with 90% probability bands (red dashed lines).

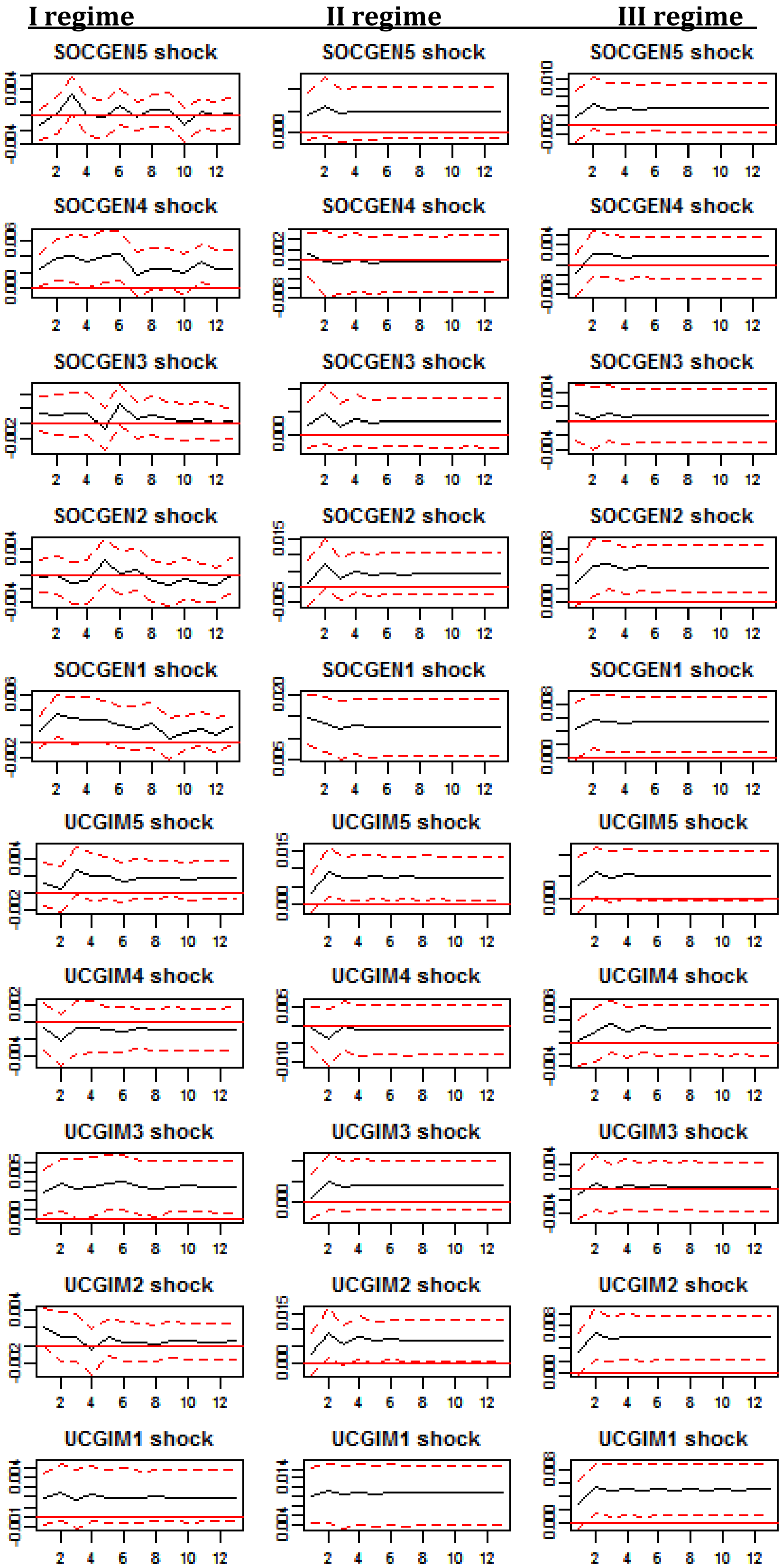

Figure 7. Cumulated IRFs of CISS to a Societe Generale bank and UniCredit Bank distress shocks

Notes: SOCGEN denotes a Societe Generale bank, UCGIM a UniCredit bank. 1 stands for a shock hitting the eurozone financial system on Monday, 2 – Tuesday, 3 – Wednesday, 4 – Thursday, 5 – Friday. The x-axis represent weeks after the shock. The responses are presented with 90% probability bands (red dashed lines).