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ESSAYS ON FINANCIAL STRESS: A MIXED FREQUENCY DATA ANALYSIS

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Introduction

This thesis is a collection of three essays based on the application of mixed frequency macro-financial data analysis to study spillovers. Time series are sampled at different frequencies: generally, financial data is observed at high-frequency (e.g. daily, weekly) and macro data is observed at lower-frequency (e.g. monthly, quarterly). A conventional approach in empirical literature using a Vector Autoregressive (VAR) models is to choose a common sampling frequency for all the variables. This requires aggregation of the high-frequency series to a low-frequency with a loss of potentially relevant high-frequency information (see Ghysels et al., 2007).

An alternative to conventional common-frequency approach is a Mixed Data Sampling, MIDAS-class models proposed by Ghysels et al. (2004) and Ghysels (2016). More specifically, Ghysels (2004) has introduced a MIDAS regression model, where a low-frequency variable is treated as a dependent and the high-frequency ones as regressors. More recently, Ghysels (2016) has proposed a multivariate extension of MIDAS regression model – a mixed sampling frequency VAR model (MF-VAR henceforth), where all high and low frequency variables are treated as endogenous.

The advantage of MF-VAR is argued in the recent literature. In Granger causality test contest, Götz et al. (2016) and Ghysels et al. (2016) show that mixed-frequency Granger causality tests are better suited to recover causal relationships when compared to the standard common low-frequency approach. In a structural VAR context, Bacchiocchi et al. (2018) propose a MIDAS-SVAR model, which is a multivariate extension of unrestricted-MIDAS model (by Foroni et al., 2015) and reverse unrestricted MIDAS model (by Foroni et al., 2018). In empirical application the authors find no relationship between US capital inflows, monetary policy and uncertainty when using common-frequency approach with quarterly data, while MIDAS-SVAR results show a strong positive impact from interest

rate shock on capital inflows when it occurs in the first two months of the quarter and the effect is negative when shock hits the economy in the last month of the quarter.

While the aforementioned MF-VAR studies rely on observable data to model mixed frequency data, the studies of Foroni and Marcelino (2014a, 2014b) use a state space approach, treating the low-frequency series as “missing data” and a low-frequency variable is interpolated to the frequency of a high-frequency variable.

In this thesis I concentrate on the application of the MF-VAR based on observable data. The main advantage of MF-VAR is that it allows the use of the standard VAR tools - impulse response, forecast error variance decomposition analysis and test for Granger causality. The estimation of the model relies on well established procedures, for instance, OLS and maximum likelihood. Moreover, Ghysels (2016) argues that the identifying restrictions implied by a Cholesky factorization are more plausible in a context of mixed frequency structural VAR.

In Chapter 1, I evaluate how important is financial distress of European Global Systemically Important Banks, GSIB, for Eurozone financial distress. The attention to the European banking sector increased during the Eurozone crisis. Since a significant amount of sovereign debt was owed by European banks, the sovereign default could lead to a failure of systemically-important European banks. In this context, regulators and policy makers agreed that the systemically important banks should become a regulatory priority.

This study contributes to the empirical literature measuring the systemic importance of the GSIBs and ranking systemically important financial institutions. Alternatively to previous studies, I measure the contribution of the European systemically important banks to the Eurozone’s financial fluctuations by performing Forecast Error Variance Decomposition (FEVD) analysis. Given the use of mixed frequency data, I fit a structural bivariate Mixed Frequency Data Sampling VAR model to daily GSI bank CDS spread and to the weekly CISS index constructed by ECB to proxy financial distress in the Eurozone. The focus on Forecast Error Variance Decomposition allows measuring the contribution of the European GSIBs to EZ financial distress and to rank systemically important financial institutions. I compare full sample and regime specific estimation results (given the evidence of structural breaks) and the findings show that the contribution of a bank CDS spread to Eurozone financial distress increases during periods of financial turmoil. In addition, I find my FEVD based rankings to be similar to the ones provided by Financial Stability Board list.

The usefulness of a VAR based on mixed frequency data is confirmed by a Likelihood

Ratio test. I show that the aggregation of the daily CDS spread data into weekly observations generate a loss of information in a VAR. Finally, I find that the shocks in MF-SVAR explain a much larger part of the FEVD than in traditional CF-SVAR model, suggesting that the contribution of the European GSIBs to EZ financial distress is underestimated in a common-frequency model.

In Chapter 2 I focus on the links between financial stress and real economic activity in Lithuania. My first contribution is to extend the monthly Financial Stress Index (CLIFS) for Lithuania computed by ECB in two dimensions. First, arguing the important role played by Scandinavian commercial banks in the Lithuanian financial sector development (three Scandinavian banks constitute approximately 73% of the total banking sector assets) I include the banking sector among its constituents (beyond bond, equity, foreign exchange markets). Second, I extend a monthly ECB financial stress index to a high-frequency (daily) horizon. Moreover, I show that a proposed daily financial stress index for Lithuania is a better predictor than a monthly index of ECB for a future path of a monthly industrial production growth in Lithuania.

My second contribution is to investigate the causal relationships between the constructed daily FSI for Lithuania and monthly industrial production growth in Lithuania, by using a Granger causality test. Given a large mismatch in frequencies of the series involved (i.e. daily vs monthly) I apply the Granger causality test developed by Götz et al. (2016) and by Ghysels et al. (2018). The empirical findings suggest that the daily Lithuanian FSI has a predictive power for monthly Lithuanian IP growth for the full sample period (October 2001 – December 2016), but not vice versa.

In Chapter 3, I examine the macro-uncertainty and financial distress connectedness among Eurozone countries. The contribution of this chapter to the existing literature is twofold. First, this study contributes to empirical literature on macro-financial connectedness between Eurozone countries. I show that macro-uncertainty and financial distress are relatively disconnected in the Eurozone (this finding is similar to the one of Jurado et al., 2015, for the US economy). Moreover, in line with the empirical studies of Cipollini et al. (2015), Ehrmann and Fratzscher (2017) and of Caporin et al. (2018), which focus only on sovereign bond markets, I also find evidence of a decrease in the degree of connectedness between the core and periphery block since the outbreak of Eurozone sovereign debt crisis. In addition, I find evidence of a shift in directional connectedness, since core (peripheral) countries are the triggers of the connectedness between macro-uncertainty and financial stress before (since) the Eurozone sovereign debt crisis. Moreover, I show that the connectedness between core and periphery Eurozone countries is occurring mainly

through financial stress. Finally, core countries (in particular Germany, Netherlands and Belgium) are the triggers of the connectedness before the Eurozone sovereign debt crisis (1997-2009), while periphery countries (in particular, Greece, Ireland and Spain) play an important role in driving connectedness in the full sample period including the Eurozone sovereign debt crisis.

Second, my contribution is also methodological. I extend a GVAR model by using the recent econometric developments by Ghysels (2016). In particular, I fit a GVAR model to two endogenous variables: a monthly Country-Level Index of Financial Stress (CLIFS) provided by ECB (see Klaus et al., 2017) and a quarterly index of uncertainty about GDP growth computed by Rossi and Sekhposyan (2017). Then, total and directional connectedness are computed by using the methodology developed by Greenwood-Nimmo et al. (2015) which extends the Diebold and Yilmaz (2012, 2014) VAR based approach to estimate the Forecast Error Variance Decomposition, FEVD, to a Global Vector Autoregressive, GVAR model.

By comparing the results obtained by MF and CF GVAR models, I show that spillovers in the CF model are underestimated. These findings would have implications for the correct implementation of policies aiming at dampening financial instability. For instance, core-periphery connectedness occurring through financial stress is 5 percentage points lower than the connectedness index obtained by MF approach. Moreover, contrary to the MF results, the common-frequency model suggests that periphery countries are net donors in terms of financial distress before Eurozone debt crisis and they become net recipients once I consider also the Euro sovereign debt crisis.

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Chapter 1

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

1.1 Introduction

The attention to the European banking sector increased during the Eurozone crisis when financial markets became increasingly sceptical about the capability of few peripheral Eurozone member states to be able to pay their government debt. Since a significant amount of sovereign debt is owed by European banks, the sovereign default could lead to a failure of systemically-important European banks. The recent global financial crisis showed how the collapse of a systemically important bank can bring all financial system into a deep crisis. In this context, 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, under distress, given their size, interconnectedness, substitutability, complexity, and cross jurisdictional activities, would be significantly harmful for the whole financial system and economic activity (BCBS, 2013; FSB, 2016).

The aim of this chapter is to contribute to the empirical literature measuring the systemic importance of the GSIBs and ranking systemically important financial institutions. More specifically, this study is along the lines of Adrian and Brunnermeier (2016). The authors propose the (ΔCoVaR) indicator of systemic risk to evaluate the financial sys-

tem loss conditional on each institution being in distress.¹ Alternatively, I measure the contribution of the European systemically important banks to the Eurozone's financial fluctuations by performing the Forecast Error Variance Decomposition (FEVD) analysis.² Moreover, I rank the European GSIBs according to the contribution of CDS spreads of each European GSIB to the FEVD of the CISS index.³

My contribution also builds on a growing strand of the literature focusing on spillovers between sovereign credit markets and systemically relevant banks in Eurozone. For instance, Alter and Schüler (2012) provide empirical evidence on risk spillovers between banks and sovereigns during the period between June 2007 and May 2010, by fitting a bivariate VAR to a sovereign CDS spread and a selected domestic bank CDS spread. The authors find evidence of contagion from bank credit spreads into the sovereign CDS market in the period before bank bailouts, while after bailouts sovereign CDS spreads impact bank CDSs more strongly. Similarly, Alter and Beyer (2014) focus on spillovers between sovereign credit markets and systemically relevant banks in Eurozone. To quantify spillovers, the authors use a vector autoregressive model fitted to daily sovereign and bank CDS series. Their main results state that spillover effects from banks to sovereigns and vice versa increase during periods of stress, suggesting an intensifying feedback loop between Eurozone banks and sovereigns.

In this chapter, I proxy the European GSIBs by using daily CDS spreads with 5-year maturity and Eurozone financial distress by a weekly composite indicator of systemic stress, CISS, for EZ (see Holló et al., 2012).⁴ Given the use of mixed frequency data, I employ a structural MF-VAR model, suggested by Ghysels (2016), to obtain the contribution of CDS spreads of each European GSIB to the Forecast Error Variance, FEVD, of the CISS index. In addition, I compare the results obtained by MF-VAR model and the traditional common-frequency (CF)SVAR model. The collected data covers the period

¹I do not focus on measuring the vulnerability of a single financial institution to distress affecting the whole financial system. The recently proposed macro-prudential indicators such as the Distress Insurance Premium (DIP), the Marginal Expected Shortfall (MES) and the Systemic Risk Measure (SRISK) put forward by Huang et al. (2012), Acharya et al. (2017), and by Brownlees and Engle (2016) focus on the expected loss of an institution when the system is in distress.

²Impulse response analysis (in section 1.4.3.2) shows that, overall, there is a positive spillover from the CDS spread of a GSIB to the CISS index.

³The CISS is a financial stress index for Eurozone, quantifying the current state of financial instability in the Eurozone financial system. It is constructed by aggregating individual stress indicators of five markets - the financial intermediaries sector, money markets, equity markets, bond markets and foreign exchange markets, into a single composite indicator (for more details see Section 1.A.1.1).

⁴The studies of Alter and Schüler (2012), Alter and Beyer (2014), Acharya and Steffen (2015), Ballester et al. (2016), Cetina and Loudis (2016), among others, focus on the use of CDS as proxy of financial institutions distress (e.g. probability of default) and explore spillover effects.

starting before the global financial crisis and ending in 28/10/2016. First, the empirical analysis is carried out using the full sample, and then, given the evidence of structural breaks (using methodology of Qu and Perron, 2007), 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.

Overall, I find that the major contribution of GSIBs distress shocks to CISS fluctuations occurred in the last regime, which covers the period between 2012 and 2016. In addition, the ordering of the GSIB in terms systemic importance using the FEVD obtained through MF VAR are similar to the rankings provided by the Financial Stability Board (FSB). The usefulness of a VAR based on mixed frequency data is confirmed by a Likelihood Ratio test. I show that the aggregation of the daily CDS spread data into weekly observations generate a loss of information in a VAR. Finally, I find that the shocks in MF-SVAR explain a much larger part of the FEVD than in traditional CF-SVAR model, suggesting that the contribution of the European GSIBs to EZ financial distress is underestimated in a common-frequency model.

The rest of the chapter is organized as follows. In section 1.2 I present the methodology. Section 1.3 describes the data. Section 1.4 discusses the results. Finally, section 1.5 concludes.

1.2 VAR Methodology

1.2.1 Traditional CF-VAR

Traditional VAR analysis is based on using time series sampled at the same (common) frequency. If data have mixed-frequency, then the observations of the high-frequency variable are aggregated to match the observations of the low-frequency series. The traditional CF-VAR model used in this study is based on average of a daily CDS spread over a week to match the weekly frequency of the composite indicator of financial stress for the Eurozone, the CISS index. Since the series are integrated of order one (according to the Augmented Dickey-fuller test), in a first stage of multivariate analysis, I transform the data into first-differences.

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

$$Ay_t = c + \sum_{i=1}^p C_i y_{t-i} + B\varepsilon_t, \quad \varepsilon_t \sim N(0, I_n) \quad (1.1)$$

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, ε_t is a (2×1) vector of orthogonalized structural shocks, including a GSI bank distress shock (ε_t^b) and a EZ financial distress shock (ε_t^f). Finally, B is a (2×2) coefficient matrix of structural shocks' standard deviations restricted to be diagonal. The corresponding reduced-form model is obtained by pre-multiplying the structural model by A^{-1} :

$$y_t = \mu + \sum_{i=1}^p \Gamma_i y_{t-i} + u_t, \quad u_t \sim N(0, \Sigma_u) \quad (1.2)$$

where the reduced form shocks have covariance matrix $E(u_t, u_t') = \Sigma_u$. Identification of the structural shocks is obtained through the Cholesky decomposition of Σ_u , and given the focus on the impact of GSI bank distress shock on EZ financial distress, the CDS spread is ordered first. Therefore, the (exactly) identifying restrictions are given by the following configuration of the structural form coefficient matrices:

$$A = \begin{pmatrix} 1 & 0 \\ a & 1 \end{pmatrix} \text{ and } B = \begin{pmatrix} b_1 & 0 \\ 0 & b_2 \end{pmatrix} \quad (1.3)$$

1.2.2 MF VAR

Recent studies (see Clements and Galvão, 2008; Foroni et al., 2015; Ghysels, 2016; Götz et al., 2016; among others) use mixed-frequency data directly, without any time aggregation. In this study I follow the approach proposed by Ghysels (2016).

I denote a low-frequency and high-frequency variable by x_L and x_H , respectively. A high-frequency variable is observed m times during a low-frequency period t . More specifically, the high-frequency variable – CDS spread, is observed 5 days during a week, $m = 5$. Since, an index $j = (1, 2, 3, 4, 5)$ is used for a specific high-frequency observation in a week t , the five daily observations (from Monday to Friday) for the high-frequency CDS spread are indicated by $x_H(t, 1), x_H(t, 2), x_H(t, 3), x_H(t, 4), x_H(t, 5)$, respectively. Next, in line with Ghysels (2016), I construct a *stacked vector* (Z_t) of six endogenous variables, appending the low-frequency series to the five high-frequency variables. Then a reduced-form

MF-VAR(p) model in a matrix notation has the following form:

$$\begin{pmatrix} x_H(t, 1) \\ x_H(t, 2) \\ x_H(t, 3) \\ x_H(t, 4) \\ x_H(t, 5) \\ x_L(t) \end{pmatrix} = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \\ \mu_4 \\ \mu_5 \\ \mu_L \end{pmatrix} + \sum_{i=1}^p \begin{pmatrix} \gamma_{11}^i & \gamma_{12}^i & \gamma_{13}^i & \gamma_{14}^i & \gamma_{15}^i & \gamma_1^i \\ \gamma_{21}^i & \gamma_{22}^i & \gamma_{23}^i & \gamma_{24}^i & \gamma_{25}^i & \gamma_2^i \\ \gamma_{31}^i & \gamma_{32}^i & \gamma_{33}^i & \gamma_{34}^i & \gamma_{35}^i & \gamma_3^i \\ \gamma_{41}^i & \gamma_{42}^i & \gamma_{43}^i & \gamma_{44}^i & \gamma_{45}^i & \gamma_4^i \\ \gamma_{51}^i & \gamma_{52}^i & \gamma_{53}^i & \gamma_{54}^i & \gamma_{55}^i & \gamma_5^i \\ \gamma_{L1}^i & \gamma_{L2}^i & \gamma_{L3}^i & \gamma_{L4}^i & \gamma_{L5}^i & \gamma_L^i \end{pmatrix} \begin{pmatrix} x_H(t-i, 1) \\ x_H(t-i, 2) \\ x_H(t-i, 3) \\ x_H(t-i, 4) \\ x_H(t-i, 5) \\ x_L(t-i) \end{pmatrix} + \begin{pmatrix} u_H(t, 1) \\ u_H(t, 2) \\ u_H(t, 3) \\ u_H(t, 4) \\ u_H(t, 5) \\ u_L(t) \end{pmatrix} \quad (1.4)$$

where a time index t is a week, as in a *traditional* VAR model.⁵ The covariance matrix of the reduced form shocks (u_t^{MF}) is:

$$u_t^{MF} = \begin{pmatrix} \sigma_{11} & \cdots & \cdots & \sigma_{1L} \\ \vdots & \sigma_{22} & \cdots & \vdots \\ \sigma_{51} & \vdots & \ddots & \vdots \\ \sigma_{L1} & \sigma_{L2} & \cdots & \sigma_{LL} \end{pmatrix} \quad (1.5)$$

Next, consider a structural MF-VAR model:

$$A \begin{pmatrix} x_H(t, 1) \\ x_H(t, 2) \\ x_H(t, 3) \\ x_H(t, 4) \\ x_H(t, 5) \\ x_L(t) \end{pmatrix} = c + \sum_{i=1}^p C_i \begin{pmatrix} x_H(t-i, 1) \\ x_H(t-i, 2) \\ x_H(t-i, 3) \\ x_H(t-i, 4) \\ x_H(t-i, 5) \\ x_L(t-i) \end{pmatrix} + B \begin{pmatrix} \varepsilon_H(t, 1) \\ \varepsilon_H(t, 2) \\ \varepsilon_H(t, 3) \\ \varepsilon_H(t, 4) \\ \varepsilon_H(t, 5) \\ \varepsilon_L(t) \end{pmatrix} \quad (1.6)$$

where A is a coefficient matrix describing contemporaneous relations between the bank CDS spread and the CISS index within a week t . The orthogonal structural shocks (with variance equal to unity), described by the six dimensional vector $\varepsilon_t^{MF} = (\varepsilon_H(t, j)', \varepsilon_L(t)')$ can be recovered from reduced-form errors, u_t^{MF} , since $u_t^{MF} = A^{-1}B\varepsilon_t^{MF}$ and $\Sigma_u^{MF} = A^{-1}BB'A^{-1}$. I use the recursive identifying scheme implied by the Cholesky decomposition of the reduced form covariance matrix, ordering the daily observations of the CDS spread first:

⁵The optimal lag length p (in weeks) is obtained through a *Bayesian information criterion*.

$$A = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ a_1 & 1 & 0 & 0 & 0 & 0 \\ a_2 & a_3 & 1 & 0 & 0 & 0 \\ a_4 & a_5 & a_6 & 1 & 0 & 0 \\ a_7 & a_8 & a_9 & a_{10} & 1 & 0 \\ a_{11} & a_{12} & a_{13} & a_{14} & a_{15} & 1 \end{pmatrix} \quad (1.7)$$

It is important to observe that the identifying scheme based on recursive ordering implies that, on impact, only the high-frequency structural shocks $\varepsilon_H(t, j)$ hit the low-frequency series (x_L) (e.g. the index of Eurozone financial stress). Therefore, the feedback from the CISS index to the bank CDS spread occurs a week after the shock onwards. Moreover, the recursive scheme implies also that a shock to a bank CDS spread on a given day has an effect only on the following days of the week. More specifically, while a shock to the CDS spread of Monday $\varepsilon_H(t, 1)$ has an effect on the following days of the week t (measured by the first column coefficients a_1, a_2, a_4, a_7), the CDS spread on Friday is only affected by a shock occurring on the same day.

The use of restrictions on lagged coefficient matrix beyond those exactly identifying the structural form impact multiplier matrix would require the use of ML joint estimation of two sets of structural form coefficients: those for the impact multiplier and those related to the autoregressive coefficients of the high and low frequency variables. Although this model is more parsimonious, it is more computationally demanding than the exactly identified model I propose. In this case, the estimation is split in two stages: in the first stage I estimate the reduced form model by OLS. In the second stage, I employ the Cholesky decomposition of reduced form covariance matrix (hence, the number of structural form parameters is only related to the structural form impact multiplier matrix).

Finally, the magnitude of the structural shocks ε_t^{MF} is measured by the main diagonal elements of matrix B :

$$B = \begin{pmatrix} b_{11} & 0 & 0 & 0 & 0 & 0 \\ 0 & b_{22} & 0 & 0 & 0 & 0 \\ 0 & 0 & b_{33} & 0 & 0 & 0 \\ 0 & 0 & 0 & b_{44} & 0 & 0 \\ 0 & 0 & 0 & 0 & b_{55} & 0 \\ 0 & 0 & 0 & 0 & 0 & b_{LL} \end{pmatrix} \quad (1.8)$$

1.2.3 Likelihood Ratio Test: MF VAR *vs* CF-VAR

I follow Bacchiocchi et al. (2018) to analyse the usefulness of the MF VAR by testing, through a LR statistics, whether aggregation of the mixed-frequency series as in traditional CF-VAR generates a loss of information. The authors suggest that the comparison between the two specifications depends on the aggregation scheme used to aggregate the high-frequency data in a CF-VAR.

Recall that the traditional CF-VAR model in eq. (1.2):

$$\Gamma(L)y_t = u_t \quad (1.9)$$

where y_t is a 2×1 column vector which includes daily observation of CDS spreads aggregated over a week (through simple average) to match the weekly frequency of the CISS index. Given a selection matrix G , the common-frequency data vector (y_t) can be mapped to the mixed-frequency data stacked vector (Z_t) as follows:

$$y_t = GZ_t \quad (1.10)$$

$$\text{with } G = \begin{pmatrix} \frac{1}{5} & \frac{1}{5} & \frac{1}{5} & \frac{1}{5} & \frac{1}{5} & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \text{ and } u_t = Gu_t^{MF}.$$

Bacchiocchi et al. (2018) shows that pre-multiplying the MF-VAR model in eq. (1.4) by the selection matrix G :

$$G\Gamma(L)^{MF}Z_t = Gu_t^{MF} \quad (1.11)$$

I get the equivalence between the reduced form MF-VAR and CF-VAR:

$$G\Gamma(L)^{MF}Z_t = \Gamma(L)y_t \quad (1.12)$$

Therefore, the LR statistics can be computed by comparing the log-likelihood of the unrestricted model, i.e. MF-VAR, with the one associated with the restricted model, i.e. CF-VAR. The test statistics $LR = -2(l^r - l^u)$ is asymptotically distributed as a χ^2 , with the degrees of freedom equal to the number of restrictions on the MF VAR coefficients. In particular, I consider 32 restrictions for each lag: eight are imposed on the parameters

capturing the relationships between high- and low-frequency variables and twenty-four are imposed on the parameters capturing the relationships between the high-frequency variables.⁶

1.2.4 Forecast Error Variance Decomposition Analysis

Once the MF VAR has been estimated, the forecast error variance decomposition (FEVD) analysis is used to analyze how the GSIBs distress shocks affect the financial stability in the Eurozone. I measure the fraction of the H-step-ahead error variance in forecasting the CISS index (x_L) attributable to shocks in GSI banks distress (ε_H) for any given forecast horizon (H) as:

$$FEVD = \theta_{L,j}(H) = \frac{\sum_{h=0}^{H-1} (e'_{x_L} \Psi_h e_j)^2}{\sum_{h=0}^{H-1} e'_{x_L} \Psi_h \Psi_h e_{x_L}} \quad (1.13)$$

where Ψ_h is the matrix of moving average structural form coefficients for horizon h .

The reduced-form stationary MF VAR in eq. (1.4) can be inverted to obtain the reduced-form Vector Moving Average representation:

$$Z_t = \sum_{h=0}^{\infty} \Phi_h u_{t-h}^{MF} \quad (1.14)$$

where $\Phi_0 = I_K$, and the remaining $\Phi_h = \sum_{i=1}^{h-1} \Phi_{h-i} \Gamma_i$. Then, the structural form coefficients in Ψ_h (in eq. 1.13) are estimated from the Moving Average representation with orthogonal white noise innovations, as follows:

$$Z_t = \sum_{h=0}^{\infty} \Psi_h \varepsilon_{t-h}^{MF} \quad (1.15)$$

where $\varepsilon_t^{MF} = A^{-1} B u_t^{MF}$ and $\Psi_h = \Phi_h A^{-1} B$.

Given that I am interested in measuring the contribution of the shocks in CDS spread to the forecast error variance of the low-frequency CISS index for the H-step-ahead horizon, I focus only on the first five coefficients of the last row of Ψ_h : $\theta_{L1}(H), \theta_{L2}(H), \theta_{L3}(H), \theta_{L4}(H), \theta_{L5}(H)$. For this purpose, I use the six dimensional selection vectors: the row vector $e'_{x_L} = [0, 0, 0, 0, 0, 1]$ and the column vector e_j which takes value 1 in only one of

⁶I consider different VAR lag length varying from one to four.

the first five rows and zero elsewhere. Finally, I compare the sum the five aforementioned coefficients with the single coefficient measuring the FEVD associated with a traditional bi-dimensional CF-VAR.

1.3 Data

This analysis concentrates on the following European banks: *BNP Paribas (FR)*, *Banco Santander S.A. (ES)*, *Barclays Bank PLC (UK)*, *Groupe Cr dit Agricole (FR)*, *Deutsche Bank AG (DE)*, *HSBC Bank PLC (UK)*, *ING Bank NV (NL)*, *Royal Bank of Scotland (UK)*, *Soci t  G n rale 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. I collect, from Bloomberg, the daily senior CDS spreads with 5-year maturity, since these contracts are generally considered the most liquid and constitute the majority of the entire CDS market.⁷

I use the Composite Indicator of Systemic Stress (CISS), proposed by Holl  et al. (2012), available from ECB, to measure financial distress in Eurozone.⁸ The weekly CISS index is based on 15 raw indicators of financial stress capturing the dynamics of five Eurozone financial markets: money, foreign exchange, banking and non-bank financial intermediaries sector, equity and bond. The construction of the index consists in two steps: first, each raw indicator is transformed through the cumulative distribution function (CDF), then, five separate sub-indexes are computed, and aggregated using time-varying pair-wise correlation (see Appendix 1.A.1.1). The CISS index varies between 0 and 1. Higher values are associated with a higher level of stress in the Eurozone.

The starting date of the sample for each bivariate VAR varies according to the availability of the CDS spread, and ends on 28/10/2016 (for more details see Table 1.1 in Appendix 1.A.4). I use 5 observations per week (from Monday to Friday) for the CDS spread. Descriptive statistics for CDS spread data for 12 analysed banks is presented in Table 1.2. The average values (means) of spreads ranges from 0.99% to 2.23%, respectively, for HSBC and Cr dit Agricole. The CDS spread maximum values are those for UniCredit, Royal Bank of Scotland and Soci t  G n rale, and they are equal to 11.53%, 8.78%, 7.96%, respectively. The CISS index values and the CDS spreads peak during the

⁷The 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, and the higher is the premium or CDS spread.

⁸The index is available at: <https://sdw.ecb.europa.eu/browse.do?node=9689689>

periods of financial turmoil (see the Figures in Appendix 1.A.2).

1.4 Empirical Evidence

1.4.1 Structural Breaks

Given the focus on an extended sample involving periods of no crisis with those associated with the global financial and Eurozone sovereign debt crisis, the multivariate analysis is not only based on the full sample, but also on sub-samples identified endogenously. For this purpose, I apply Qu and Perron (2007) methodology (see Appendix 1.A.1.2) to investigate whether there have been structural changes in the traditional CF-VAR fitted to the CISS index and each of the 12 GSIBs CDS spreads (in first difference). More specifically, I focus on breaks in the reduced-form residuals covariance matrix since they underlie shifts in the corresponding Cholesky factorization used to derive the structural form moving average coefficients used to compute the FEVD. Moreover, I argue that the number of breaks detected endogenously is conservative since the estimation of a traditional reduced-form VAR relies on time aggregation and it is bound to discover linkages between the CISS index and CDS spread weaker than the ones that can be obtained by using mixed-frequency data.

Table 1.3 and Figure 1.1 show the results of the Qu and Perron (2007) test. I report the number of structural breaks and the associated dates for the 12 VAR models considered in the analysis. In particular, Table 1.3 shows the results associated with the $SEQ(l+1|1)$ test.⁹ The trimming parameter ε chosen for a regime minimal length is the same for all dataset and is set equal to 0.2, thus, each regime has a length of $T \times 0.2$. The maximum number of break points (M) considered for datasets having more than 700 weekly observations is set equal to three, while one break is allowed for those having less than 500 observations.¹⁰ The choice of three as the maximum number of breaks is motivated by the sample under investigation covering the 2002-2016 period hit by two periods of major financial turmoil: the global financial crisis and the European debt crisis.¹¹

⁹I do not report the results on double maximum tests (WDmax) since I always reject the null hypothesis of no break *vs* existence of at least one breakpoint.

¹⁰I impose $M = 3$ for the following banks: BNP Paribas, Banco Santander, Barclays Bank, Deutsche Bank, HSBC Bank, ING Bank, Royal Bank of Scotland, Societe Generale, UBS and UniCredit; I impose $M = 1$ for the following banks: Cr dit Agricole SA and Standard Chartered Bank.

¹¹More specifically, the maximum of three break points allow the four possible regimes: (i) the relatively “tranquil” period before the global financial crisis (2002-2007), (ii) the global financial crisis (caused by the turmoil in the US subprime mortgage market, 2007-2009), (iii) the peak of crisis associated with Eurozone

Let me firstly consider the models with $M = 3$. The $SEQ(3|2)$ test allows rejecting the null hypothesis of two structural break points against the alternative of three in two VAR models: one including HSBC Bank and another one including UBS. Since I cannot reject the null hypothesis of $SEQ(3|2)$ test for eight remaining VAR models, where M is set equal to three, I conclude that there is evidence of two breaks. Finally, I find evidence of one structural break for the VAR models (including either Crédit Agricole or Standard Chartered Bank) where M is set equal to one.

The results in this section suggest that the identified structural break points can be related to important systemic changes. The three break points cases, associated with HSBC and UBS banks, identify separately a tranquil period (before July 2007), from the global financial crisis (caused by the turmoil in the US subprime mortgage market), which led several banks to severe liquidity problems, and the one associated with Eurozone sovereign debt (starting from mid-2010). While the cases of two break points, identify separately only the tranquil regime (pre July 2007) from a period of financial turmoil related to the subprime and Eurozone sovereign debt markets.

1.4.2 LR Test: MF VAR *vs* CF VAR

Table 1.4 shows the results of the LR test that show whether there is a loss of information in a VAR model based on the weekly CISS index and on the aggregation of the daily CDS spread data into weekly observations. I can observe that the null of equivalence between the traditional CF VAR and the MF VAR is strongly rejected. The results suggest that each of the estimated MF VAR models provide more accurate results than the traditional VAR. Therefore, aggregating the mixed-frequency data to a low-frequency generates a loss of information.

1.4.3 The Importance of GSI Banks Distress to EZ Financial Stability

1.4.3.1 FEVD: importance of G-SIB shocks

Table 1.5 gives the percentage of the forecast error variance of the CISS index that can be attributed to innovations in GSI banks distress at different forecast horizons: 1, 2, 3, 4 weeks ahead. The FEVD is computed, first, for the full sample and then separately for each regime (i.e. sub-sample), which has been identified through the structural break

sovereign debt (2009-2012), and (iv) the period after the Eurozone sovereign debt crisis (2012-2016).

test used in the first stage of the analysis. It is important to notice that, when the focus is on the MF-SVAR, I compute the sum of the FEVD of each day of the week to make comparison with the aggregate ones associated with the traditional CF-SVAR.

I first comment on the FEVD results associated with the MF-SVAR. Table 1.6, which provide a summary of results, shows that the role played by a bank distress shock in explaining the fluctuations of the EZ financial stress index increases when I move from one week to a one month forecast horizon. In particular, if the focus is on the full sample period, a GSIBs' distress shock account (on average) for 7.5% of the EZ financial stress variability at 4-week horizon (see the mean values given in Panel A of Table 1.6). Inspection of the other three panels (B-D) of Table 1.6 shows that (on average) the contribution of GSI banks distress shocks to EZ financial stress variation have increased over the years. More specifically, the mean value of FEVD (for the four week ahead forecast horizon) for the pre-crisis sub-sample (see Panel B) and for the crisis sub-samples (see Panel C and D) are equal to 6.83%, 9.03% and 9.79%.

In particular, from Table 1.5, which shows the contribution of each bank separately, I can observe that only Santander and RBS bank distress shocks explain more than 10% of the EZ financial stress variation (at 4-week horizon) during the period preceding global financial crisis (before July 2007). The number of banks contributing more than 10% to the CISS forecast error variance (at 4-week horizon) increases to eight (Barclays, Crédit Agricole, Deutsche Bank, HSBC, ING, Royal Bank of Scotland, Standard Chartered and UBS banks) during the global financial and Eurozone sovereign debt crisis period (July 2007 – October 2016). Furthermore, I find that the major contribution of GSIBs distress shocks to CISS fluctuations at 4-week horizon occurs in the last regime.

The results for the CF-SVAR approach are shown in columns with label CF in each Panel (1-12) of Table 1.5. Inspection of CF-SVAR results confirms the empirical findings of MF-SVAR: the contribution of the GSI banks distress shock to the fluctuation of EZ financial stress has been increasing over the years. It is important to observe that the shocks in MF-SVAR model explain a larger part of the FEVD than in CF-SVAR model.¹² This finding is confirmed by Table 1.6, which shows the descriptive stats of FEVD results in Table 1.5. I find that in MF approach not only the mean values, but also the max and min of the FEVD shares across each GSIB institution are bigger than those corresponding to a CF-SVAR model.

¹²These findings are similar to those obtained by Bacchiocchi et al. (2018). 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 MF-SVAR.

1.4.3.2 Impulse response to structural shocks

The regime specific cumulative impulse responses based on MF-SVAR model (see figures in section 1.A.3) complement the FEVD analysis used to assess the importance of GSI banks distress shocks for the dynamics of EZ financial distress. The impulse response analyses show that, overall, there is a positive spillover from the CDS spread of a GSIB to the CISS index. More specifically, Figures 1.2 - 1.6 show the response (over a 12 week horizon) of the proxy of Eurozone financial distress to a one standard deviation shock to the CDS spread of a GSIB.

The findings also suggest that a shock observed at the beginning of the week, especially on 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 have an immediate effect, while the shocks on Tuesday-Friday takes more time to reach their strongest impact.

1.4.3.3 Rankings: the Most Important Banks for EZ Financial Distress

In Table 1.7 I rank the European GSIBs according to the FEVD results at 4-week horizon obtained by estimating a regime specific MF-VAR. More specifically, the ranking is provided for three sub-samples, Pre-Crisis Regime, Crisis Regime 1 and Crisis Regime 2 (see Table 1.7), which involve the period before the financial turmoil, the global financial and the European sovereign debt crises and the period after. From Table 1.7 I can observe that, before the global financial crisis, while Banco Santander and RBS were the largest contributors to the fluctuations of EZ financial distress (the corresponding FEVD values are 13.76% and 11.19%, respectively), the financial stress of the other banks were considerably less important. Moreover, during Crisis Regime 1, associated with the global financial crisis and the European sovereign debt crisis, there is an important increase in the role played by each European GSIBs (especially DB) in shaping CISS dynamics, with the exception of RBS and Banco Santander. Since the start of the global financial crisis to the most recent years, UBS and HSBC have played an important role and have remained among the top four contributors of EZ financial distress fluctuations. Standard Chartered is the bank showing the largest swing, since its contribution to Eurozone financial distress drops from 10% (during the second regime) to 5.63% (during the third regime starting from March 2010). As for the third regime (observed over 2012-2016), the four largest contributors to EZ distress are: UBS (13.82%), DB (13.14%), Barclays (12.86%) and HSBC (12.49%). In contrast, I observe that UniCredit bank and Société Générale bank

are consistently among the least important for EZ financial fluctuations over the three regimes.

I also compare the role of GSI banks headquartered in Eurozone countries with the one related to GSI banks headquartered in non-Eurozone countries for EZ financial distress. First, the ranking in Table 1.7 suggests that the non-Eurozone GSIBs are as well important as EZ-GSIBs. In particular, UK banks (Barclays, Standard Chartered, HSBC and RBS) and UBS (which is headquartered in Switzerland) are among the four largest contributors in at least one of the regimes. Moreover, the role played by non-Eurozone GSIBs appears to have been increasing since September 2007. More specifically, while only RBS explains more than 10% of the EZ financial distress fluctuations during the first regime, non-EZ banks are the largest contributors over the second regime.

Finally, I compare the benchmark rankings in Table 1.8 (available over the 2013-2016 period) with the ones obtained from the estimation of the Crisis Regime 2 MF VAR (see last column of Table 1.7). I find the results obtained in this section to be similar to the FSB list. More specifically, UBS and HSBC banks, which are ranked among the top four, are regarded as the most systemically risky according to the FSB list. Moreover, in line with FSB, I rank Barclays and Deutsche Bank among the top four systemically risky. Furthermore, the least systemically important banks in the list (Santander, Standard Chartered, Société Générale and UniCredit), are also considered the least systemically important according to FSB.

1.5 Conclusions

In this chapter I evaluate how important is financial distress of European GSI banks for Eurozone financial stability. I use CDS spread (available on daily basis) and the CISS index (available at weekly frequency) as proxies of financial stress for GSI banks and the Eurozone, respectively. I focus on the Forecast Error Variance Decomposition, to measure the contribution of the European GSIBs to EZ financial distress by fitting a bivariate VAR based either on common frequency data or on mixed frequency data, e.g. a MF VAR (see Ghysels, 2016). The usefulness of a VAR based on mixed frequency data sampling is confirmed by a Likelihood Ratio test. I also distinguish between full sample analysis and a regime specific one (given the evidence of structural breaks). The empirical findings suggest that the contribution of the European GSIBs to EZ financial distress has increased over the sample period under investigation, once I move from a pre-crisis period to the

one associated with financial turmoil related to global financial and Eurozone sovereign debt crises. Moreover, the MF-SVAR empirical findings suggest a more important role of GSI bank distress for the CISS variability than the one suggested by estimation of a traditional CF-SVAR model. Finally, I find the rankings based on FEVD to be similar to the ones provided by Financial Stability Board list.

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1.A Appendix

1.A.1 Methodology

1.A.1.1 CISS index

The European Central Bank periodically publishes a weekly Composite Indicator for Systemic Stress (CISS), developed by Holló et al. (2012). The aim of financial stress indices (FSIs) such as the CISS is to measure the current state of instability, i.e. the current level of frictions, stresses and strains in the financial system.

Data used for CISS construction. The CISS comprises 15 market-based financial stress indicators equally split into five categories: the financial intermediaries sector, money markets, equity markets, bond markets and foreign exchange markets, arguably representing the most important segments of a financial system. A separate financial stress sub-index is computed for each of these five market segments, where each sub-index includes three stress indicators.¹³

Transformation of raw stress indicators. Each of the 15 raw indicators is transformed into standardized measures, by using an empirical cumulative distribution function (CDF). The empirical CDF is computed as:

$$z_n = F_n(x_n) = \begin{cases} \frac{r}{n} & \text{for } x_{[r]} \leq x_t \leq x_{[r+1]} \\ 1 & \text{for } x_n \geq x_{[n]} \end{cases} \quad (1.16)$$

where $r = (1, 2, \dots, n - 1)$ is a ranking number, n the total number of observations in the sample. This method of standardization consists in converting the 15 raw financial

¹³ **Money market** stress is captured by: realized volatility of the 3-month Euribor rate; interest rate spread between 3-month Euribor and 3-month French T-bills; and MFI emergency lending at Eurosystem central banks.

Bond market stress is represented by: realised volatility of the German 10-year benchmark government bond index; yield spread between A-rated non-financial corporations and government bonds; and 10-year interest rate swap spread.

Equity market stress is represented by: realised volatility of the Datastream non-financial sector stock market index; CMAX for the Datastream non-financial sector stock market index; and stock-bond correlation.

Financial intermediaries stress is captured by: realised volatility of the idiosyncratic equity return of the Datastream bank sector stock market index over the total market index; yield spread between A-rated financial and non-financial corporation's; and CMAX for the financial sector equity market index.

Foreign exchange market stress is represented by: realised volatility of the euro exchange rate vis-à-vis the US dollar, the Japanese Yen and the British Pound, respectively.

stress indicators into new series which are unit-free and ranging between 0 and 1. By this procedure, the values of individual stress indicator are ranked in the first step and then divided by the total number of observations (n). The rank of 1 is assigned to the minimum value in the sample and n to a maximum. Then, the three stress factors ($j = 1, 2, 3$) of each market category ($i = 1, 2, \dots, 5$) are finally aggregated into their respective sub-index by taking their arithmetic average.

Aggregation. The CISS is computed as follows:

$$FSI = (w \times s_t)C_t(w \times s_t)' \quad (1.17)$$

where $w = (w_1, w_2, w_3, w_4, w_5)$ is a vector of sub-index weights, the vector of sub-indices is denoted by $s_t = (s_{1,t}, s_{2,t}, s_{3,t}, s_{4,t}, s_{5,t})$.¹⁴ C_t is the matrix of time-varying cross-correlation coefficients $\rho_{ij,t}$ between the sub-indexes i and j :

$$C_t = \begin{bmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \rho_{14,t} & \rho_{15,t} \\ \rho_{21,t} & 1 & \rho_{23,t} & \rho_{24,t} & \rho_{25,t} \\ \rho_{31,t} & \rho_{32,t} & 1 & \rho_{34,t} & \rho_{35,t} \\ \rho_{41,t} & \rho_{42,t} & \rho_{43,t} & 1 & \rho_{45,t} \\ \rho_{51,t} & \rho_{52,t} & \rho_{53,t} & \rho_{54,t} & 1 \end{bmatrix} \quad (1.18)$$

The time-varying cross-correlations $\rho_{ij,t}$ are estimated recursively on the basis of exponentially-weighted moving averages (EWMA).

1.A.1.2 Structural Change Points in VAR models

I use Qu and Perron (2007) methodology to test for structural change points in a VAR model. In particular, I test for the structural break points in a reduced-form vector autoregressive model with two endogenous variables and one lag:

¹⁴Weights are estimated on the basis of their average relative impact on industrial production growth measured by the cumulated impulse responses from a variety of different specifications of standard linear VAR models.

$$y_t = \mu + \Gamma y_{t-1} + u_t \quad (1.19)$$

where $y_t = (\Delta CISS_t, \Delta cds_t)'$ is a vector of weekly endogenous variables observed at week t , μ is a (2×1) vector of intercepts, Γ is a (2×2) coefficient matrix of the model and an error term u_t has a mean zero and a covariance $E(u_t u_t') = \Sigma$. When testing for structural breaks, I allow only a covariance matrix of residuals, Σ , to change.

Following the authors' notation, I denote M as total number of structural changes in the system of equations 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, 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 $T_{j-1}+1 \leq t \leq T_j$. For the estimation of the parameters $\hat{M}, \hat{T}_1, \dots, \hat{T}_M, \hat{\Sigma}_1, \dots, \hat{\Sigma}_{M+1}$ in the VAR(1) model (see eq. 1.19) it is convenient to rewrite the model in a matrix form as:

$$y_t = x_t' \beta + u_t \quad (1.20)$$

where $x_t' = (I_2 \oplus (1, \Delta CISS_{t-1}, \Delta cds_{t-1}))$. The estimation is based on a restricted quasi-maximum likelihood that assumes serially uncorrelated Gaussian errors. Conditional on the given break dates (T_1, \dots, T_M) , the Gaussian quasi-likelihood ratio is:

$$LR_T = \frac{\prod_{j=1}^{m+1} \prod_{t=T_{j-1}+1}^{T_j} f(y_t | x_t; \beta_j; \Sigma_j)}{\prod_{j=1}^{m+1} \prod_{t=T_{j-1}^0+1}^{T_j^0} f(y_t | x_t; \beta_j^0; \Sigma_j^0)} \quad (1.21)$$

where $f(y_t | x_t; \beta_j; \Sigma_j) = \frac{1}{2\pi^{n/2} |\Sigma_j|^{1/2}} \exp \left\{ -\frac{1}{2} [y_t - x_t' \beta_j]' \Sigma_j^{-1} [y_t - x_t' \beta_j] \right\}$.

The estimation procedure consists in estimating the log-likelihood values for all possible segments (at most $T(T-1)/2$), and then assessing which particular combination of $M+1$ segments leads to the highest likelihood value.¹⁵ This is achieved by using a dynamic programming algorithm (by Bai and Perron, 2003; Qu and Perron, 2007). In order to determine the number of break points (M) in the model, I rely on tests suggested by Qu and Perron (2007). Firstly, I test if at least one structural break is present in the model i.e. I test a null hypothesis (H_0) of no structural break versus (H_A) an unknown number of breaks given some upper bound. For this, I use a *double maximum test* ($WDmax$),

¹⁵In practice, less than $T(T-1)/2$ segments are permissible, since some minimum distance between the break points may be imposed and a maximum number of breaks (M) may be allowed.

which statistic is defined for some fixed weights (a_m) as:

$$WDmaxLR_T(M) = \max_{(1 \leq m \leq M)} [a_m \sup_{(\lambda_1, \dots, \lambda_m) \in \Lambda_\epsilon} 2 \ln(LR_T)] \quad (1.22)$$

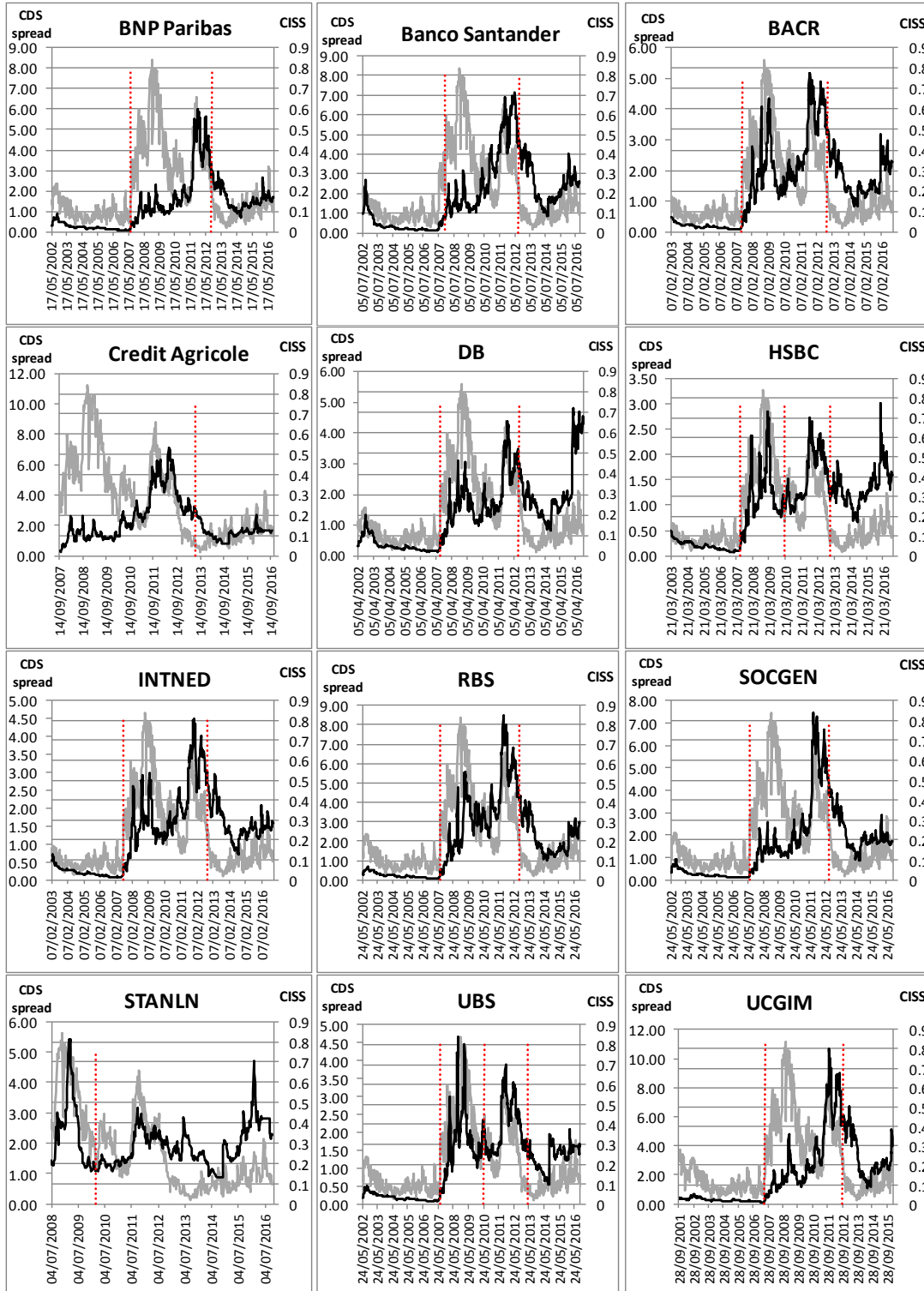
If the WDmax test rejects the null hypothesis, I use a sequential test $SEQ(l+1|l)$ test. This test is based on a sequential testing procedure considering the null hypothesis (H_0) of l breaks against an alternative hypothesis (H_A) of $l+1$ structural breaks. The $SEQ(l+1|l)$ test is defined as:

$$SEQ(l+1|l) = \max_{1 \leq j \leq l+1} \sup_{\tau \in \Lambda_{j,\epsilon}} lr_T(\hat{T}_1, \dots, \hat{T}_{j-1}, \tau, \hat{T}_j, \dots, \hat{T}_l) - lr(\hat{T}_1, \dots, \hat{T}_l) \quad (1.23)$$

where a procedure to test the null hypothesis of l breaks versus the alternative hypothesis of $l+1$ breaks consists in performing a one break test for each of the $(l+1)$ segments defined by the partition $(\hat{T}_1, \dots, \hat{T}_l)$ and assessing whether the maximum of the tests is significant.

1.A.2 Time Series Plots and Structural Breaks

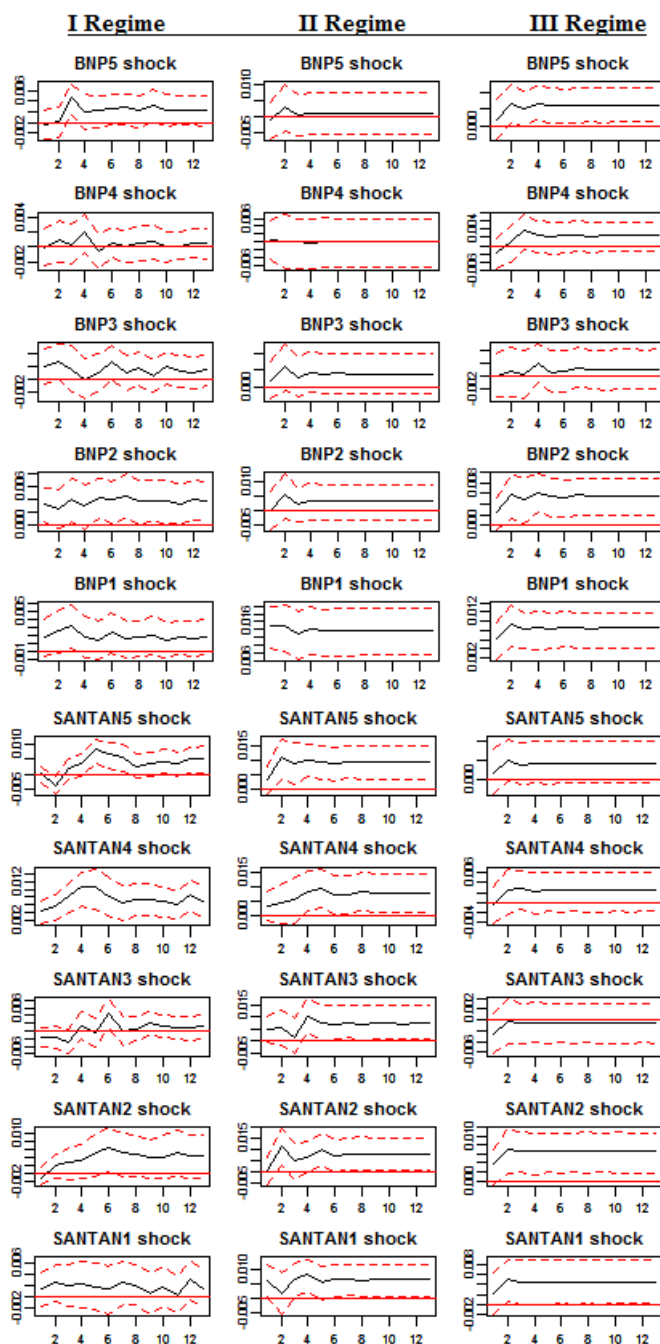
Figure 1.1: Structural Break Points



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

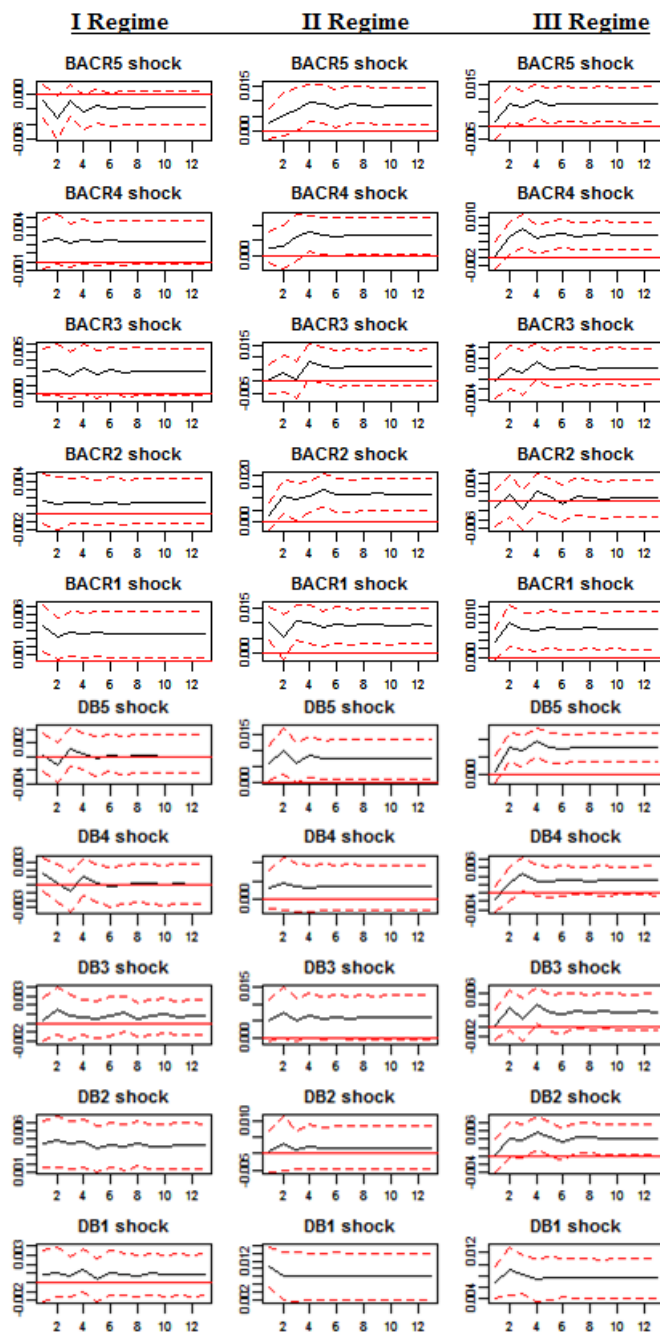
1.A.3 Impulse Response Analysis Plots

Figure 1.2: Cumulated IRFs of CISS to a BNP Paribas and Santander distress shocks



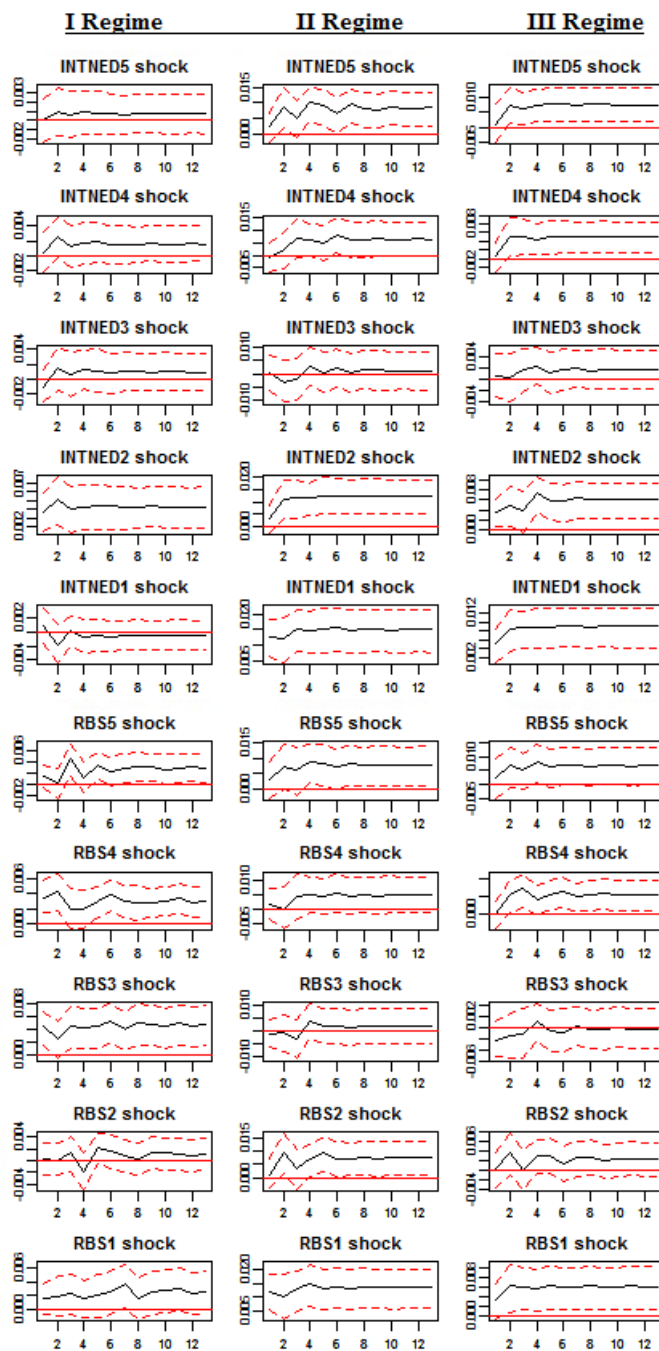
Notes: BNP indicates a BNP Paribas bank, SANTAN denotes a Santander bank. 1 stands for a shock hitting the Eurozone financial system on Monday, 2 – Tuesday, 3 – Wednesday, 4 – Thursday, 5 – Friday. The x-axis represent weeks after the shock. The responses are presented with 90% probability bands (red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

Figure 1.3: Cumulated IRFs of CISS to a Barclays and Deutsche Bank distress shocks



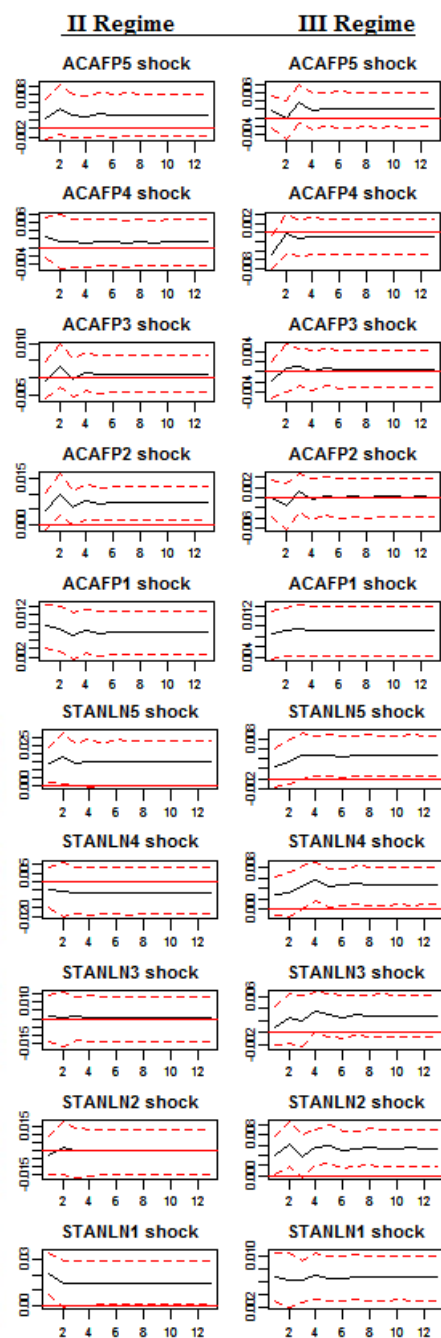
Notes: BACR indicates a Barclays bank, DB – a Deutsche bank. 1 stands for a shock hitting the Eurozone financial system on Monday, 2 – Tuesday, 3 – Wednesday, 4 – Thursday, 5 – Friday. The x-axis represent weeks after the shock. The responses are presented with 90% probability bands (red dashed lines).

Figure 1.4: Cumulated IRFs of CISS to a ING and Royal Bank of Scotland distress shocks



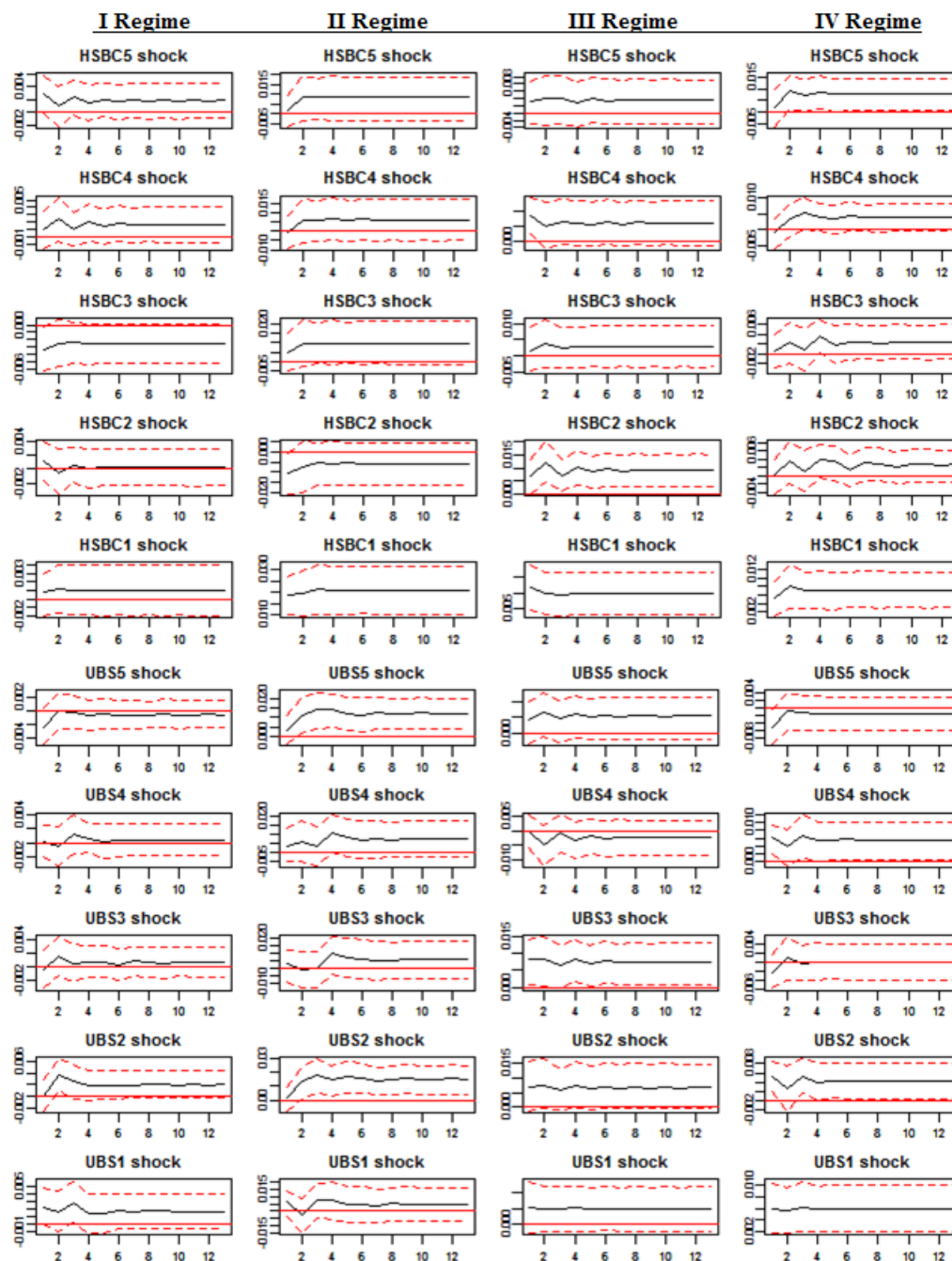
Notes: INTNED indicates a ING Bank, RBS denotes a Royal Bank of Scotland1 stands for a shock hitting the Eurozone financial system on Monday, 2 – Tuesday, 3 – Wednesday, 4 – Thursday, 5 – Friday. The x-axis represent weeks after the shock. The responses are presented with 90% probability bands (red dashed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

Figure 1.5: Cumulated IRFs of CISS to a Crédit Agricole and Standard Chartered distress shocks



Notes: ACAFP denotes a Crédit 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 1.6: Cumulated IRFs of CISS to a HSBC and UBS 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).

1.A.4 Tables

Table 1.1: Dataset

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

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

Table 1.2: Descriptive statistics of CDS spreads

	Mean	Median	MAX	MIN	St.dev	Observations		Unit
						(daily)	(weekly)	
BNP Paribas SA	1.25	1.08	6.21	0.09	1.2	3775	755	%
Banco Santander SA	1.85	1.48	7.32	0.12	1.67	3745	749	%
Barclays Bank PLC	1.49	1.38	5.42	0.08	1.24	3590	718	%
Crédit Agricole SA	2.23	1.65	7.25	0.23	1.41	2385	477	%
Deutsche Bank AG	1.38	1.32	5.24	0.14	1.1	3810	762	%
HSBC Bank PLC	0.99	1.03	3.14	0.08	0.68	3560	712	%
ING Bank NV	1.26	1.28	4.68	0.07	1	3590	718	%
Royal Bank of Scotland	1.97	1.52	8.78	0.07	1.88	3775	755	%
Société Générale SA	1.53	1.29	7.96	0.09	1.51	3775	755	%
Standard Chartered Bank	1.98	1.77	5.55	0.88	0.81	2180	436	%
UBS AG	1.15	1.25	5.38	0.07	0.94	3775	755	%
UniCredit SpA	2.14	1.52	11.53	0.12	2.21	3945	789	%

Table 1.3: Structural break dates and $SEQ_T(l+1|l)$ test results

CDS spread variable	Number of breaks	Break dates	SEQ (l+1 l) test statistics
BNP Paribas	2	13/07/2007	The Seq(2 1) test is : 158.253
		12/10/2012	The Seq(3 2) test is : 0.000
Banco Santander	2	14/12/2007	The Seq(2 1) test is : 121.149
		12/10/2012	The Seq(3 2) test is : 0.000
Barclays Bank	2	06/07/2007	The Seq(2 1) test is : 142.645
		12/10/2012	The Seq(3 2) test is : 0.000
Crédit Agricole*	1	28/06/2013	
Deutsche Bank	2	13/07/2007	The Seq(2 1) test is : 104.634
		10/08/2012	The Seq(3 2) test is : 0.000
HSBC Bank	3	06/07/2007	
		26/03/2010	The Seq(3 2) test is : 67.670
		28/12/2012	
ING Bank	2	13/07/2007	The Seq(2 1) test is : 168.804
		28/09/2012	The Seq(3 2) test is : 0.000
Royal Bank of Scotland	2	13/07/2007	The Seq(2 1) test is : 197.305
		12/10/2012	The Seq(3 2) test is : 0.000
Société Générale	2	13/07/2007	The Seq(2 1) test is : 154.560
		07/09/2012	The Seq(3 2) test is : 0.000
Standard Chartered Bank*	1	05/03/2010	
UBS	3	13/07/2007	
		11/06/2010	The Seq(3 2) test is : 53.177
		03/05/2013	
UniCredit	2	13/07/2007	The Seq(2 1) test is : 109.226
		12/10/2012	The Seq(3 2) test is : 0.000

Notes: The * marks the VAR models where I test for only one structural break (M=1), hence, in this case, inference on structural breaks is based only on WDmax test. I consider M=3 for all other VAR models. The first column indicates a bivariate VAR model including as endogenous variables one of the twelve GSIB CDS spread and the CISS index. The second column gives the number of breaks detected endogenously. The third column gives the dates of the break points. The last column gives the $SEQ(l+1|l)$ test statistics. The 5% critical values for the $Seq(2|1)$ and the $Seq(3|2)$ tests are 15.458 and 16.337, respectively.

Table 1.4: LR test statistics for testing MF-VAR vs CF-VAR

Regime	Lag order	BNP Paribas	Santander	Barclays	DB	ING	RBS	Société G.	UniCredit	Crédit Ag.	Standard Ch.	HSBC	UBS
Full sample	1	6963	5151	6237	7031	8210	5373	6367	5351	3388	3586	8570	7427
	2	7321	5612	6739	7514	8790	5918	6847	5710	3623	3903	9129	8013
	3	7676	5947	7039	7852	9062	6188	7281	6034	3779	4126	9411	8445
	4	7858	6126	7196	8049	9215	6399	7531	6252	3920	4232	9582	8575
I regime	1	7339	5447	7365	6328	6698	7411	7007	6726	1765	2705	6653	6808
	2	7562	5795	7460	6695	7137	7734	7221	7013	1923	2918	6759	6994
	3	7727	6081	7613	6819	7249	7917	7472	7186	2020	3045	6868	7121
	4	7863	6294	7697	6940	7395	7998	7615	7322	2122	3119	6966	7208
II regime	1	1651	954	1648	1926	2374	1094	1439	1163	2253	872	1360	978
	2	1788	1140	1850	2095	2624	1297	1621	1298	2408	941	1514	1189
	3	1935	1265	1970	2236	2738	1403	1800	1418	2508	1112	1609	1282
	4	2012	1333	2035	2304	2805	1480	1907	1506	2587	1197	1687	1328
III regime	1	2501	1769	2184	1863	2787	1969	2259	1381			1651	1442
	2	2682	1943	2390	2070	2956	2194	2443	1535			1769	1569
	3	2801	2043	2530	2185	3046	2303	2562	1655			1842	1701
	4	2900	2132	2623	2290	3145	2388	2677	1740			1892	1785
IV regime	1											2466	2555
	2											2646	2694
	3											2756	2833
	4											2831	2880

Notes: The figures are the Likelihood Ratio, LR, statistics for testing the null of equivalence of MF-VAR with the traditional CF-VAR, as suggested by Bacchiocchi et al., (2018). Rejection of the null hypothesis implies that aggregating the mixed-frequency series as in traditional CF-VAR generates a loss of information. The LR statistics is computed by comparing the log-likelihood of the unrestricted model, i.e. MF-VAR(l^u), with the one associated with the restricted model, i.e. CF-VAR(l^r). The test statistics $LR = -2(l^r - l^u)$ is asymptotically distributed as a χ^2 , with the degrees of freedom given by the number of restrictions (32 restrictions for each lag) on the MF VAR coefficients. I report the LR test statistics in the table and p-values are close to zero, suggesting a strong rejection of the null hypothesis.

Table 1.5: FEVD for EZ financial distress subject to GSI banks distress shocks

Panel (1): BNP Paribas									
Full sample:			I regime:		II regime:		III regime:		
13/05/2002 - 28/10/2016			13/05/2002 - 12/07/2007		13/07/2007 - 11/10/2012		12/10/2012 - 28/10/2016		
H	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	
1	3.04	3.37	2.68	1.15	5.7	3.55	4.53	3.14	
2	5.19	3.24	2.6	1.37	6.85	3.47	7.95	4.03	
3	6.19	3.36	5.43	1.37	7.47	3.47	8.79	4.05	
4	8.53	3.34	7.13	1.37	7.59	3.47	9.39	4.05	

Panel (2): Santander									
Full sample:			I regime:		II regime:		III regime:		
24/06/2002 - 28/10/2016			24/06/2002 - 13/12/2007		14/12/2007 - 11/10/2012		12/10/2012 - 28/10/2016		
H	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	
1	1.13	2.49	3.44	0	2.08	3.32	2.49	1.84	
2	4.29	2.54	6.53	2.09	6.42	3.17	5.57	3.2	
3	5.16	2.53	11.03	2.3	8.11	3.17	5.66	3.19	
4	7.17	2.53	13.76	2.51	9.98	3.17	5.7	3.19	

Panel (3): Barclays									
Full sample:			I regime:		II regime:		III regime:		
27/01/2003 - 28/10/2016			27/01/2003 - 05/07/2007		06/07/2007 - 11/10/2012		12/10/2012 - 28/10/2016		
H	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	
1	2.42	2.66	5.24	3.54	3.3	2.63	1.78	1.77	
2	4.17	2.57	5.6	3.37	5.67	2.54	9.76	3.68	
3	4.58	3.02	6.32	3.37	6.63	2.53	10.91	3.71	
4	6.23	3.03	6.7	3.37	8.14	2.53	12.86	3.72	

Panel (4): Deutsche Bank (DB)									
Full sample:			I regime:		II regime:		III regime:		
25/05/2002 - 28/10/2016			25/03/2002 - 12/07/2007		13/07/2007 - 09/08/2012		10/08/2012 - 28/10/2016		
H	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	
1	3.39	4.36	3.5	0.23	4.45	4.46	4.91	3.73	
2	4.73	4.09	3.54	0.33	5.02	4.39	11.12	5.63	
3	5.23	4.44	4.46	0.33	5.61	4.38	11.76	5.61	
4	7.63	4.42	4.99	0.33	5.77	4.38	13.14	5.61	

Notes: Each panel present the FEVD of CISS index that can be attributed to innovations in GSI banks distress for each model separately. The results are reported for each regime, where each row provides results specific to a forecast horizon H, varying from 1 to 4 weeks ahead. The column SUM(MF) gives the sum of FEVD relative to forecast horizon H across the five days of the week.

Table 1.5: (Continued)

Panel (5): ING Bank									
Full sample:			I regime:		II regime:		III regime:		
27/01/2003 - 28/10/2016			27/01/2003 - 12/07/2007		13/07/2007 - 27/09/2012		28/09/2012 - 28/10/2016		
H	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	
1	3.57	4.16	2.42	2.27	4.72	4.4	3.74	6.07	
2	5.44	3.9	4.7	2.02	7.24	4.29	9	6.06	
3	6.4	4.58	5.61	2.06	8.23	4.3	9.19	6.03	
4	8.38	4.55	5.74	2.06	9.28	4.3	10.32	6.03	

Panel (6): Royal Bank of Scotland (RBS)									
Full sample:			I regime:		II regime:		III regime:		
13/05/2002 - 28/10/2016			13/05/2002 - 12/07/2007		13/07/2007 - 11/10/2012		12/10/2012 - 28/10/2016		
H	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	
1	2.7	2.13	5.52	1.36	4.07	2.14	2.14	1.42	
2	4.66	2.06	5.39	1.29	6.1	2.11	7.96	2.6	
3	5.77	2.21	8.8	1.28	7.43	2.11	9.3	2.59	
4	8.36	2.2	11.19	1.28	8.88	2.11	11.41	2.59	

Panel (7): Société Générale (SG)									
Full sample:			I regime:		II regime:		III regime:		
13/05/2002 - 28/10/2016			13/05/2002 - 12/07/2007		13/07/2007 - 06/09/2012		07/09/2012 - 28/10/2016		
H	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	
1	3.52	3.64	1.66	0.21	5.74	3.87	2.86	3.61	
2	5.36	3.41	2.53	0.9	6.6	3.74	5.26	3.85	
3	5.86	3.59	3.59	0.9	7.35	3.74	5.43	3.84	
4	8.12	3.57	4.75	0.92	7.55	3.74	5.57	3.84	

Panel (8): UniCredit									
Full sample:			I regime:		II regime:		III regime:		
17/09/2001 - 28/10/2016			17/09/2001 - 12/07/2007		13/07/2007 - 11/10/2012		12/10/2012 - 28/10/2016		
H	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	
1	2.46	2.46	2.44	0.54	3.14	2.61	2.54	2.44	
2	4.66	2.52	2.58	0.65	5.18	2.77	4.96	3.49	
3	5.16	2.79	3.52	0.63	5.87	2.78	5.3	3.48	
4	6.9	2.78	3.88	0.63	6.06	2.79	5.46	3.48	

Notes: Each panel present the FEVD of CISS index that can be attributed to innovations in GSI banks distress for each model separately. The results are reported for each regime, where each row provides results specific to a forecast horizon H, varying from 1 to 4 weeks ahead. The column SUM(MF) gives the sum of FEVD relative to forecast horizon H across the five days of the week.

Table 1.5: (Continued)

<u>Panel (9): Crédit Agricole (CA)</u>						
Full sample: 10/09/2007 - 28/10/2016			I regime: 10/09/2007 - 27/06/2013		II regime: 28/06/2013 - 28/10/2016	
H	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF
1	3.43	2.3	3.35	2.66	7.97	0.64
2	4.79	2.27	4.57	2.58	9.78	1.39
3	5.4	2.26	5.48	2.58	11.29	1.39
4	5.93	2.26	5.68	2.58	11.67	1.39

<u>Panel (10): Standard Chartered Bank (S.Ch.)</u>						
Full sample: 23/06/2008 - 28/10/2016			I regime: 23/06/2008 - 04/03/2010		II regime: 05/03/2010 - 28/10/2016	
H	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF
1	4.37	4.08	10.11	4.86	4.68	2.34
2	5.58	3.81	10.97	5.13	4.79	2.42
3	5.91	3.98	11.27	5.14	5.25	2.41
4	7.63	3.94	11.3	5.14	5.63	2.41

Notes: Each panel present the FEVD of CISS index that can be attributed to innovations in GSI banks distress for each model separately. The results are reported for each regime, where each row provides results specific to a forecast horizon H, varying from 1 to 4 weeks ahead. The column SUM(MF) gives the sum of FEVD relative to forecast horizon H across the five days of the week.

Table 1.5: (Continued)

Panel (11): HSBC			I regime:			II regime:			III regime:			IV regime:		
Full sample:			10/03/2003 - 05/07/2007			06/07/2007 - 25/03/2010			26/03/2010 - 27/12/2012			28/12/2012 - 28/10/2016		
H	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF
1	3.33	4.14	3.15	0.04	8.55	3.07	11.45	5.35	3.04	4.02	10.01	4.81	10.01	4.81
2	7.07	4.24	3.91	0.04	10.36	3.49	12.65	5.18	10.01	4.81	11.13	4.81	11.13	4.81
3	7.42	4.36	4.42	0.04	10.46	3.48	13.74	5.17	11.13	4.81	12.49	4.81	12.49	4.81
4	9.29	4.35	4.64	0.04	10.47	3.48	14.18	5.17	12.49	4.81				
Panel (12): UBS			I regime:			II regime:			III regime:			IV regime:		
Full sample:			13/05/2002 - 12/07/2007			13/07/2007 - 10/06/2010			11/06/2010 - 02/05/2013			03/05/2013 - 28/10/2016		
H	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF	SUM (MF)	CF
1	2.2	2.65	1.57	0.76	1.38	2.66	7.24	3.93	10.42	2.61	10.42	2.61	10.42	2.61
2	4.02	2.47	4.25	1	6.85	2.65	7.81	3.77	12.7	2.51	12.7	2.51	12.7	2.51
3	4.93	3.45	5.11	1	9.2	2.65	8.91	3.77	13.66	2.51	13.66	2.51	13.66	2.51
4	6.21	3.43	5.5	1.01	12.07	2.65	9.51	3.77	13.82	2.51	13.82	2.51	13.82	2.51

Notes: Each panel present the FEVD of CISS index that can be attributed to innovations in GSI banks distress for each model separately. The results are reported for each regime, where each row provides results specific to a forecast horizon H, varying from 1 to 4 weeks ahead. The column SUM(MF) gives the sum of FEVD relative to forecast horizon H across the five days of the week.

Table 1.6: Descriptive statistics of FEVD for EZ financial stress subject to GSI banks distress shocks

	MF-SVAR				Traditional-SVAR			
A. Full sample								
H:	1	2	3	4	1	2	3	4
max	4.37	7.07	7.42	9.29	4.36	4.24	4.58	4.55
min	1.13	4.02	4.58	5.93	2.13	2.06	2.21	2.2
mean	2.96	5	5.67	7.53	3.2	3.09	3.38	3.37
sd.dev	0.8	0.79	0.74	1.01	0.8	0.74	0.8	0.79
B. Period I								
H:	1	2	3	4	1	2	3	4
Max	5.52	6.53	11.03	13.76	3.54	3.37	3.37	3.37
Min	1.57	2.53	3.52	3.88	0	0.04	0.04	0.04
Mean	3.16	4.16	5.83	6.83	1.01	1.31	1.33	1.35
sd.dev	1.34	1.4	2.38	3.18	1.14	0.98	1	1.03
C. Period II								
H:	1	2	3	4	1	2	3	4
max	11.45	12.65	13.74	14.18	5.35	5.18	5.17	5.17
min	1.38	4.57	5.48	5.68	2.14	2.11	2.11	2.11
mean	5.38	7.31	8.27	9.03	3.53	3.52	3.52	3.52
sd.dev	2.99	2.4	2.33	2.48	0.97	0.96	0.96	0.96
D. Period III								
H:	1	2	3	4	1	2	3	4
max	10.42	12.7	13.66	13.82	6.07	6.06	6.03	6.03
min	1.78	4.79	5.25	5.46	0.64	1.39	1.39	1.39
mean	4.26	8.24	8.58	9.79	2.8	3.64	3.64	3.64
sd.dev	2.57	2.62	2.93	3.32	1.44	1.37	1.36	1.36

Notes: This table provides descriptive stats of FEVD results associated to the twelve different VAR models (each corresponding to a specific GSIB) given in Table 1.5, Panel (1-12). The columns 1 to 4 for both (MF SVAR and Traditional SVAR) give the FEVD for the forecast horizons, ranging from one week to four weeks ahead. The label Period I refers to a first regime for all banks except Crédit Agricole, Standard Chartered. The label Period III refers to the last regime of all the banks. Period II refers to the remaining regimes.

Table 1.7: MF VAR regime specific rankings

Pre-Crisis Regime		Crisis Regime I		Crisis Regime II	
1. Santander	(13.76)	1. HSBC	(12.32)	1. UBS	(13.82)
2. RBS	(11.19)	2. Standard Ch.	(11.30)	2. DB	(13.14)
3. BNP Paribas	(7.13)	3. UBS	(10.52)	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 Gen.	(4.75)	8. BNP Paribas	(7.59)	8. BNP Paribas	(9.39)
9. HSBC	(4.64)	9. Société Gen.	(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 Gen.	(5.57)
		12. Crédit Agricole	(5.68)	12. UniCredit	(5.46)

Notes: I provide the ranking of the European GSIBs according their contribution to the EZ financial distress measured by the FEVD results at 4-week horizon obtained by using MF-VAR approach (see Table 1.5). The figures FEVD, measuring the contribution of GSIBs distress shocks to CISS fluctuations at 4-week horizon are reported in brackets. The rankings are for three different sub-samples identified through Qu and Perron (2007) structural break test. In particular, the Pre-Crisis Regime coincides with the first sub-sample (see Table 1.5 for the start and ending dates). The ranking for the Pre-Crisis Regime does not include Crédit Agricole and Standard Chartered given that the CDS data available for the two banks start in 2007, 2008, respectively. Moreover, the Crisis Regime 2 coincides with last sub-sample (see Table 5 for the start and ending dates). The Crisis Regime 1 coincides with the period before the last sub-sample (see Table 1.5 for the start and ending dates). The only exception regarding the sub-samples associated with Crisis Regime 1 are UBS and HSBC for which the figures reported in this Table are an average of the FEVD results corresponding to second and third regime in Table 1.5 (see Panel 11 and 12).

Table 1.8: Benchmark rankings: Financial Stability Board

	2013	2014	2015	2016
4th bucket	HSBC	HSBC	HSBC	
3rd bucket	Barclays, DB, BNP Paribas	Barclays, DB, BNP Paribas	Barclays, DB, BNP Paribas	HSBC, DB, BNP Paribas
2nd bucket	UBS, RBS, Crédit Agricole	RBS		Barclays
1st bucket	ING Bank, Santander, Société Générale, Standard Chart., UniCredit	Crédit Agricole, UBS, ING Bank, Santander, Société Générale, Standard Chart., UniCredit	Credit Agricole, RBS, UBS, ING Bank, Santander, Société Générale, Standard Chart., UniCredit	Crédit Agricole, RBS, UBS ING Bank, Santander, Société Gén., Standard Chart., UniCredit

Notes: I report the banks allocated in the buckets (the 4th bucket is associated with highest capital requirements). I report only the rankings for the banks taken under the consideration in this analysis.

Chapter 2

Financial distress and real economic activity in Lithuania: a Granger causality test based on MF VAR

2.1 Introduction

Measuring financial stress has become more prominent since the global financial crisis. Central banks and international organizations have constructed financial stress indexes (FSI) in order to detect signs of financial stress in the whole financial system and to monitor the state of financial stability. Recently, European Central Bank has introduced a monthly Country-Level Index of Financial Stress (CLIFS) for each of the 27 European Union countries (Klaus et al., 2017), including Lithuania.¹ This index is constructed by aggregating six financial distress measures, representing the uncertainty and sharp corrections in market prices, that covers only three financial market sectors: bond, stock and foreign exchange markets.

In this chapter, first, I seek to improve a monthly Country-Level Index of Financial Stress (CLIFS) for Lithuania (by Klaus et al., 2017) along two dimensions. First, I extend a monthly ECB financial stress index to a high-frequency (*daily*) horizon and, then, by arguing an important role played by Scandinavian commercial banks in the Lithuanian financial sector development, I include the banking sector among its constituents (beyond

¹Financial stress indexes were introduced for US (Hakkio and Keeton, 2009; Kliesen and Smith, 2010; Brave and Butters, 2011; Oet et al., 2011), Canada (Illing and Liu, 2006), major advanced and emerging counties (Cardarelli et al., 2011; Balakrishnan et al., 2011, respectively) and Eurozone as a whole (Hollo et al., 2012) among others.

bond, equity, foreign exchange markets).² More specifically, Lithuanian financial sector is dominated by Scandinavian-owned commercial banks. The three largest banks in Lithuania – SEB, Swedbank and DnB – to a significant extent have contributed to the Lithuanian economic growth over the 2000-2007 period.³ In particular, the growth was fuelled by cheap credit provided by the banks that drove up domestic demand and led to the formation of a ‘bubble’ in the Lithuanian real estate market. In 2009 the domestic real estate ‘bubble’ burst and the global financial crisis have led Lithuania into the biggest recession since the independence period. Gross Domestic Product of Lithuania fell -15% in 2009 compared to the previous year.⁴

In the second step of the analysis, I contribute to empirical literature exploring the linkages between financial stress and real economic activity. Some studies have recently focused on financial uncertainty as a possible driver of the US business cycle. More specifically, the study of Bloom (2009) obtain an indicator of financial uncertainty by aggregating firm specific financial uncertainty and assess its impact on real economic activity (employment and industrial production). Ludvigson, Ma, and Ng (2019) extract financial uncertainty as a latent variable from a dynamic factor model fitted to a large dataset of financial time series and they assess the impact on real economic activity, proxied by log of real industrial production. Gilchrist, Sim, and Zakrajsek (2014) provide a micro and macro based analysis showing that financial frictions are an important part of the mechanism through which uncertainty shocks affect the economy. The authors at macro-level, using a structural vector autoregressive (SVAR) model assess the interactions between uncertainty, credit spreads, and economic activity. The results show that the interaction between financial frictions (proxied by credit spreads) and uncertainty are important to assess how fluctuations in the latter are propagated to the real economy. Unanticipated increases in uncertainty imply a rise in credit spreads, leading to a decline in real GDP that is driven primarily by the protracted drop in the investment component of aggregate spending. In contrast, shocks to financial disturbances (orthogonal to credit spreads) have a large effect on economic activity.

Moreover, a number of empirical studies find that an increase in financial stress has

²Also the Bank of England paper by Chatterjee et al. (2017) introduce a FSI for the United Kingdom by extending the CLIFS index by Klaus et al. (2017). The authors incorporate three additional sub-indices that represent stress in corporate bond, money and housing markets.

³Since 2017 the Baltic operations of *DnB* and *Nordea* banks were merged to a new bank - *Luminor*.

⁴While I emphasize the dependence of the Lithuanian financial system from foreign banks, a recent study by Rubio and Comunale (2018) emphasize the vulnerability of the Lithuanian housing markets to Euro area common shock, given that Lithuania has variable-rate mortgages and a higher LTV cap than its European partners.

an adverse impact on the overall economic activity. Hakkio and Keeton (2009) show that an increase in financial stress leads to persistent business cycle downturns. More recently, Chau and Deesomsak (2014) show that the lagged values of financial distress have a significant predictive power for the overall U.S. economic activity. As for the Eurozone, Holló et al. (2012) find that an increase in the financial distress, proxied by a CISS index, leads to a collapse in industrial production (only for values of the index above a threshold). More recently, Kremer (2016) shows that the CISS index Granger causes EU real GDP growth.

While the aforementioned studies are based on a common frequency dataset, in this chapter, I investigate a causal relationship between a *daily* financial stress index for Lithuania and a *monthly* Lithuanian industrial production growth. For this purpose, I use a Granger (non-) causality test applied to a mixed-frequency VAR. As argued by Ghysels et al. (2016), the use of mixed-frequency data allows a more accurate analysis of the causal patterns than a test based on traditional common-frequency data. In addition, given that the mixed-frequency VAR is characterised by a large mismatch in frequencies of the series involved (e.g. daily vs monthly), I apply the Granger causality test developed by Götz et al. (2016) and by Ghysels et al. (2018).

The findings are in line with Cardarelli et al. (2011) suggesting that banking sector stress tends to be associated with larger negative IP growth than stress episodes related only with bond, equity and foreign exchange sectors. More specifically, in a common-frequency framework I find that the inclusion of the banking sector related stress in the financial stress index for Lithuania provides more information about the future path of IP growth in Lithuania. Finally, I show that a proposed *daily* financial stress index for Lithuania is a better predictor for a future path of a monthly industrial production growth than a *monthly* CLIFS index of ECB.

This chapter is structured as follows. Section 2.2 describes the recent stylized facts about the Lithuanian financial system and the real economic activity. Section 2.3 discusses the empirical literature on Financial Stress Index. Section 2.4 describes my contribution to the construction of FSI for Lithuania. Section 2.5 describes the Granger causality test based on the MF VAR. Section 2.6 discusses the empirical evidence, and section 2.7 concludes.

2.2 Stylized Facts for Lithuania

The development of the Lithuanian financial system over the period 2001-2016, measured by financial system's asset-to-GDP ratio, is shown in Figure 2.1.⁵ The financial system's growth (from 35.7% of GDP in 2001 to 84.5% of GDP in 2016) was mainly driven by the banking sector expansion. In fact, the asset-to-GDP ratio of the banking sector increased from 31.4% in 2001 to 66.7% in 2016.

In total, there are six banks and eight foreign bank branches operating in Lithuanian banking sector. Figure 2.2 shows that the Lithuanian banking sector is dominated by three Scandinavian-owned commercial banks: Swedish *SEB* bank and *Swedbank*, and Norwegian *DnB* bank. In particular, the assets of the three Scandinavian banks constitute around 73% of the total banking sector assets in 2016. Due to the high concentration in the Lithuanian banking sector the three major banks produce a massive systemic effect on the Lithuanian financial sector.

In the eight-year period from 2000 to 2007, the Lithuanian economy experienced one of the highest economic growth rates within the European Union. As suggested by Kuodis and Ramanauskas (2009), the growth was fuelled by easy accesses to cheap credit provided by the large Scandinavian-owned commercial banks. On the other hand, the cheap credit and high income expectations gave a strong boost to the construction sector, which led to a formation of a "bubble" in the Lithuanian real estate market.

In 2009 Lithuania went into the biggest recession since the independence period (i.e. since 1990). In the first quarter of 2009 the Lithuanian industrial production felt more than 25% compared to the same period in the previous year.⁶ Lithuanian economy was hit by a double-crisis: external one, caused by global financial crisis and internal one, caused by a strong decline in the domestic demand (due to households and firms facing difficulties in meeting their liabilities to credit institutions).

At the end of 2011, the fifth largest Lithuanian bank, *SNORAS* bank, went bankrupt. According to the Bank of Lithuania data, *SNORAS* bank constituted 6.2% of total banking sector loans and 13.0% of deposits. In February 2013, another Lithuanian bank - *Ukio bankas* - went bankrupt. The bank was not a major credit provider, however, it was the fourth in terms of deposit holdings. Nevertheless, the suspension of several institutions did not cause any major turbulence in the financial system.

At the beginning of 2013, Lithuania's economy bounced back and grew at one of the

⁵Source: Bank of Lithuania: <https://www.lb.lt/en/main-indicators-of-banking-sector-activities>

⁶Source: Lithuanian Department of Statistics: <https://www.stat.gov.lt/en>.

fastest rates in the EU. However, in the following years the economic growth slowed down due to the uncertainty caused by the Russia-Ukraine conflict and import restriction to Russia in 2014. At the beginning of 2016, the distress in the banking sector increased due to the concerns regarding the real estate sector in Sweden. While I emphasize the dependence of the Lithuanian financial system from foreign banks, a recent study by Rubio and Comunale (2018) emphasize the vulnerability of the Lithuanian housing markets to Euro area common shock, given that Lithuania has variable-rate mortgages and a higher LTV cap than its European partners.

2.3 Financial Stress Index

Since the start of the global financial crisis, a number of studies have developed indices of financial stress (FSI) which are used to measure the vulnerabilities in the financial system. The first study is the one by Illing and Liu (2006) introducing a FSI for the Canadian financial system combining (through principal component analysis) information on 11 financial market series representative of the banking, foreign exchange, debt and equity markets. The IMF study by Cardarelli et al. (2011) introduces FSIs for 17 advanced economies. Through variance-equal weighting method, the authors combine information on three financial market segments: banking, securities markets and foreign currency.⁷ Similarly, the IMF study by Balakrishnan et al. (2011) uses the methodology of Cardarelli et al. (2009) to construct a financial stress index for emerging countries.

As for the US, the first study to provide an index monitoring stress in the financial markets is the Kansas City FSI developed by Hakkio and Keeton (2009).⁸ The authors use a principal component analysis to combine 11 indicators, representing the key features of financial stress in the US financial system, into an overall index. Kliesen and Smith (2010) propose a St. Louis Fed Financial Stress Index by using 18 weekly data series.⁹ Brave and Butters (2011) introduce the National Financial Conditions Index (NFCI), monitoring the financial conditions in banking sector, money, debt and equity markets.¹⁰ The authors show that the NFCI is useful in forecasting growth in US gross domestic product and business investment from two to four quarters ahead. Finally, another FSI index is the

⁷By using a variance-equal weighting method each component is computed as a deviation from its mean and weighted by the inverse of its variance (Balakrishnan et al., 2011).

⁸Chen et al. (2014) examine the link between Kansas City FSI and oil prices. Index is available at: <https://www.kansascityfed.org/research/indicatorsdata/kcfsi>.

⁹The index is available at: <https://fred.stlouisfed.org/series/STLFSI>.

¹⁰The index is available at: <https://www.chicagofed.org/research/data/nfci/background>.

Cleveland Fed's Financial Stress Index, developed by Oet et al. (2011).¹¹ The index uses daily data collected from four financial market sectors — credit, foreign exchange, equity, and interbank markets, which are aggregated into the composite indicator by applying time-varying credit weights.

The European Central Bank (ECB) periodically publishes a weekly Composite Indicator for Systemic Stress (CISS), developed by Holló et al. (2012).¹² The CISS index is constructed by aggregating 15 raw indicators of financial stress capturing the developments in five sectors of the Euro area: the money, foreign exchange, equity, bond and non-bank financial intermediaries securities markets.

The ECB database also provides a monthly Country-Level indicator of financial stress, CLIFS, developed by Klaus et al., (2017) for each Eurozone country, including Lithuania.¹³ The methodology for the construction of the CLIFS index is similar to the one suggested by Holló et al. (2012) for the CISS index. However, the CLIFS captures systemic stress only in three financial market segments: equity, long term bonds and foreign currency markets.¹⁴

2.4 Construction of Financial Stress Index for Lithuania

In this section I describe the construction of the *daily* financial stress index for Lithuania. More specifically, the construction involves three steps: section 2.4.1 describes the financial time series selected for each sub-sector; section 2.4.2 explains the methodology used for the transformation of market specific stress indicators; section 2.4.3 describes how individual indicators are aggregated into the final index.

2.4.1 Data and market indicators

I construct a *daily* FSI for Lithuania by using 12 market specific indicators (see Table 2.1). Similarly to Klaus et al. (2017), I use:

- a) a Lithuanian stock market index - OMX Vilnius (OMXV) - for the equity market,
- b) a 10-year government bond yields - to monitor stress in the bond market,

¹¹Nazlioglu et al. (2015) analyse a volatility transmission between oil prices and Cleveland FSI. Index was discontinued in May 2016.

¹²CISS index is available at: <http://sdw.ecb.europa.eu/browse.do?node=9693347>.

¹³CLIFS indexes are available at: <https://sdw.ecb.europa.eu/browse.do?node=9693347>.

¹⁴As argued by Klaus et al. (2017), other sectors are not considered because the availability of data capturing stress in 27 countries is limited both in the time and cross-sectional dimension.

c) and compute a *daily* real effective exchange rate for Lithuania - in order to monitor stress in the foreign exchange market.

Moreover, beyond the three financial markets considered by Klaus et al. (2017), I also consider the stress in a banking sector, which I proxy by the stock prices of the three major banks operating in Lithuania: *Swedbank*, *DnB* and *SEB bank*.¹⁵ The construction, data sources and the time spans of indicators are described below.

2.4.1.1 Bond market

To measure a distress in Lithuanian bond market I collect a daily 10-year Lithuanian government bond yields for the period ranging from 01/10/2001 to 30/12/2016. The 10-year Lithuanian government bond yields ($R10_{LT,\tilde{t}}$) in the real terms are given by:

$$rR10_{LT,\tilde{t}} = R10_{LT,\tilde{t}} - \frac{CPI_{LT,t} - CPI_{LT,t-12}}{CPI_{LT,t-12}} \times 100 \quad (2.1)$$

where $R10_{LT,\tilde{t}}$ is the nominal 10-year government bond yield and $CPI_{LT,t}$ is the Consumer Price Index for Lithuania; \tilde{t} denotes days and t indicates months. Since the CPI is available only on monthly frequency, I simply interpolate the monthly CPI to a daily frequency. Then, I estimate two components of the bond market sub-index:

(i) *daily realized volatility* ($VrR10_{LT,\tilde{t}}$) obtained from the absolute daily changes in the real 10-year Lithuanian government bond yields ($rR10_{LT,\tilde{t}}$). In line with Klaus et al. (2017) I standardize the changes in the real 10-year Lithuanian government bond yields ($chrR10_{LT,\tilde{t}}$) through a 10 year rolling standard deviation (i.e. the window size is set equal to 2520 working days):

$$\left\{ \begin{array}{l} chrR10_{LT,\tilde{t}} = rR10_{LT,\tilde{t}} - rR10_{LT,\tilde{t}-1} \\ chr\widetilde{R10}_{LT,\tilde{t}} = \frac{chrR10_{LT,\tilde{t}}}{\sigma_{chrR10_{LT,\tilde{t},\tilde{t}-10years}}} \\ VrR10_{LT,\tilde{t}} = |chr\widetilde{R10}_{LT,\tilde{t}}| \end{array} \right. \quad (2.2)$$

(ii) *cumulative difference* ($CDIFF_{\tilde{t}}$) computed as a maximum increase in Lithuanian real government bond spread over a two-year rolling window (i.e. over the previous $T = 2$ years). In particular the real government bond spread with respect to Germany ($rR10_{DE,\tilde{t}}$) is given by:¹⁶

¹⁵Klaus et al. (2017) capture the stress in the banking sector by using the bank stock price indices from Datastream. However, it is not available for Lithuania.

¹⁶The daily data on Lithuania bond yields is obtained as the difference of the daily spread with German

$$\begin{cases} rSpread_{\tilde{t}} = rR10_{LT,\tilde{t}} - rR10_{DE,\tilde{t}} \\ CDIFF_{\tilde{t}} = rSpread_{\tilde{t}} - \min_{i=0,\dots,T}(rSpread_{\tilde{t}-i}) \end{cases} \quad (2.3)$$

2.4.1.2 Equity market

The Lithuanian stock market index, OMX Vilnius (OMXV), includes all the stocks listed on the main and secondary lists on the Vilnius Stock Exchange. The stock market index in real terms is given as:¹⁷

$$rOMXV_{\tilde{t}} = \frac{OMXV_{\tilde{t}}}{CPI_{LT,\tilde{t}}} \quad (2.4)$$

Similarly to the bond market, I follow the suggestion of Klaus et al. (2017) and focus on:

(i) *daily realized volatility* ($VOMXV_{\tilde{t}}$) obtained from the absolute daily log stock market returns:

$$\begin{cases} \ln rOMXV_{\tilde{t}} = \log(rOMXV_{\tilde{t}}) - \log(rOMXV_{\tilde{t}-1}) \\ \ln r\widetilde{OMXV}_{\tilde{t}} = \frac{\ln rOMXV_{\tilde{t}}}{\sigma_{\ln rOMXV_{\tilde{t},\tilde{t}-10years}}} \\ VOMXV_{\tilde{t}} = \left| \ln r\widetilde{OMXV}_{\tilde{t}} \right| \end{cases} \quad (2.5)$$

where the returns are standardized by using a 10 year rolling window standard deviation.

(ii) *cumulative maximum loss* ($CMAX_{\tilde{t}}$), estimated by comparing the value of $rOMXV_{\tilde{t}}$ at day \tilde{t} with its maximum value over the previous T periods ($T = 2$ years, 507 days).

$$CMAX_{\tilde{t}} = 1 - \frac{rOMXV_{\tilde{t}}}{\max_{i=0,1,\dots,T}(rOMXV_{\tilde{t}-i})} \quad (2.6)$$

where the backward rolling window is fixed for the first 2 years (04/01/2000 – 31/12/2001).

2.4.1.3 Foreign exchange market

The Lithuanian foreign exchange market dynamics is monitored by focusing on the *real effective exchange rate*, REER. However, the Bank of International Settlements (BIS) and

10 year government bond yield available from *Ycharts*:

https://ycharts.com/indicators/lithuaniagermany_10_year_bond_spread, and the daily 10-year German government bond yields available from Bundesbank database. Then, I use the monthly CPI for Lithuania and for Germany, available from OECD to convert the nominal yields into real term.

¹⁷*Note:* CPI is available only on monthly frequency, therefore, I simply interpolate it to a daily frequency.

the ECB Statistical Data Warehouse (SDW) publish the REER for Lithuania only at low frequencies (monthly, quarterly or annual). Therefore, I construct a *daily* REER.

Unlike the bilateral exchange rate that involves two currencies, the effective exchange rate is an index that describes the strength of a currency relative to a basket of other currencies. In particular, I calculate the REER for Lithuania as the geometric weighted average of bilateral nominal exchange rates of litas vis-à-vis the currency of the major trading partners. The major trading partners are: the whole Eurozone (euro), Estonia (kroon), Latvia (lats), China (yuan renminbi), Czech Republic (koruna), Denmark (krone), Japan (yen), Norway (krone), Poland (złoty), Russia (ruble), Sweden (krona), Turkey (lira), United Kingdom (pound sterling), United States of America (dollar).¹⁸ The nominal bilateral currencies are then converted in purchasing power of Lithuanian consumers by using the country specific consumer price index (CPI) (Schmitz et al., 2013):

$$REER^i = \prod_{i=1}^N \left(\frac{e_{LT,i}^i CPI_{LT}^i}{CPI_i^i} \right)^{w_i} \quad (2.7)$$

where N is the number of major trading partner countries; $e_{LT,i}^i$ is a bilateral exchange rate of the litas vis-à-vis the currency of partner country i ; w_i is the trade weight assigned to the currency of a trading partner; the CPI for Lithuania and for the partner country i are CPI_{LT}^i and CPI_i^i respectively.¹⁹ The weights assigned to the major trading partners are shown in Table 2.2. The 11 Eurozone countries and other 13 major trading partner countries cover 91.4% of Lithuanian total trade in the period 2008 – 2010. The weights are adjusted considering 91.4% to be the total trade (see second row of Table 2.2). For the comparison, Figure 2.3 shows that *daily* REER (in figure aggregated to monthly frequency) is almost identical to the *monthly* REER from BIS.

Then, similarly to bond and stock market, the stress in foreign exchange market is monitored by measuring the following two components:

(i) *daily realized volatility* ($VREER_i$) computed as the absolute value of daily growth rate of real effective exchange rate. I divide the growth rate by a 10 year rolling standard deviation (with the window set equal to 2520 working days):

¹⁸Estonia and Latvia joined the Eurozone in 2011 and 2014, respectively.

¹⁹The bilateral exchange rates for litas and its major trading partners are collected from the Bank of Lithuania (BoL); the CPI data is taken from OECD and the trading weights from BIS. *Note:* CPI is available only on monthly frequency, therefore, I simply interpolate it to a daily frequency.

$$\left\{ \begin{array}{l} \ln REER_{\tilde{t}} = \log(REER_{\tilde{t}}) - \log(REER_{\tilde{t}-1}) \\ \ln \widetilde{REER}_{\tilde{t}} = \frac{\ln REER_{\tilde{t}}}{\sigma_{\ln REER_{\tilde{t}, \tilde{t}-10years}}} \\ VREER_{\tilde{t}} = \left| \ln \widetilde{REER}_{\tilde{t}} \right| \end{array} \right. \quad (2.8)$$

(ii) *cumulative change* (CUMUL) of REER over six months ($i = 6$ months, or 126 working days):

$$CUMUL_{\tilde{t}} = |REER_{\tilde{t}} - REER_{\tilde{t}-i}| \quad (2.9)$$

2.4.1.4 Banking sector

In order to measure the stress in the Lithuanian banking sector, I monitor the stock prices of the three major Scandinavian banks: the Norwegian *DnB* bank and the two Swedish banks – *Swedbank* and *SEB*. In particular, the banking sector sub-index consists of six components. For each of the bank I estimate two components:²⁰

(i) *daily realized volatility* of the idiosyncratic part of the bank stock price returns ($VBKS_{B,\tilde{t}}$). The idiosyncratic component ($\epsilon_{B,\tilde{t}}$) is the estimated residual from a regression of the bank specific *real* stock price return ($\ln BK S_{B,\tilde{t}}$) on the *real* total stock market index ($\ln rSX_{c,\tilde{t}}$):

$$\left\{ \begin{array}{l} \ln BK S_{B,\tilde{t}} = \log(rBK S_{B,\tilde{t}}) - \log(rBK S_{B,\tilde{t}-1}) \\ \ln BK S_{B,\tilde{t}} = \beta_{B,\tilde{t}} \times \ln rSX_{c,\tilde{t}} + \epsilon_{B,\tilde{t}} \\ \tilde{\epsilon}_{B,\tilde{t}} = \frac{\epsilon_{B,\tilde{t}}}{\sigma_{\epsilon_{B,\tilde{t}, \tilde{t}-10years}}} \\ VBKS_{B,\tilde{t}} = \left| \tilde{\epsilon}_{B,\tilde{t}} \right| \end{array} \right. \quad (2.10)$$

where the regression is estimated by using a rolling window of two years (fixed for the first two years). The stock market indexes (indexed by $c = OMXS30, OBX$) of Sweden stock market (OMXS30) and Norwegian stock market (OBX) and bank specific stock prices (indexed by $B = Swedbank, SEB, DnB$) are converted in real terms by using the CPI for the related countries, respectively, as: $\frac{SX_{c,\tilde{t}}}{CPI_{\tilde{t}}}$ and $\frac{BK S_{B,\tilde{t}}}{CPI_{\tilde{t}}}$.²¹

²⁰I follow the methodology by Klaus et al. (2017) for the components' construction. However, note that the authors do not include the banking sector in the CLIFS for Lithuania.

²¹The OMXS30 is a stock market index for the Stockholm Stock Exchange that consists of the 30 most traded stock classes (including SEB bank and Swedbank stocks). The OBX Index is a stock market index which lists 25 most liquid companies (including *DnB* bank) of the Oslo Stock Exchange in Norway. The

(ii) *cumulative maximum loss* of bank stock prices ($CMAXB_B$) for each bank is estimated by comparing the value of $rBKS_B$ at time \ddot{t} with its maximum value over the previous T periods ($T = 2$ years, 502 working days):

$$CBKS_{B,\ddot{t}} = 1 - \frac{rBKS_{B,\ddot{t}}}{\max_{i=0,1,\dots,T}(rBKS_{B,\ddot{t}-i})} \quad (2.11)$$

2.4.2 Transformation of raw stress indicators

In order to aggregate the twelve individual stress indicators into a single financial stress index, firstly, I need to standardize each indicator to have a common unit. Following Holló et al. (2012) and Klaus et al. (2017), the standardization of stress indicators is based on empirical cumulative distribution function (CDF). This method of standardization consists in converting the six financial stress indicators into new series which are unit-free and ranging between 0 and 1. By this procedure, in the first step, the values of individual stress indicator are ranked and then divided by the total number of observations (n). The rank of 1 is assigned to the minimum value in the sample and n to a maximum.

The empirical CDF is computed as:

$$z_n = F_n(x_n) = \begin{cases} \frac{r}{n} & \text{for } x_{[r]} \leq x_t \leq x_{[r+1]} \\ 1 & \text{for } x_n \geq x_{[n]} \end{cases} \quad (2.12)$$

where $r = \{1, 2, \dots, n - 1\}$ is a rank number, n the total number of observations in the sample.²² The CDF is computed over an initial window of 10 years, after this period, the transformation is applied recursively over expanding samples with one new observation added at a time (keeping the ranks of previous observations fixed).

2.4.3 Aggregation

Once the twelve stress indicators have been transformed, I aggregate them into the final FSI. The aggregation consists in two steps. In the first step, the transformed individual stress indicators capturing stress in a specific financial market are combined (by arithmetic

data on *Swedbank* and *SEB bank* stock prices as well as OMXS30 index are from *NASDAQ database*. The data on *DnB* bank stock prices is collected from *DnB database* and the OBX index from *Oslo Børs database*. Note: CPI is available only on monthly frequency, therefore, I simply interpolate it to a daily frequency.

²²If the same value of x occurs more than once, the rank number assigned to each of the observations is given as the average of rankings involved.

average) to obtain four sub-indexes: the bond market sub-index (S_{Bond}), the stock market sub-index (S_{Eq}), the foreign exchange market sub-index (S_{FX}) and the banking sector sub-index (S_{Bank}):

$$\left\{ \begin{array}{l} S_{Bond,\tilde{t}} = \frac{VrR10_{\tilde{t}} + CDIFF_{\tilde{t}}}{2} \\ S_{Eq,\tilde{t}} = \frac{VOMXV_{\tilde{t}} + CMAX_{\tilde{t}}}{2} \\ S_{FX,\tilde{t}} = \frac{VREER_{\tilde{t}} + CUMUL_{\tilde{t}}}{2} \\ S_{Bank,\tilde{t}} = \frac{VBKS_{Swed,\tilde{t}} + CBKS_{Swed,\tilde{t}} + VBKS_{SEB,\tilde{t}} + CBKS_{SEB,\tilde{t}} + VBKS_{DnB,\tilde{t}} + CBKS_{DnB,\tilde{t}}}{6} \end{array} \right. \quad (2.13)$$

Once the sub-indices are computed, I aggregate them into the final FSI by using the approach based on the portfolio theory suggested by Holló et al. (2012) for the CISS index construction and used more recently by Louzis and Vouldis (2013), Johansson and Bonthron (2013) and by Klaus et al. (2017). Therefore, the FSI for Lithuania is computed as follows:

$$FSI_{\tilde{t}} = (w \times s_{\tilde{t}}) C_{\tilde{t}} (w \times s_{\tilde{t}})' \quad (2.14)$$

where $s_{\tilde{t}} = (S_{Bond,\tilde{t}}, S_{Eq,\tilde{t}}, S_{FX,\tilde{t}}, S_{Bank,\tilde{t}})$ is a vector of the sub-indexes, $C_{\tilde{t}}$ is the matrix of time-varying cross-correlation coefficients between the four sub-indexes and w is a sub-index weight. Similarly to Klaus et al. (2017), I give the same weight to each sub-index ($w = \frac{1}{4}$).²³

The portfolio based approach allows taking into account the systemic co-movement across the financial market segments through time-varying cross-correlations between the sub-indexes. The stronger is the correlation of financial stress across the sub-indexes, the more weight is attributed to the FSI. The time-varying cross-correlation $\rho_{i,j,\tilde{t}}$ between sub-indexes i and j is estimated recursively using the exponentially weighted moving averages (EWMA) method. In particular, the covariances ($\sigma_{i,j,\tilde{t}}$) and volatilities ($\sigma_{i,\tilde{t}}^2$) are estimated as follows:

²³Holló et al. (2012) estimate the weights of the sub-indexes in the CISS index by using a bivariate linear VAR and, then, by computing the cumulated impulse response of industrial production growth to a one standard deviation shock to a sub-sector index. However, the authors find that the differences between the CISS computed with impulse response based weights and the one with equal weights are not large.

$$\left\{ \begin{array}{l} \sigma_{i,j,\ddot{t}} = \lambda \sigma_{i,j,\ddot{t}-1} + (1 - \lambda) \bar{S}_{i,\ddot{t}} \bar{S}_{j,\ddot{t}} \\ \sigma_{i,\ddot{t}}^2 = \lambda \sigma_{i,\ddot{t}-1}^2 + (1 - \lambda) \bar{S}_{i,\ddot{t}}^2 \\ \rho_{i,j,\ddot{t}} = \frac{\sigma_{i,j,\ddot{t}}}{\sigma_{i,\ddot{t}} \sigma_{j,\ddot{t}}} \end{array} \right. C_{\ddot{t}} = \begin{bmatrix} 1 & \rho_{Eq,Bond,\ddot{t}} & \rho_{FX,Eq,\ddot{t}} & \rho_{Bank,Eq,\ddot{t}} \\ \rho_{Bond,Eq,\ddot{t}} & 1 & \rho_{FX,Bond,\ddot{t}} & \rho_{Bank,Bond,\ddot{t}} \\ \rho_{Bond,FX,\ddot{t}} & \rho_{Eq,FX,\ddot{t}} & 1 & \rho_{Bank,FX,\ddot{t}} \\ \rho_{Bond,Bank,\ddot{t}} & \rho_{Eq,Bank,\ddot{t}} & \rho_{FX,Bank,\ddot{t}} & 1 \end{bmatrix} \quad (2.15)$$

where $i, j = \{Bond, Eq, FX, Bank\}$, $i \neq j$, with $\bar{S}_{i,\ddot{t}} = (S_{i,\ddot{t}} - 0.5)$ denoting demeaned sub-indexes obtained by subtracting their *theoretical* median value (i.e. 0.5). In line with Klaus et al. (2017), I keep the smoothing parameter $\lambda = 0.85$ constant. The initial values for the covariance and the volatilities (for $\ddot{t} = 1$ which is associated with 2/10/2001) are set equal to the corresponding average values over the two years (i.e. the period running from 2/10/2001 to 30/9/2002).

2.4.4 Daily financial stress index for Lithuania

The evolution of the sub-indexes used for Lithuanian financial stress index construction, over the period 2/10/2001 – 30/12/2016, is displayed in Figure 2.4. Figure 2.4 shows that the financial distress in bond, equity, foreign exchange and banking sectors reaches the peak during the period of global financial crisis. In particular, the stock market sub-index peaks in October 2008, the foreign exchange sub-index in January 2009, the banking sub-index in March 2009 and bond sub-index in June 2009.

Figure 2.5 shows the contribution of each sub-index to the overall distress in the Lithuanian financial system. The contribution of each sub-index increases during the global financial crisis (during mid-2007 – mid-2009) and the major contributor is the banking sector. As expected, during the European sovereign debt crisis period (beginning of 2011 – 2012) the bond market sub-index is the main contributing factor to financial stress. It is also worth noting that the foreign exchange sub-index results as the major contributor to the overall stress in Lithuania in 2015. In particular, distress in the Lithuanian foreign exchange market has increased at the end-2014, when the Russian economy was in a downturn due to the fall in the oil prices and the Russia-Ukraine conflict.

Figure 2.6 shows the time-varying correlations between the four sub-indices, which

quantifies the systemic risk of the Lithuanian financial system. The relatively high correlation coefficient between each pair of market sub-indices associated with relatively high values of all sub-indices is observed over the period from December 2008 to September 2009.

The total *daily* financial stress index for Lithuania is presented in Figure 2.7. Figure 2.7 shows that the Lithuanian financial system did not experience high levels of financial stress over the period 2001-2007. However, the index starts to increase at the beginning of 2008 and reaches a peak right after the collapse of the US investment bank Lehman Brothers. Although the financial distress slightly diminishes at the end of 2009, the rising concerns regarding the sustainability of sovereign debt in the some of Eurozone countries (Greece and later Italy, among others) leads to high values of the stress index in May 2010 and over September - October 2011. Furthermore, Figure 2.7 shows that the failure of two domestic banks: *SNORAS* (in November 2011), which was the third largest bank by deposits and the fifth largest by assets and of *Ukio bankas* (in February 2013), did not affect the stability of the entire financial system.

Finally, Figure 2.8 compares the *daily* FSI with an alternative *monthly* financial stress index for Lithuania by Klaus et al. (2017), which is available at ECB database. Note, that for a more straightforward comparison, for the moment, I aggregate the daily FSI to a monthly frequency. Figure 2.8 shows that the two indexes peaks during the GFC. However, while the FSI peaks in the beginning of 2009, the ECB index reach the highest stress level in the mid-2009.

2.5 Mixed Frequency Granger (non-) Causality test

There is an important link between financial stress and the real sector. A number of empirical studies find that increase in financial stress, measured by a financial stress index, can produce substantial spillovers and have significant effects on the real economy.²⁴ Hollo et al. (2012) find that in the high-stress regimes the increase in the EZ financial distress leads to a collapse in industrial production, while in the low-stress regime it does not have any statistically significant impact. More recently, Kremer (2016) shows that the CISS index Granger cause EU real GDP growth. While the aforementioned studies are based

²⁴For instance, when financial markets suffer from high distress increased uncertainty about asset value decreases the value of collateral. As the consequence, shocks affecting the creditworthiness lead to increased swings in output. At the same time, economic activity is affected by the fact that bank capital is eroded, which forces banks to deleverage and decrease the lending to businesses.

on a common low frequency dataset, in this section, I investigate a causal relationship between a *daily* financial stress index for Lithuania (constructed in section 2.4) and a *monthly* Lithuanian industrial production growth.

2.5.1 Mixed Frequency VAR

Consider two time series sampled at different frequencies: a low-frequency series x_L and a high-frequency series x_H . A high-frequency series is observed m times during a low-frequency period t . According to Ghysels (2016), the mixed frequency VAR model can deal either with a case of a small m (e.g. when the series are sampled at quarterly/annual or weekly/daily frequency), or with a case of a large m (e.g. when the series are sampled at daily/monthly or weekly/quarterly frequency). In this chapter, I focus on the large m case: one series is sampled at *monthly* and the other one at *daily* frequency.

In MF-VAR all observations of period t (i.e. high and low frequency observations) are stacked into a column vector by treating the m observations of the high-frequency series as if they were distinct endogenous variables. Let $x_H(t, 1)$ be the first high-frequency observation of x_H in low frequency period t (e.g. the first daily observation of the month t), a $x_H(t, 2)$ – the second, and $x_H(t, m)$ – the last one. Consider a high-frequency vector in t -period as $[x_H(t, 1), x_H(t, 2), x_H(t, j), \dots, x_H(t, m)]'$. Then, a mixed frequency vector with one high and one low frequency variable is denoted as $Z(t) = [x_H(t, 1)', \dots, x_H(t, m)', x_L(t)']'$, with the dimension $K \times 1$, where $K = m + 1$.

A reduced-form vector autoregressive model with mixed-frequency data (MF-VAR(p)) is given by:²⁵

$$\begin{pmatrix} x_H(t, 1) \\ \vdots \\ x_H(t, m) \\ x_L(t) \end{pmatrix} = \begin{pmatrix} \mu_1 \\ \vdots \\ \mu_m \\ \mu_{m+1} \end{pmatrix} + \sum_{k=1}^p \begin{pmatrix} d_{11,k} & \cdots & d_{1m,k} & c_{1,k} \\ \vdots & \ddots & \vdots & \vdots \\ d_{m1,k} & \cdots & d_{mm,k} & c_{m,k} \\ b_{1,k} & \cdots & b_{m,k} & a_k \end{pmatrix} \begin{pmatrix} x_H(t-k, 1) \\ \vdots \\ x_H(t-k, m) \\ x_L(t-k) \end{pmatrix} + \begin{pmatrix} u_H(t, 1) \\ \vdots \\ u_H(t, m) \\ u_L(t) \end{pmatrix}$$

or

$$Z(t) = \mu + \sum_{k=1}^p \Gamma_k Z(t-k) + u_t \quad (2.16)$$

The coefficients b 's and c 's capture the causality from a high-frequency variable x_H to the low frequency variable x_L , and the causality from x_L to x_H , respectively. More specifically, testing for Granger (non-) causality implies the following null hypothesis:

- **High-to-low (non-) causality.** x_H does not Granger cause x_L if and only if:

²⁵The parameters in Γ are estimated by using an OLS estimator.

$$H_0 : b_{1,k} = \dots = b_{m,k} = 0; \text{ for } k = 1, \dots, p \quad (2.17)$$

- **Low-to-high (non-) causality.** x_L does not Granger cause x_H if and only if:

$$H_0 : c_{1,k} = \dots = c_{m,k} = 0; \text{ for } k = 1, \dots, p \quad (2.18)$$

2.5.2 Granger causality test

Given that the mixed-frequency VAR in section 2.5.1 is characterized by a large mismatch in sampling frequencies of the series involved (i.e. daily *vs* monthly), in this section I describe the Granger causality tests that take into account this issue. Götzt et al. (2016) develop a test for a *high-to-low* and *low-to-high* Granger causality in a mixed-frequency VAR by using a Wald test. The Wald test is based on the unrestricted MF-VAR in (2.16). Let $\hat{\Gamma}$ denote an OLS estimates of the coefficient matrices for the lagged endogenous variables in the MF-VAR (2.16) and define R a matrix that picks the set of coefficients of interest for Granger (non-) causality test i.e. $Rvec(\hat{\Gamma})$. Then, the Wald test statistic is constructed as:

$$\hat{\xi}_W = [Rvec(\hat{\Gamma})]'(R\hat{\Omega}R')^{-1}[Rvec(\hat{\Gamma})] \quad (2.19)$$

with

$$\hat{\Omega} = (W'W)^{-1} \otimes \hat{\Sigma} \quad (2.20)$$

where $\hat{\Sigma} = \frac{1}{T_L} \hat{u}'\hat{u}$ is the covariance matrix of the disturbance terms in (2.16) and W is the regressor set. However, in a mixed-frequency model with a large m an asymptotic Wald test may exhibit size distortions when the number of zero restrictions is relatively large, compared to a sample size (Götzt et al., 2016; Ghysels et al., 2018). Therefore, Götzt et al. (2016) rely on bootstrap in order to draw an inference based on the Wald test.²⁶

Ghysels et al. (2018) propose a *max-test* only for *high-to-low* Granger causality case with a large number of zero restrictions. More specifically, the *max-test* statistic is based on pm parsimonious regression models:

$$x_L(t) = \mu_i + \sum_{k=1}^p a_{k,i} x_L(t-k) + \beta_i x_H(t-1, m+1-i) + u_{L,i}(t), \quad (2.21)$$

²⁶Montecarlo simulations in Götzt et al. (2016) show that bootstrap variants of *high-to-low* and *low-to-high* causality tests improve the empirical size.

where index $i \in \{1, \dots, pm\}$ is in high-frequency terms and the second argument $(m+1-i)$ of x_H can be less than 1 (since $i > m$ occurs when $p > 1$). Each i^{th} model contains p low-frequency autoregressive lags of x_L and only the i^{th} high-frequency lag of x_H . I estimate the parsimonious model pm times. It is important to notice that the β_i in parsimonious models (2.21) and b 's in unrestricted model (2.16) generally are not equivalent. I estimate the parameters in each i^{th} model by OLS to get $\hat{\beta}_i = \{\hat{\beta}_1, \dots, \hat{\beta}_{pm}\}$. Then, I formulate a *max-test statistic* as:

$$\hat{\mathcal{T}}_{T_L} = \max_{1 \leq i \leq pm} \{(\sqrt{T_L} \hat{\beta}_i)^2\} \quad (2.22)$$

where T_L is a low-frequency sample size. The mixed-frequency *max-test statistics* $\hat{\mathcal{T}}_{T_L}$ has a non-standard asymptotic distribution under the null hypothesis in (2.17). Therefore, I follow Ghysels et al., (2018) and rely on a simulation-based p-value.

Rewrite each parsimonious regression model in (eq. (2.21)) as:

$$x_L(t) = X_i'(t) \times \theta_i + u_{L,i}(t) \quad (2.23)$$

for $i = 1, \dots, pm$, where $X_i(t) = [1, x_L(t-1), \dots, x_L(t-p), x_H(i)]'$, $\theta_i = [\mu_i, a_{1,i}, \dots, a_{p,i}, \beta_i]'$ and all parameters across the pm models are stacked as $\theta = [\theta_1', \dots, \theta_{pm}']'$. Define a selection matrix R that selects $\beta = [\beta_1, \dots, \beta_{pm}]'$ from θ such that $\beta = R\theta$:

$$R = \begin{bmatrix} 0_{1 \times (1+p)} & 1 & 0_{1 \times (1+p)} & 0 & \cdots & 0_{1 \times (1+p)} & 0 \\ 0_{1 \times (1+p)} & 0 & 0_{1 \times (1+p)} & 1 & \cdots & 0_{1 \times (1+p)} & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0_{1 \times (1+p)} & 1 & 0_{1 \times (1+p)} & 0 & \cdots & 0_{1 \times (1+p)} & 1 \end{bmatrix}_{pm \times (p+2)pm} \quad (2.24)$$

Under the null hypothesis consider $\hat{\mathcal{T}}_{T_L} \xrightarrow{d} \max_{1 \leq i \leq pm} \{\mathcal{N}_i^2\}$ (see eq. (2.22)) as $T_L \rightarrow \infty$, where $\mathcal{N} = [\mathcal{N}_1, \dots, \mathcal{N}_{pm}]'$ is distributed as $N(0, V)$ with covariance matrix:

$$V \equiv R \times Sigma \times R' \quad (2.25)$$

where

$$Sigma = \begin{bmatrix} \Sigma_{1 \times 1} & \cdots & \Sigma_{1 \times (pm)} \\ \vdots & \ddots & \vdots \\ \Sigma_{(pm) \times 1} & \cdots & \Sigma_{(pm) \times (pm)} \end{bmatrix}$$

$$\Sigma_{i \times j} = G_{ii}^{-1} \Lambda_{ij} G_{jj}^{-1}, \quad G_{ii} = E[X_i(t) X_i'(t)], \quad \Lambda_{ij} = E[\epsilon_t^2 X_i(t) X_j'(t)] \text{ for } i, j \in \{1, \dots, pm\}.$$

Let \hat{V}_{T_L} be a consistent estimator for V . In the first step, draw M samples of vectors $\mathcal{N} = \{\mathcal{N}^{(1)}, \dots, \mathcal{N}^{(M)}\}$ independently from $N(0, \hat{V}_{T_L})$. In the second step, transform $\mathcal{N} = \{\mathcal{N}^{(1)}, \dots, \mathcal{N}^{(M)}\}$ to be distributed as $N(0, \hat{V}_{T_L})$. Finally, compute artificial test statistics $\hat{\mathcal{T}}_{T_L}^{(j)} = \max\{(\mathcal{N}_1^{(j)})^2, \dots, (\mathcal{N}_{pm}^{(j)})^2\}$ for $j = 1, \dots, M$. An asymptotic p-value approximation for $\hat{\mathcal{T}}_{T_L}$ is:

$$\hat{p}_{T_L, M} = \frac{1}{M} \sum_{j=1}^M I(\hat{\mathcal{T}}_{T_L}^{(j)} > \hat{\mathcal{T}}_{T_L}) \quad (2.26)$$

where $I(A)$ is the indicator function that equals 1 if A occurs and 0 otherwise.

2.6 Empirical Evidence

2.6.1 Data

I focus on the *daily* Lithuanian FSI (constructed in section 2.4) and *monthly* industrial production (IP) growth in Lithuania for the sample period running from October 2, 2001 to December 30, 2016, yielding a sample size of $T_L = 183$ months. In line with Holló et al. (2012) and Klaus et al. (2017) I use a year-to-year IP growth estimated as 12th month log-difference. I use a seasonally and working day adjusted data on Lithuanian industrial production, which is available from the Lithuanian Department of Statistics.

Figure 2.9 plots the data. The figure suggests that Lithuanian economy has experienced a high growth up to the end-2008. With the beginning of the global financial crisis, the IP shrank decreasing for 14 consecutive months (from November 2008 to January 2010), peaking at (minus) -31.4% in April 2009.

The *daily* Lithuanian FSI, constructed in section 2.4, has a varying number of *daily* observations within each *month*, ranging from 18 to 23 observations. In order to perform a MF Granger causality test, for simplicity, I assume that the maximum number of *daily* observations that is available in each month throughout the sample is 18 ($m = 18$). More specifically, the *daily* Lithuanian FSI series are modified as follows:

$$FSI_H(t, j) \quad \text{for } j = 1, \dots, 18 \quad (2.27)$$

where the last $m(t) - 18$ observations at the end of each month are disregarded (see Götz et al., 2016).²⁷ This modification gives a dataset with $T_L = 183$ low-frequency observations,

²⁷Note that the $x_H(t, 1)$ is not necessarily the first day of the month. For example, October 1, 2016 fall

$m = 18$ and $m \times T_L = 3294$ high-frequency observations. Therefore, when setting the VAR MF model specification, the stacked vector of endogenous variables has a dimension $K = 19$. The Phillips and Perron (1988) test for unit-root suggest that the data are stationary (at 10-percent significance level).

2.6.2 Granger causality tests

To test for Granger causality from the *daily* Lithuanian FSI (FSI_H) to *monthly* IP growth in Lithuania (IP_L) I focus on the last row of MF-VAR(2) specification in (2.16):

$$IP_L(t) = \mu_{19} + \sum_{k=1}^2 a_k IP_L(t-k) + \sum_{i=1}^{36} b_i FSI_H(t-1, 18+1-i) + u_L(t) \quad (2.28)$$

where I regress the *monthly* IP growth onto a constant (μ_{19}), $p = 2$ months of lagged low-frequency variable (IP growth), $pm = 36$ days of lagged high-frequency variable (FSI for Lithuania).²⁸ The Wald test developed by Götz et al. (2016) consider the unrestricted model described in (2.16). The model is estimated by using ordinary least squares. The p-values for the Wald test for the null hypothesis $H_0 : b_1 = \dots = b_{36} = 0$ in eq. (2.17) are computed using 1999 bootstrap replications.²⁹

The *max-test* by Ghysels et al. (2018) is based on *parsimonious* regression models:

$$IP_L(t) = \mu_i + \sum_{k=1}^2 a_{ki} IP_L(t-k) + \beta_i FSI_H(t-1, 18+1-i) + u_{L,i}(t) \quad (2.29)$$

for $i = \{1, \dots, 36\}$, where each i^{th} model contains $p = 2$ months of lagged IP growth and only the i^{th} daily lag of FSI for Lithuania.³⁰ I estimate the *parsimonious* model 36 times. The number of parameters to estimate in the *parsimonious* regression model is 4 (1+2+1) against 39 (1+2+36) in the *full regression* model in eq.(2.28).³¹ For the robustness check

on Sunday. Thus, October 3, 2016 is considered as the first observation of the month $x_H(t, 1)$.

²⁸The model specification is chosen according to the suggestions of Ghysels et al. (2018). More specifically, I perform a Ljung-Box Q-test to test for the absence of serial correlation in residuals of the full regression model eq. (2.28). The p-values for Q-test are reported in Appendix, Table 2.5.

²⁹For bootstrap, I use a code provided by Götz et al. (2016).

³⁰Following Ghysels et al. (2018) p-values are computed based on the robust covariance matrix with 100 000 draws from an approximation to the limit distribution under non-causality.

³¹I estimate 4 parameters in each i^{th} parsimonious model eq. (2.29): (i) a constant (α_{0i}), (ii) two coefficients related to the lagged IP growth (a_{1i}, a_{2i}) and (iii) one coefficient related to the lagged FSI

I also try the different model specifications: MF-VAR(1) and MF-VAR(3).

To test for Granger causality from *monthly* IP growth to *daily* FSI for Lithuania, defined as $H_0 : c_1 = \dots = c_{36} = 0$ in (2.18), I focus on an unrestricted model in (2.16) (see last column of the model) and I use the Wald statistics eq. (2.19) developed by Götz et al. (2016).

2.6.3 Empirical findings

2.6.3.1 Full sample analysis

The full sample results in Table 2.3 panel (A) show that the *daily* Lithuanian FSI has a predictive power for *monthly* Lithuanian IP growth for the period (October 2001 – December 2016), but not vice versa. More specifically, the p-values suggest that, for any MF-VAR model specification (with lag order (p) equal to 1, 2, or 3), there is evidence of unidirectional causality from *daily* Lithuanian FSI to *monthly* IP growth in Lithuania. In fact, while both the *max-test* and the Wald test reject the null hypothesis that FSI does not Granger cause IP growth at 10% significance level, I cannot reject the null hypothesis that IP growth does not Granger cause FSI.

In addition, the analysis is in line with other studies (see Hakkio and Keeton, 2009, among others) which find that an increase in financial stress has an adverse impact on the overall economic activity. In particular, Figure 2.10 shows that the point estimates of the coefficients β_i for each i^{th} parsimonious model (eq. 2.29) used to evaluate the effect of financial stress on economic activity is negative and statistically significant (at 95% confidence interval).

Further, in order to evaluate the index, I compare the *daily* FSI for Lithuania with alternative financial stress indexes. Specifically, I test for Granger causality between *monthly* IP growth in Lithuania and (i) a *daily* FSI for Lithuania, constructed by taking into consideration only three sub-indexes - bond, equity and foreign exchange (excluding banking sub-index), (ii) a *monthly* FSI for Lithuania (composed of 4 sub-sectors: bond, equity, foreign exchange and banking), obtained by averaging the daily FSI to a monthly frequency, and (iii) a *monthly* CLIFS index provided by ECB and developed Klaus et al. (2017), which is composed of only three sub-indexes - bond, equity and foreign exchange.

As for case (i), the p-values in Table 2.3 panel (B) suggest that a *daily* FSI for Lithuania, constructed by taking into consideration only three sub-indexes - bond, equity

(β_i).

and foreign exchange (excluding banking sub-index), is also a good predictor for a *monthly* IP growth in Lithuania. More specifically, for any MF-VAR specification (with lag order equal to 1, 2 or 3) the *daily* FSI (3 sub-indexes) Granger cause a *monthly* IP growth in Lithuania, but not vice versa. Furthermore, the point estimates of the coefficients β_i for each i^{th} parsimonious model (eq. 2.29) in Figure 2.11 shows that an increase in financial stress in equity, bond and foreign exchange sectors leads to a slowdown in IP growth in Lithuania, although the effect is slightly smaller compared to the *daily* FSI that also contains the banking sector related stress sub-index.

As for case (ii), I use a common frequency VAR(1) to test for Granger causality between *monthly* IP growth in Lithuania and a *monthly* FSI for Lithuania (composed of 4 sub-sectors: bond, equity, foreign exchange and banking). The p-values in Table 2.3 panel (C) suggest a unidirectional causality from a *monthly* FSI to a *monthly* IP growth, since I can reject the null hypothesis of non-causality relying on an asymptotic and a bootstrap version of a Wald test. Moreover, a common frequency regression results in Table 2.4 panel A show that an increase in financial stress has a negative and statistically significant impact on the IP growth in Lithuania.

As for case (iii), I investigate the causal relationship between the *monthly* CLIFS developed by Klaus et al. (2017) and the *monthly* Lithuanian IP growth series.³² For this purpose, I use an asymptotic and a bootstrap Wald test for testing bi-directional Granger causality. The full sample results in Table 2.3 panel (D), based on VAR(2) model, suggest that I cannot reject the null hypothesis of non-causality in both directions. This empirical finding is confirmed by the common frequency regression results in Table 2.4 panel (B) suggesting that a CLIFS index has a negative impact on IP growth in Lithuania, although the effect is not statistically significant.

To summarize, the empirical findings suggest the importance of including the banking sector into the financial stress index (and the use of a mixed frequency dataset), otherwise the negative causal effect on IP growth would not be detected.

2.6.3.2 Rolling-window analysis

I also assess if there is any evidence of changes in the causality between the *daily* FSI for Lithuania and *monthly* IP growth over the full sample period. For this purpose, I implement a rolling-window Granger causality test, fixing the window size to 84 months

³²The index is composed of 3 sub-sectors, reflecting the stress in equity, bond and foreign exchange market.

(i.e. seven years).³³ This gives a total of 100 sub-samples, where the first sub-sample covers the period from October 2001 to September 2008 and the last sub-sample covers the period from January 2010 to December 2016. In line with the full sample analysis, I use a *max-test* developed by Ghysels et al. (2018) and the Wald test developed by Götz et al. (2016) for each sub-sample.

Figure 2.12 plots the rolling window p-values for each causality test over the 100 windows (the last observation of each sub-sample period is shown on the horizontal axis). More specifically, Panel A and B show the *max-test* and the Wald test p-values for the null hypothesis that a *daily* FSI does not Granger cause the *monthly* IP growth in Lithuania. The p-values of the Wald test for the causality in the opposite direction are presented in the panel C of Figure 2.12.

In line with full sample analysis, the results suggest that I cannot reject the null hypothesis that IP growth in Lithuania does not Granger cause the financial distress in Lithuania at 10% significance level. On the contrary, I find that a *daily* financial stress index for Lithuania has a predictive power for *monthly* Lithuanian IP growth (at 10% significance level) for most of the considered sub-samples, according to the *max-test* and to the Wald test (see Panel A – B in Figure 2.12). In particular, the *max-test* (see panel A) confirms the causality from FSI to IP growth from April 2009 to March 2016, and the Wald test (see panel B) detects a significant causality from the January 2010 to January 2016.³⁴

Furthermore, the p-values of a rolling window analysis in Figure 2.13 panel (A)-(B) suggest that a *daily* FSI for Lithuania, constructed by aggregating only 3 sub-indexes (bond, equity and foreign exchange) is also a good predictor of *monthly* Lithuanian IP growth, since I can reject the null hypothesis of non-causality at 10% significance level in most of the considered sub-samples. Panel C shows that IP growth does not Granger cause financial distress in the sub-samples covering the period from July 2009 to November 2013. Moreover, the p-values in Figure 2.14 of an asymptotic Wald test implemented for a rolling window analysis suggest a unidirectional causality from *monthly* FSI, composed of 4 sub-indexes (bond, equity, foreign exchange and banking), to *monthly* IP growth, since I can reject the null hypothesis of non-causality in most of the sub-samples (see panel A). In line with the full sample analysis, the only case associated with no evidence of causality in both directions is when I focus on the relationship between *monthly* CLIFS index by

³³The rolling-window analysis uses a fixed-length window, which moves sequentially from the beginning to the end of the sample period by adding one observation ahead and dropping one from the behind.

³⁴Note that I report the last observation of the sub-sample period.

Klaus et al. (2017) and *monthly* IP growth. More specifically, the rolling window analysis results in Figure 2.15 suggest no causality between *monthly* CLIFS index by Klaus et al. (2017) and *monthly* IP growth.

2.7 Conclusions

In this chapter, first, I construct a *daily* Financial Stress Index (FSI) for Lithuania. In particular, I extend the monthly Financial Stress Index (FSI) for Lithuania, computed by ECB (see Klaus et al, 2017), to a high-frequency (*daily*) horizon and, given the important role played by a banking sector in the Lithuanian economic development in the recent decade, I include the banking sector among its constituents (beyond bond, equity, foreign exchange markets).

Moreover, I investigate the causal relationships between the *daily* FSI for Lithuania and *monthly* industrial production growth, using a Granger causality test applied to a mixed-frequency VAR characterised by a large mismatch in sampling frequencies of the series involved (i.e. *daily* vs *monthly*). The empirical findings suggest that the *daily* Lithuanian FSI has a predictive power for *monthly* Lithuanian IP growth for the full sample period (October 2001 – December 2016), but not vice versa. These results are also confirmed by a rolling-window analysis, where I allow the causal relationship to vary over time. Moreover, the analysis is in line with the empirical studies (see Hakkio and Keeton, 2009, among the others) showing that an increase in financial stress has an adverse impact on the overall economic activity. In particular, I show that a banking stress in Lithuania leads to a stronger decline in IP growth.

Finally, I show that the constructed *daily* FSI for Lithuania is a better predictor for monthly industrial production growth than a *monthly* Country-Level Indicator of Financial Stress developed by ECB (Klaus et al., 2017).

Overall, the findings for Lithuania suggest that the leading indicator properties of an FSI index for Lithuania with respect to industrial production growth can be enhanced if I take into account the banking sector and I use *daily* observations.

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2.A Appendix

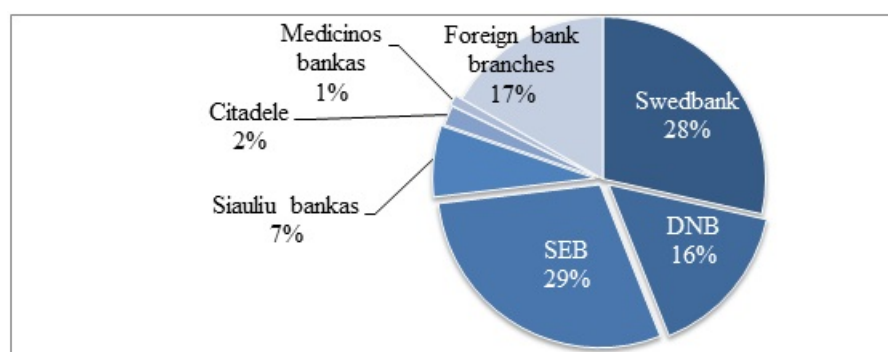
2.A.1 Figures: stylized facts for Lithuania

Figure 2.1: The development of Lithuanian financial system 2001-2016



Source: Bank of Lithuania (<https://www.lb.lt/en/financial-stability#ex-1-1>).

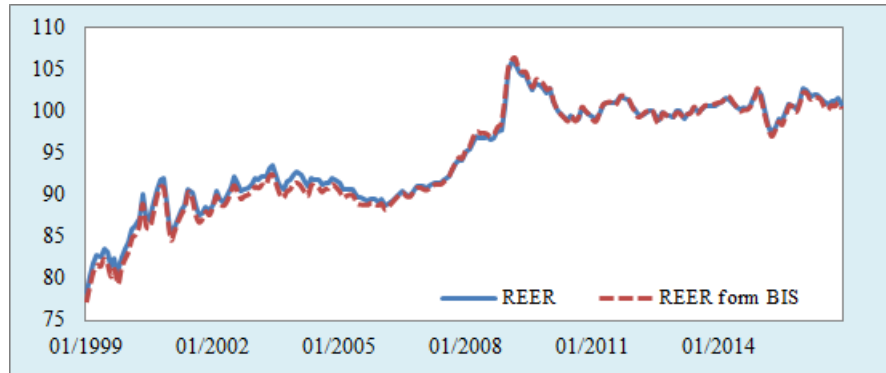
Figure 2.2: Lithuanian banking sector structure by assets (end-2016)



Source: Bank of Lithuania (<https://www.lb.lt/en/main-indicators-of-banking-sector-activities>).

2.A.2 Figures: FSI for Lithuania

Figure 2.3: Our REER in comparison with the REER for Lithuania from BIS



Notes: The straight line is the monthly REER index I compute by aggregating daily data. The dotted line is the monthly REER index available from BIS.

Figure 2.4: Sub-indexes (2001-2016)

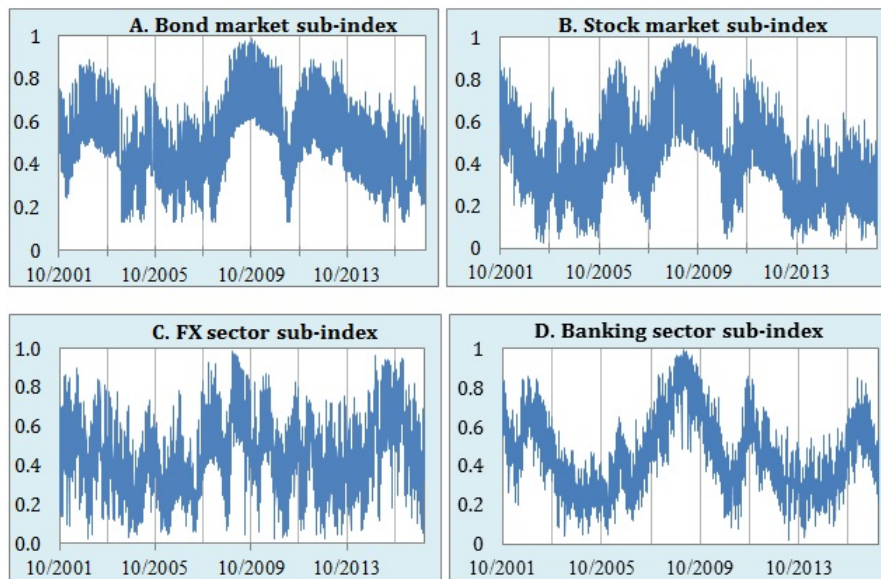


Figure 2.5: Contribution of the sub-indexes to the overall FSI

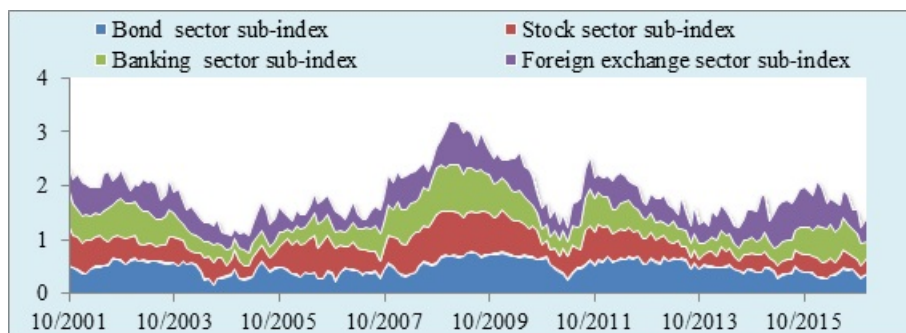
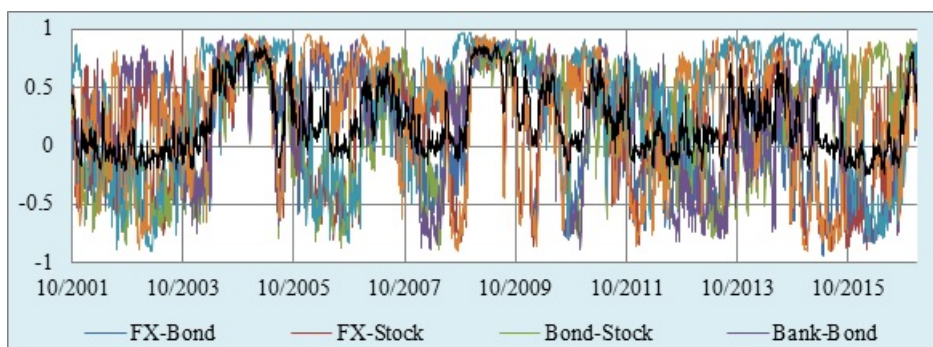
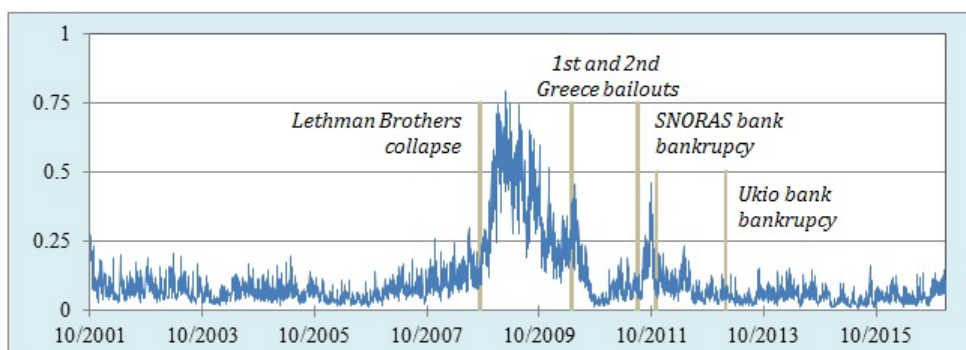


Figure 2.6: Time varying cross-correlations between the sub-indexes



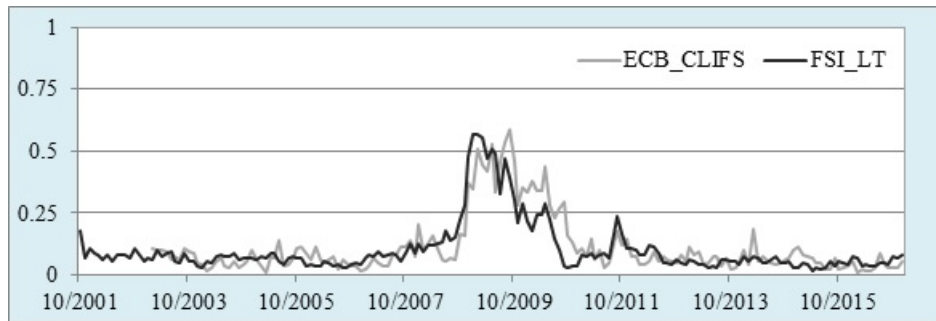
Notes: I use EWMA with smoothing parameter 0.85 (see eq. 2.15) to estimate the pairwise correlations among sub-sectors.

Figure 2.7: Daily financial stress index for Lithuania



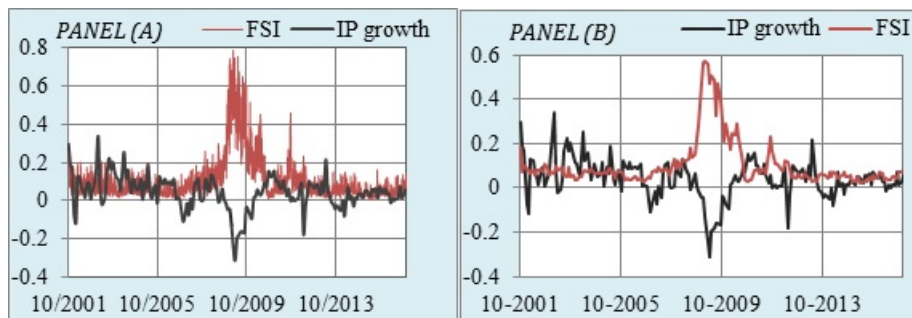
Notes: Bars are associated with the following crisis events: the bankruptcy of US investment bank Lethman Brothers, first and second Greece bailouts, and *SNORAS* and *Ukio bankas* bankruptcy.

Figure 2.8: Comparison between FSI and a CLIFS for Lithuania from ECB



Notes: The bold line is daily Lithuanian FSI aggregated into monthly frequency. The grey line is the monthly Lithuanian CLIFS index available from ECB at: <https://sdw.ecb.europa.eu/browse.do?node=9693347>.

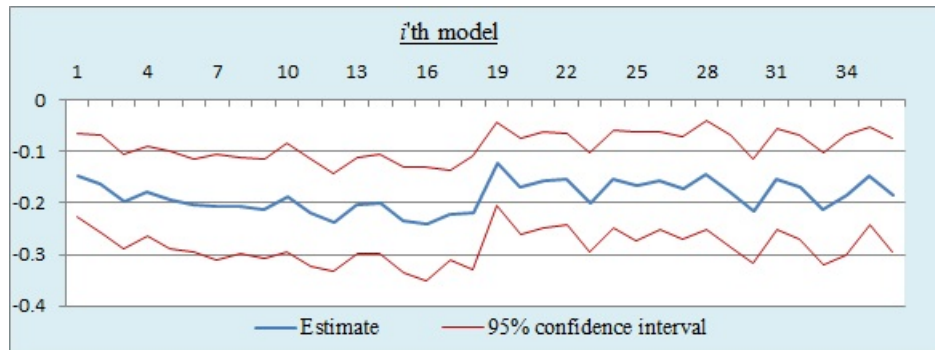
Figure 2.9: Lithuanian industrial production growth and FSI for Lithuania



Notes: In PANEL (A) I show the daily FSI, while in PANEL (B) the index is aggregated to monthly frequency. The IP growth is estimated as 12th month difference in log output, for a period October 2001 - December 2016. IP growth is in black colour and FSI is in red colour.

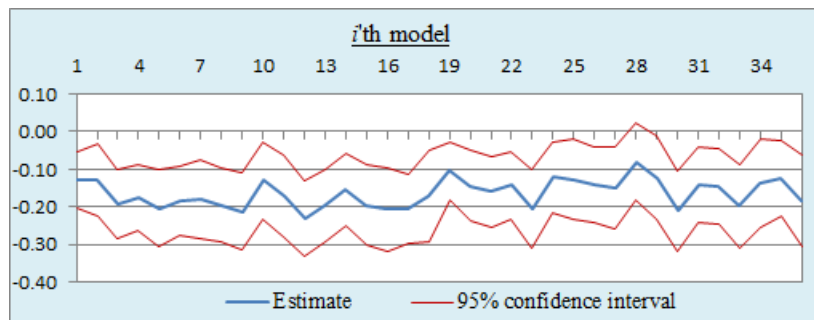
2.A.3 Figures: full sample analysis

Figure 2.10: *Daily* FSI (4 sub-indexes): the β_i coefficient values in each i^{th} model



Notes: The plot shows the point estimates of the coefficients β_i for each i^{th} parsimonious model (see eq. 2.29) and the confidence bands ($\pm 2 \times Str.Error$).

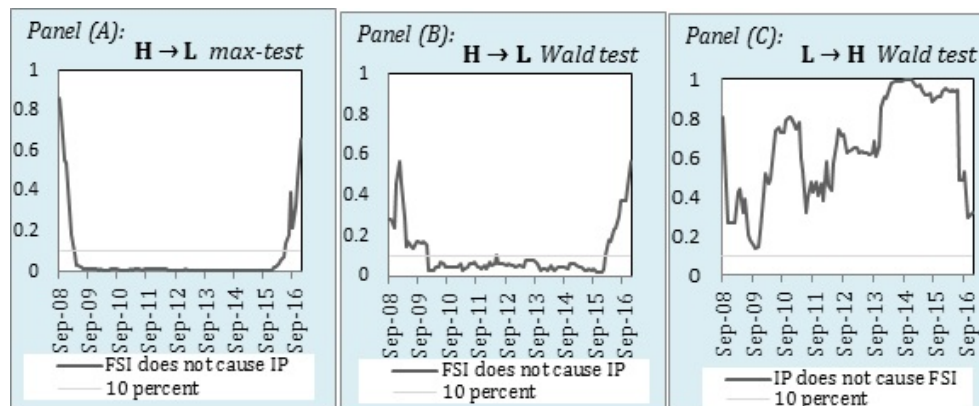
Figure 2.11: *Daily* FSI (3 sub-indexes): the β_i coefficient values in each i^{th} model



Notes: The plot shows the point estimates of the coefficients β_i for each i^{th} parsimonious model (see eq. 2.29) and the confidence bands (calculated as: Estimate $\pm 2 \times Str.Error$). I consider a *daily* FSI constructed by aggregating only 3 sub-indexes: bond, equity and foreign exchange.

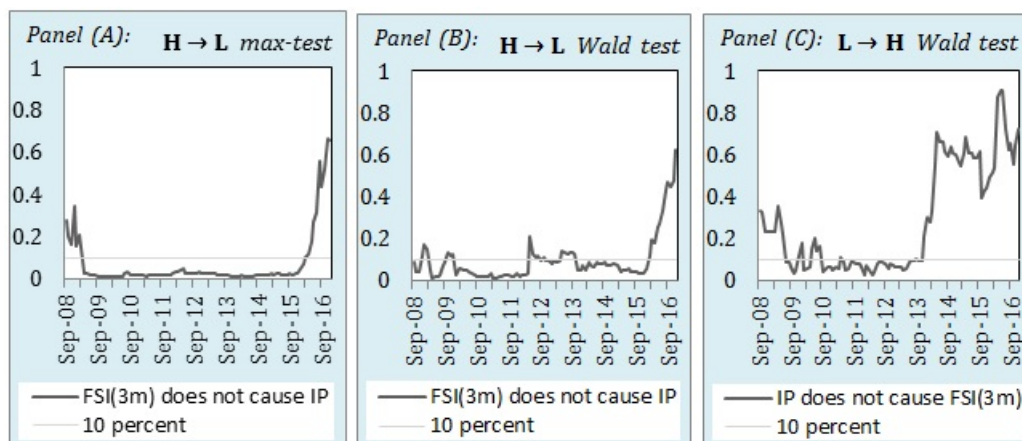
2.A.4 Figures: rolling window analysis

Figure 2.12: P-values for rolling window analysis (*daily* FSI composed of 4 sub-indexes)

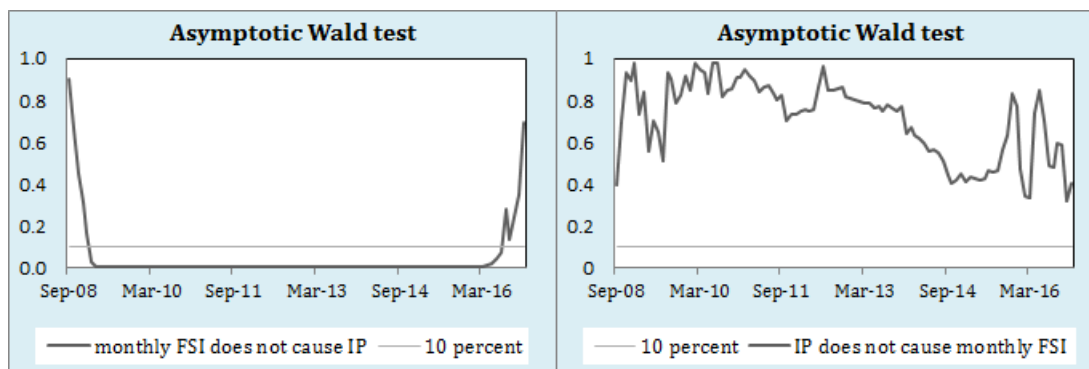


Note: I test for Granger causality between *daily* FSI for Lithuania (constructed in section 2.4) and *monthly* IP growth. Each test is based on MF-VAR (2) model and implemented by using a rolling window of 84 months (i.e. seven years). The x axes represent the 100 sub-samples, where the first sub-sample covers the period from October 2001 to September 2008, the second sub-sample covers the period from November 2001 to October 2008 and the last sub-sample covers January 2010 - December 2016 (the last observation of each sub-sample period is shown on the x axis). The y axes represent the p-values. The significance level of 10% is indicated by a light grey line.

Figure 2.13: P-values for rolling window analysis (*daily* FSI composed of 3 sub-indexes)

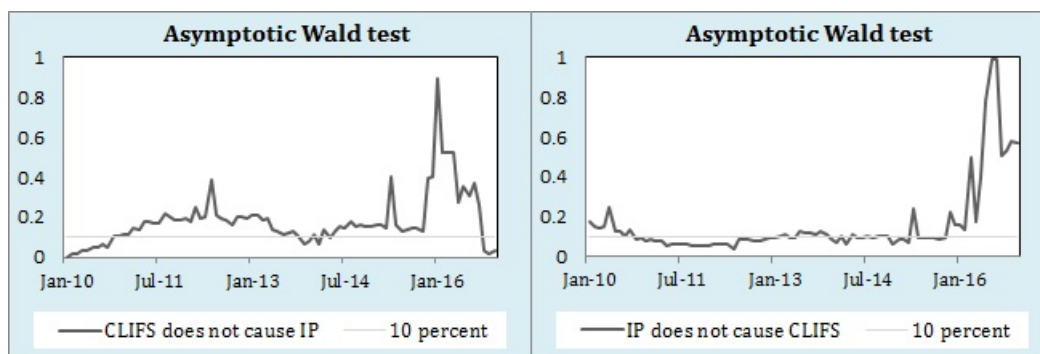


Note: I consider a *daily* FSI for Lithuania constructed by aggregating only 3 sub-indexes (bond, equity and foreign exchange). Each test is based on MF-VAR (2) model and implemented by using a rolling window of 84 months (i.e. seven years). The x axes represent the 100 subsamples, where the first covers the period from October 2001 to September 2008, the second one from November 2001 to October 2008 and the last one January 2010 - December 2016. The y axes represent the p-values. The significance level of 10% is indicated by a light grey line.

Figure 2.14: P-values for rolling window analysis (*monthly* FSI composed of 4 sub-indexes)

Note: I consider an asymptotic Wald test between common frequency variables: a *daily* FSI for Lithuania (composed of 4 sub-indexes) aggregated to *monthly* frequency and *monthly* IP growth. An optimal lag length for each sub-sample is obtained by using a SC criteria. Each test is implemented by using a rolling window of 84 months (i.e. seven years). The x axes represent the 100 subsamples, where the first covers the period from October 2001 to September 2008, the second one from November 2001 to October 2008 and the last one January 2010 - December 2016. The y axes represent the p-values. The significance level of 10% is indicated by a light grey line.

Figure 2.15: P-values for rolling window analysis (CLIFS index for Lithuania)



Note: I consider an asymptotic Wald test between monthly CLIFS index by ECB and monthly IP growth, implemented by using a rolling window of 84 months (i.e. seven years). An optimal lag length for each sub-sample is obtained by using a SC criteria. The x axes represent the 84 subsamples, where the first covers the period from February 2003 to January 2010, the second one from March 2003 to February 2010 and the last one January 2010 - December 2016. The y axes represent the p-values. The significance level of 10% is indicated by a light grey line.

2.A.5 Tables

Table 2.1: Indicators used for the Lithuanian FSI construction

Market	Indicator	Notation
Bond market	Realized daily volatility of 10y Lithuanian government bond yields	$VrR10_t$
	Cumulative difference of Lithuanian and German 10y bond yields	$CDIFF_t$
Equity market	Realized daily volatility of OMXV	$VOMXV_t$
	The cumulative maximum loss (CMAX) of OMXV	$CMAX_t$
Foreign exchange market	Realized daily volatility of REER	$VREER_t$
	Cumulative change over six months of REER	$CUMUL_t$
Banking sector: Swedbank	Realized volatility of the idiosyncratic Swedbank stock price returns	$VBKS_{Swed,t}$
	CMAX of Swedbank stock prices	$CBKS_{Swed,t}$
Banking sector: SEB bank	Realized volatility of the idiosyncratic SEB bank stock price returns	$VBKS_{SEB,t}$
	CMAX of SEB bank stock prices	$CBKS_{SEB,t}$
Banking sector: DnB bank	Realized volatility of the idiosyncratic DnB stock price returns	$VBKS_{DnB,t}$
	CMAX of DnB bank stock prices	$CBKS_{DnB,t}$

Notes: all data is in real terms.

Table 2.2: Lithuanian's major trading partners, market share in %

	EZ	EE	LV	CN	CZ	DK	JP	NO	PL	RU	SE	TR	US	GB	Tot
LT	41.6	2.9	6.8	4.3	2.1	2.9	0.7	1.6	9.5	7.6	4.1	0.9	3.2	3.1	91.4
LT_{adj}	45.5	3.2	7.5	4.7	2.3	3.1	0.8	1.8	10.4	8.4	4.5	1.0	3.5	3.4	100

Notes: based on trade in 2008 – 2010. EZ – Eurozone (Austria 1.4, Belgium 4.0, Finland 2.7, France 4.8, Denmark 17.1, Ireland 0.3, Italy 5.3, Luxembourg 0.2, Netherlands 3.8, Portugal 0.3, Spain 1.7); EE – Estonia, LV – Latvia CN – China, CZ – Czech Republic, DK – Denmark, JP – Japan, NO – Norway, PL – Poland, RU – Russia, SE – Sweden, TR – Turkey, US – United States, GB – United Kingdom. Data is taken from BIS.

Table 2.3: P-values for Granger Causality test (full sample analysis)

Panel (A): Daily FSI (including 4 sub-indexes) and monthly IP growth			
H ₀ : <i>daily</i> FSI \rightarrow <i>monthly</i> IP growth		H ₀ : <i>monthly</i> IP growth \rightarrow <i>daily</i> FSI	
Test	Wald test (bootstrap version)	max-test	Wald test (bootstrap version)
MF-VAR(1)	0.001	0.004	0.233
MF-VAR(2)	0.026	0.008	0.127
MF-VAR(3)	0.071	0.013	0.394

Panel (B): Daily FSI (3 sub-indexes) and monthly IP growth			
H ₀ : <i>daily</i> FSI \rightarrow <i>monthly</i> IP growth		H ₀ : <i>monthly</i> IP growth \rightarrow <i>daily</i> FSI	
Test	Wald test (bootstrap version)	max-test	Wald test (bootstrap version)
MF-VAR(1)	0.001	0.006	0.236
MF-VAR(2)	0.009	0.014	0.314
MF-VAR(3)	0.080	0.019	0.472

Panel (C): Monthly FSI (4 sub-indexes) and IP growth				
H ₀ : <i>monthly</i> FSI \rightarrow <i>monthly</i> IP			H ₀ : <i>monthly</i> IP \rightarrow <i>monthly</i> FSI	
	Wald test (bootstrap version)	Wald test (asymptotic)	Wald test (bootstrap version)	Wald test (asymptotic)
CF-VAR(1)	0.001	0.000	0.876	0.850

Panel (D): Monthly ECB Country-Level FSI (3 sub-indexes) and IP growth				
H ₀ : <i>monthly</i> FSI \rightarrow <i>monthly</i> IP			H ₀ : <i>monthly</i> IP \rightarrow <i>monthly</i> FSI	
	Wald test (bootstrap version)	Wald test (asymptotic)	Wald test (bootstrap version)	Wald test (asymptotic)
CF-VAR(2)	0.209	0.181	0.174	0.140

Notes: In panel (A) and (B) I investigate the causality between daily and monthly series. For this, I fit a MF-VAR specification with 1, 2, 3 lags and I use a max-test by Ghysels et al. (2018) and bootstrap version of Wald test by Götz et al. (2016). In panel (C) and (D) I test for Granger causality between two monthly series. For this purpose, I fit a common-frequency VAR model, where the optimal lag length is chosen by using a Bayesian information criteria and I use an asymptotic and a bootstrap version of a Wald test.

Table 2.4: Regression results (full sample analysis)

Panel (A):		Panel (B):
<i>monthly</i> FSI (4 markets)		<i>monthly</i> CLIFS (by Klaus et al., 2017)
const	0.043 (0.008)***	0.018 (0.008)*
IP_{t-1}	0.520 (0.059)***	0.593 (0.079)***
FSI_{t-1}	-0.236 (0.049)***	-0.113 (0.086)
IP_{t-2}		0.115 (0.075)
FSI_{t-2}		0.039 (0.085)
Signif. codes:		0 '***' 0.001 '**' 0.01 '*' 0.05

Notes: panel (A) present the point estimates for the coefficients in $IP_t = const_t + a \times IP_{t-1} + b \times FSI_{t-1} + u_t$ and panel (B) for the coefficients in $IP_t = const_t + \sum_{k=1}^2 a_k \times IP_{t-k} + \sum_{k=1}^2 b_k \times CLIFS_{t-k} + u_t$.

Table 2.5: Q test (full sample analysis)

	Lag order (p, pm):	k = 1	k = 5	k = 18
FSI with 4 sub-sectors	MF-VAR (1)	0.624	0.887	0.035
	MF-VAR (2)	0.987	0.981	0.119
	MF-VAR (3)	0.796	0.68	0.023

Notes: I find that a model with $p = 2$ and $pm = 36$ is better specified in terms of absence of residual correlation than other models taken under the consideration. In fact, when the model is fitted with $p = 2$ and $pm = 36$ I cannot reject the null hypothesis of no serial correlation in the residuals at 5% significance level, since the p-values of the test are $\{0.987, 0.981, 0.119\}$, respectively, for each lag $\{1, 5, 18\}$.

Chapter 3

Mixed Frequency GVAR analysis of macro-uncertainty and financial stress spillovers in the Eurozone

3.1 Introduction

The empirical literature studying uncertainty of macroeconomic activity and financial stress has been growing since the disruption of the Global Financial Crisis (GFC). The focus of this chapter is on the Eurozone and I aim to assess, first, how close the indices of macroeconomic uncertainty and financial markets uncertainty are to each other. Recently, Jurado et al. (2015) show that, in the US, the stock market uncertainty and macroeconomic uncertainty are different since the index of macroeconomic uncertainty they construct identifies far fewer episodes of turmoil than those captured by stock market volatility. Caldara et al. (2016) discriminate between financial and economic uncertainty shocks in the US by means of a statistical approach to Structural VAR identification following the penalty function described by Uhlig (2003). The authors conclude that while the economic uncertainty channel plays a negligible role in the transmission of financial shocks, the financial channel plays an important role in the transmission of economic uncertainty shocks. I contribute to the literature by using the methodology developed by Greenwood-Nimmo et al. (2015) which extends the Diebold and Yilmaz (2012, 2014) VAR based approach to estimate the Forecast Error Variance Decomposition, FEVD, to a Global Vector Autoregressive, GVAR model. As suggested by Diebold and Yilmaz, the FEVD can be used to derive pairwise and aggregated indices of connectedness.

In this study, the GVAR is fitted to two endogenous variables: a *monthly* Country-Level Index of Financial Stress (CLIFS) provided by ECB (see Klaus et al., 2017) and a *quarterly* index of uncertainty about GDP growth computed by Rossi and Sekhposyan (2017). The GVAR can be estimated using OLS fitted to a (Eurozone) country specific VAR. In order to rely on a relatively large sample of time series observations for each endogenous variable, I concentrate on the Eurozone countries for which data is available over an extended sample. The number of Eurozone countries is ten. Five of them are core Eurozone countries (Austria, Belgium, France, Germany, Netherlands) and the remaining ones are peripheral countries, PIIGS, (Greece, Ireland, Italy, Portugal and Spain). The analysis is carried considering either a sub-sample period ending in 2009 (which includes, as a period of turmoil, only the Global Financial Crisis, GFC) or the full sample period (1997-2015), which includes also the Eurozone sovereign debt crisis. The degree of connection between the macro-uncertainty block and the financial stress block within the Eurozone is obtained by aggregating the pairwise FEVD.

Moreover while a large number of studies analyse the role of uncertainty spillovers (second moment) on the the real economy (first moment), I focus on spillovers of second moments. In a seminal work, Bloom (2009) analyse the relationship between real activity and uncertainty, proxied by stock market volatility. Using a VAR model the author find that uncertainty has a large real impact, generating a substantial decrease in output and employment over the following 6 months. Jurado, Ludvigson and Ng (2015) find that macro uncertainty shocks account for up to 29 percent of the forecast error variance in industrial production, depending on the VAR forecast horizon, while stock market volatility explains at most 7 percent. Baker, Bloom and Davis (2016) develop a new index of economic policy uncertainty (EPU) and show that innovations in economic policy uncertainty signal declines in investment, output and employment in the United States and in 12 major economies.

The second contribution is to the empirical literature studying transmission of financial stress and/or economic uncertainty across countries. The financial stress spillovers have been investigated by Balakrishnan et al. (2011), Dovern and Van Rye (2014), Apostolakis and Papadopoulos (2014, 2015), Apostolakis (2016). Rossi and Sekhposyan (2017) explore transmission of economic uncertainty shocks across countries. My focus is on the linkages between financial stress and economic uncertainty across Eurozone countries. In particular, I am mainly interested in assessing the spillovers (measured through GVAR based FEVD) from the core to periphery and vice versa. The analysis of connectedness between core and periphery is disaggregated, first, by distinguishing between the macro-uncertainty and

financial stress blocks, and, then, by investigating the role played by each specific country.

Third, my contribution is also methodological: I extend a GVAR model by using the recent econometric developments by Ghysels (2016) which allows the use of mixed-frequency (MF) data directly in the VAR model rather than aggregating the high-frequency variable to low-frequency before the estimation (which is a standard approach).¹ As argued by Ghysels (2016), the inclusion of the financial data sampled at a high-frequency is relevant because it results in a more informative sample than in a standard common-frequency (CF) approach.

The main findings can be summarized as follows. First, the estimates show that macro-uncertainty and financial stress blocks are disconnected, given that spillovers from each block account only for a quarter of the Forecast Error Variance. Moreover, I find evidence of a decrease in the degree of connectedness between the core and periphery block since the outbreak of Eurozone sovereign debt crisis. In addition, I find evidence of a shift in directional connectedness, since core (peripheral) countries are the triggers of the connectedness between macro-uncertainty and financial stress before (since) the Eurozone sovereign debt crisis. I also find that connectedness between core and periphery is occurring mainly through financial stress, although it decreases during Eurozone sovereign debt market crisis, given a strong decline in the financial stress spillovers from core to periphery. Moreover, I find evidence that the main contributors of the (decreased) connectedness after the Eurozone sovereign debt crisis are Greece, Ireland and Portugal.

Finally, by comparing the results obtained by MF and CF GVAR models, I show that spillovers in the CF model are underestimated. These findings would have implications for the correct implementation of policies aiming at dampening financial instability. For instance, core-periphery connectedness occurring through financial stress is 5 percentage points lower than the connectedness index obtained by MF approach. Moreover, contrary to the MF results, the common-frequency model suggests that periphery countries are net donors in terms of financial distress before Eurozone debt crisis and they become net recipients once I consider also the Euro sovereign debt crisis.

The structure of this chapter is as follows: section 3.2 reviews the related literature and specifies the contribution; section 3.3 explains the methodology; section 3.4 describes the data; the main results are presented in Section 3.5 and 3.6. Section 3.7 concludes.

¹To my knowledge only the study of Cotter et al. (2017) uses the DY approach relying on the estimation of a VAR fitted to mixed-frequency data to analyse spillovers between the real and financial sides of the US economy. The authors show that additional high-frequency information produces estimated spillovers that are typically higher than those from an analogous common-frequency approach.

3.2 Literature Review

Conditional volatility models have been used to study macroeconomic uncertainty. Fountas et al. (2006) uses the multivariate GARCH model fitted to monthly US industrial production and inflation to capture macroeconomic uncertainty. Henzel and Rengel (2017) use an Exponentially Weighted Moving Average model to model volatility of two common latent variables (extracted through the estimation of a Dynamic Factor Model) underlying US macroeconomic uncertainty. The first factor captures business cycle uncertainty, while the second factor represents oil and commodity price uncertainty. Recently, stochastic volatility has been used to model macro-economic uncertainty. More specifically, Jurado et al. (2015) use stochastic volatility of a latent variable extracted from a Dynamic Factor Model fitted to a large macro-time series dataset for the US. Alessandri and Mumtaz (2018) use stochastic volatility of structural innovations underlying Structural VAR. While the previous studies focus only on the US, another strand of the literature broaden the focus and derive an index of economic policy uncertainty, EPU, computed by combining “uncertainty-related” keywords in news publications for a number of countries (see Baker et al., 2016). More recently, Rossi and Sekhposyan (2017) rely on the quantile of the unconditional distribution of the forecast errors to derive an index of uncertainty about real economic activity for a number of Eurozone countries. Few authors have constructed a global index of uncertainty (pooling information on different countries). More specifically, Baker et al. (2016) have constructed an EPU index for Europe (involving only seven countries); Berger et al. (2017) have used stochastic volatility to model time varying volatility of a latent factor extracted from a DFM fitted a set of output growth and inflation-time series for OECD countries.

The empirical literature on the financial stress index monitoring the evolution of distress affecting different sectors of financial markets (mainly stock, bonds, banking and foreign exchange) is growing. While the studies of Hakkio and Keeton (2009) for the US use principal component analysis and by Hollo et al. (2012) for the Eurozone use portfolio weights to aggregate normalized raw stress indicators of different financial markets within a country, Chau and Deesomsak (2014) use Diebold-Yilmaz (2012, 2014) connectedness analysis to study equity, debt, banking, and foreign exchange markets in the US.

The first study to examine spillovers of financial stress across countries is the one by Balakrishnan et al. (2011), exploring the transmission of stress from advanced to emerging economies. Doornik and Van Roye (2014) use Global VAR model to analyse the spillovers from a shock to US financial stress to other countries. To proxy a financial distress

the authors construct country-specific financial stress index, which is based on variables representing the financial distress in banking sector, stock markets, bond markets, money markets and foreign exchange markets. Apostolakis and Papadopoulos (2014) examine the interdependences of financial stress indices across G7 countries for the 1981–2009 period using dynamic conditional correlations. Apostolakis and Papadopoulos (2015) use Diebold and Yilmaz methodology (2012, 2014) to analyse interdependence and spillovers of three financial stress sub-indices (banking, securities and foreign exchange) both within and across major advanced countries. The Diebold and Yilmaz (2012, 2014) methodology is also used by Apostolakis (2016) to examine financial stress spillovers in five Asian countries, namely, China, South Korea, Malaysia, Thailand, and the Philippines, during turmoil periods. The study of Rossi e Sekhposyan (2017) has examined the spillovers across the macroeconomic uncertainty indices of 17 Eurozone countries.

The links between uncertainty and financial stress has been neglected in the previous literature. To the best of my knowledge, the paper by Liow et al. (2018) is the only exception.² The authors use Diebold and Yilmaz (2012, 2014) methodology to examine the spillovers of economic policy uncertainty, measured by EPU index, and those related to financial stress in stock, real estate, bond and currency markets. They find that international spillovers across seven major world economies play an important role in the transmission of shocks to policy uncertainty and to financial market stress.

3.3 Empirical Methodology

I compute the macro-financial spillovers using the generalized connectedness measures (GCM) developed by Greenwood-Nimmo et al. (2015) who extend the Diebold and Yilmaz (2014) Generalised FEVDs (GFEVDs) analysis to a GVAR model. The GVAR model in this chapter is based on 10 country specific VAR, each including the same set of the variables sampled at different frequencies: (i) *quarterly* real economy indicators (i.e. GDP growth uncertainty index by Rossi and Sekhposyan, 2017) and (ii) *monthly* financial indicators (i.e. country-specific indicators of financial stress, by Klaus et al., 2017). More specifically, I extend the country specific MF VAR methodology put forward by Ghysels (2016) to a GVAR and I also compare the empirical findings with the standard common-frequency GVAR model (based on aggregating the high-frequency series into low frequency).

²See also the study of Sun et al. (2017) which provides a short analysis on the dynamics between EPU and financial stress, by using a multi-scale correlation framework.

3.3.1 GVAR model using mixed-frequency data

The GVAR model is constructed by combining 10 country-specific models, indexed by $i = 1, 2 \dots N$. Each country-specific model (i) includes the following variables sampled at different frequencies: a *quarterly* GDP growth uncertainty index GDP_i (i.e. a low-frequency variable) and *monthly* indicator of financial stress $CLIFS_i$ (i.e. a high-frequency variable). A high-frequency series is observed $m = 3$ times during a low-frequency period t . Let $CLIFS_i(t, 1)$ be the first high frequency observation in low frequency period t (i.e. the first monthly observation of the quarter t), a $CLIFS_i(t, 2)$ – the second observation, and $CLIFS_i(t, 3)$ – the last one. In MF-VAR (by Ghysels, 2016) all observations of period t are stacked into a column vector by treating the m observations of the high frequency series as if they were the distinct endogenous variables.

A mixed-frequency vector of endogenous variables for country i is composed of $k_i = 4$ variables and is given as:

$$Z_{i,t} = [CLIFS_i(t, 1)', CLIFS_i(t, 2)', CLIFS_i(t, 3)', GDP_i(t)'] \quad (3.1)$$

A corresponding standard common-frequency (CF) data vector for country i , which contains both the high-frequency and the low-frequency variables observed at the low-frequency (i.e. *quarter*), has the following composition:

$$Z_{i,t}^L = [CLIFS_i(t)', GDP_i(t)'] \quad (3.2)$$

where the *monthly* variable is aggregated to the *quarterly* frequency as: $\frac{1}{3} \sum_{j=1}^3 CLIFS_i(t, j)$.

Consider now each country i represented by a mixed-frequency vector autoregressive model augmented by a set of foreign variables $Z_{i,t}^*$. Specifically, a MF-VARX(1,1) model is set up for each county i as:

$$Z_{i,t} = c_i + \Gamma_i Z_{i,t-1} + \Lambda_{i0} Z_{i,t}^* + \Lambda_{i1} Z_{i,t-1}^* + u_{i,t} \quad (3.3)$$

for $i = 1, \dots, N$ countries and $t = 1, \dots, T$ low-frequency time periods.³ Furthermore, $Z_{i,t-1}$ is a $k_i \times 1$ vector of lagged country-specific (domestic) variables (in eq. (3.1)), $Z_{i,t}^*$ is a $k_i \times 1$ vector of country-specific foreign variables, c_i is a constant and $u_{i,t}$ is a $k_i \times 1$ vector of serially uncorrelated innovations, with Σ_{u_i} being a sample variance-covariance matrix of the reduced-form residuals; Γ_i is a $k_i \times k_i$ coefficient matrix associated to lagged

³Due to the small number of quarterly observations i.e. 72 observations available, I set lag orders to one. Then, I estimate a VARX(1,1) model by using OLS estimator for each country separately.

domestic variables, Λ_{i0} and Λ_{i1} are $k_i \times k_i$ coefficient matrices related to, respectively, contemporaneous and lagged foreign variables.⁴

The vector of foreign variables $Z_{i,t}^*$ in a country specific MF-VARX is constructed as a weighted averages of other countries' variables:

$$Z_{i,t}^* = W_i Z_t \quad (3.4)$$

where $Z_t = [Z'_{1,t}, Z'_{2,t}, \dots, Z'_{N,t}]'$ is a $k \times 1$ vector including all endogenous variables of the system ($k = \sum_{i=1}^N k_i = 40$ in this study in a MF case) and W_i is a $k_i \times k$ link matrix:

$$W_i = \begin{pmatrix} w_{i1}I_{k_i} & \cdots & w_{ii}I_{k_i} & \cdots & w_{iN}I_{k_i} \end{pmatrix} \quad (3.5)$$

with the 4×4 matrix $w_{ii} = 0$ and with the 4×4 matrix w_{ig} given by fixed trade weights obtained from BIS over the period 2011-2013 (see Table 3.1).⁵ For instance, the link matrix for Austria (AT) is as follows:

$$W_{AT} = \begin{pmatrix} 0 & 0 & 0 & 0 & w_{AT,BE} & 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & 0 & 0 & w_{AT,BE} & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & w_{AT,BE} & 0 & \cdots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & w_{AT,BE} & \cdots & w_{AT,ES} \end{pmatrix} \quad (3.6)$$

where $w_{AT,g}$ is taken from Table 3.1. This implies that the foreign variables in $Z_{i,t}^*$ eq. (3.4) for Austria are given by:

$$Z_{AT,t}^* = W_{AT} Z_t = \begin{pmatrix} CLIFS_{AT}^*(t,1) \\ CLIFS_{AT}^*(t,2) \\ CLIFS_{AT}^*(t,3) \\ GDP_{AT}^*(t) \end{pmatrix} \quad (3.7)$$

In the first stage of the analysis, each country specific MF-VARX in (3.3) is estimated by using OLS like a standard country specific CF-VARX. In the second stage, the $N = 10$ models are combined into the global model. Suppose S_i is a $k_i \times k$ selection matrix that picks up country-specific variables from the global vector of mixed-frequency endogenous variables (Z_t) such that:

⁴Similarly, I can implement a corresponding standard VARX model by considering the low-frequency vector (3.2) in the eq. (3.3), instead of mixed-frequency vector (3.1).

⁵The use of trade weights is in line with the Global VAR analysis of Cesa-Bianchi (2013) and of Greenwood-Nimmo et al. (2015).

$$Z_{i,t} = S_i Z_t \quad (3.8)$$

Then, by substituting (3.4) and (3.8) in (3.3), I rewrite a country-specific MF-VARX(1) in terms of Z_t :

$$(S_i Z_t) = c_i + \Gamma_i(S_i Z_{t-1}) + \Lambda_{i0}(W_i Z_t) + \Lambda_{i1}(W_i Z_{t-1}) + u_{i,t} \quad (3.9)$$

Re-arrange:

$$(S_i - \Lambda_{i0} W_i) Z_t = c_i + (\Gamma_i S_i + \Lambda_{i1} W_i) Z_{t-1} + u_{i,t} \quad (3.10)$$

Re-name:

$$G_i Z_t = c_i + H_i Z_{t-1} + u_{i,t} \quad (3.11)$$

Finally, the GVAR model is built by simply stacking up all the $i = 1, 2, \dots, N$ country-specific models in a global model:

$$G Z_t = c + H Z_{t-1} + u_t \quad (3.12)$$

where $G = (G'_1, G'_2, \dots, G'_N)'$, $H = (H'_1, H'_2, \dots, H'_N)'$, $c = (c'_1, c'_2, \dots, c'_N)'$ and $u_t = (u'_{1,t}, u'_{2,t}, \dots, u'_{N,t})'$. If the G matrix in (3.12) is non-singular, I can invert it and obtain a GVAR model in its reduced form:

$$Z_t = \mu + F Z_{t-1} + v_t \quad (3.13)$$

where $F = G^{-1}H$, $v_t = G^{-1}u_t$ and $\mu = G^{-1}c$.

3.3.2 Generalized connectedness measures (GCMS)

3.3.2.1 Generalized FEVD

I use the connectedness measures proposed by Diebold Yilmaz (2014) and based on the order-invariant generalised FEVD and extended to GVAR by Greenwood-Nimmo (2015):

$$GFVD = \tilde{\theta}_{l \leftarrow j}(H) = \frac{\sigma_{u,jj}^{-1} \sum_{h=0}^{H-1} (e'_l \Phi_h G^{-1} \Sigma_u e_j)^2}{\sum_{h=0}^{H-1} e'_l \Phi_h \Sigma_v \Phi_h e_l} \quad (3.14)$$

for $l, j = 1, \dots, k$, where $H = 4, 8$ is a forecast horizon, $\sigma_{u,jj}^{-1}$ are the standard deviations of the residual process of the j -th equation in the system (i.e. squared root of diagonal elements of Σ_u matrix in (3.12)), $\Sigma_v = G^{-1}\Sigma_u(G^{-1})'$, e_l (e_j) is a $k \times 1$ selection vector whose l -th (j -th) element is equal to unity and zeros elsewhere, the matrix G is obtained from eq. (3.12). The Φ_h is a coefficient matrix from the infinite order moving average (MA) representation of the GVAR model in (3.13):

$$Z_t = \sum_{h=0}^{\infty} \Phi_h \nu_{t-h} \quad (3.15)$$

with $\Phi_0 = I_k$ and $\Phi_h = F\Phi_{h-1}$ and the matrix F is obtained from estimation of the reduced form model given in (3.13). The non-diagonality of Σ_v implies that the sum of elements in each row of the variance decomposition does not need to sum to unity across j (i.e. $\sum_{j=1}^k \theta_{lj}(H) \neq 1$).

The mix of high frequency and low frequency variables could help to justify the use a Global Structural VAR identified through a recursive ordering (where there is low frequency series does not and a contemporaneous impact on the high frequency variable). However, given that the high-frequency series in the study are those related to uncertainty in financial markets which are typically regarded as forward looking, I prefer to depart from the structural form modelling approach and use the generalized impulse response approach which is invariant to variable ordering.

Therefore, in order to restore a percentage interpretation to the GFEVD, I follow Diebold and Yilmaz (2012) to normalize each entry of the variance decomposition matrix by the row of sum as:

$$\theta_{l \leftarrow j}(H) = \frac{\tilde{\theta}_{l \leftarrow j}(H)}{\sum_{j=1}^k \tilde{\theta}_{l \leftarrow j}(H)} \quad (3.16)$$

such that $\sum_{j=1}^k \theta_{lj}(H) = 1$ and $\sum_{l,j=1}^k \theta_{lj}(H) = k$.

3.3.2.2 The MF connectedness matrix

The resulting connectedness matrix, for MF-GVAR model with mixed-frequency vector in (3.1), is given in a general form as:

$$\mathbb{C}_{MF}^{(H)} = \begin{bmatrix} \theta_{1 \leftarrow 1}(H) & \theta_{1 \leftarrow 2}(H) & \theta_{1 \leftarrow m}(H) & \theta_{1 \leftarrow k_1}(H) & \cdots & \theta_{1 \leftarrow k}(H) \\ \theta_{2 \leftarrow 1}(H) & \theta_{2 \leftarrow 2}(H) & \theta_{2 \leftarrow m}(H) & \theta_{2 \leftarrow k_1}(H) & \cdots & \theta_{2 \leftarrow k}(H) \\ \theta_{m \leftarrow 1}(H) & \theta_{m \leftarrow 2}(H) & \theta_{m \leftarrow m}(H) & \theta_{m \leftarrow k_1}(H) & \cdots & \theta_{m \leftarrow k}(H) \\ \theta_{k_1 \leftarrow 1}(H) & \theta_{k_1 \leftarrow 2}(H) & \theta_{k_1 \leftarrow m}(H) & \theta_{k_1 \leftarrow k_1}(H) & \cdots & \theta_{k_1 \leftarrow k}(H) \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \theta_{k \leftarrow 1}(H) & \theta_{k \leftarrow 2}(H) & \theta_{k \leftarrow m}(H) & \theta_{k \leftarrow k_1}(H) & \cdots & \theta_{k \leftarrow k}(H) \end{bmatrix} \quad (3.17)$$

for $H = 4, 8$, where $m = 3$, $k_1 = 4$, $k = \sum_{i=1}^N k_i = 40$ for $i = (1, 2, \dots, 10)$ countries.⁶ For instance, the first row of the matrix (3.17) characterizes the fraction of the H -step-ahead error variance in forecasting the financial distress in Austria in the first month of the quarter (variable 1) that is attributable to shocks in: (i) itself, measured by element $\theta_{1 \leftarrow 1}(H)$; (ii) financial distress in Austria in the second month of the quarter (variable 2), measured by $\theta_{1 \leftarrow 2}(H)$; (iii) financial distress in Austria in the last month of the quarter (variable 3), measured by $\theta_{1 \leftarrow m}(H)$; (iv) quarterly GDP growth uncertainty in Austria (variable 4), measured by element $\theta_{1 \leftarrow k_1}(H)$; (v) quarterly GDP growth uncertainty in the last of the 10 Eurozone countries considered, that is Spain (variable 40), denoted by $\theta_{1 \leftarrow k}(H)$.

The corresponding connectedness matrix for CF-GVAR model, considering common-frequency data vector (in eq. 3.2), has the following specification:

$$\mathbb{C}_{CF}^{(H)} = \begin{bmatrix} \phi_{1 \leftarrow 1}(H) & \phi_{1 \leftarrow K_1}(H) & \cdots & \phi_{1 \leftarrow K}(H) \\ \phi_{K_1 \leftarrow 1}(H) & \phi_{K_1 \leftarrow K_1}(H) & \cdots & \phi_{K_1 \leftarrow K}(H) \\ \vdots & \vdots & \ddots & \vdots \\ \phi_{K \leftarrow 1}(H) & \phi_{K \leftarrow K_1}(H) & \cdots & \phi_{K \leftarrow K}(H) \end{bmatrix} \quad (3.18)$$

for $H = 4, 8$, where $K_1 = 2$, $K = \sum_{i=1}^N K_i = 20$ for $i = (1, 2, \dots, 10)$ countries. For instance, the $\phi_{1 \leftarrow 1}(H)$ measures the fraction of the H -step-ahead error variance in forecasting the quarterly financial distress in Austria that is attributable to shocks in itself; the element $\phi_{1 \leftarrow K_1}(H)$ characterizes the effects of the shocks to quarterly GDP growth uncertainty in Austria on the quarterly financial distress, and the element $\phi_{1 \leftarrow K}(H)$ denotes the contribution of the quarterly GDP growth uncertainty in Spain on the quarterly

⁶As in a common-frequency case, the generic element $\theta_{l \leftarrow j}(H)$ represents the proportion of the H -step-ahead FEVD of variable l accounted by innovations in variable j . The contribution of the shock to the l -th variable itself is denoted by $\theta_{l \leftarrow l}(H)$, while the other elements of the l -th row, $l \neq j$, capture the spillovers from the other variables in the system to variable l .

financial distress in Austria.

First stage aggregation

The MF connectedness matrix in (3.17) incorporates a large volume of information about the spillovers between the variables in the system, resulting in 40^2 elements compared to 20^2 elements in the CF connectedness matrix in (3.18). In the MF form, the dynamics between the GDP growth uncertainty and financial distress in each country i is characterised not by a single element of the GFEVD, like in a CF case, but by multiple elements. For instance, the sub-array $[\theta_{1\leftarrow k_1}(H), \theta_{2\leftarrow k_1}(H), \theta_{m\leftarrow k_1}(H)]'$ in the MF-GFEVD specification given by eq. (3.17) corresponds to a single element $\phi_{1\leftarrow 2}(H)$ in CF-GFEVD in (3.18). In order to facilitate the interpretation and comparability between MF and CF connectedness matrixes, I can transform the $\mathbb{C}_{MF}^{(H)}$ by grouping the elements related with m high-frequency observations in each country i into sub-arrays (blocks).

The MF-GFEVD $\mathbb{C}_{MF}^{(H)}$ in (3.17) expressed in an aggregated form is given by:⁷

$$\mathbb{C}_{AGG(MF)}^{(H)} = \begin{bmatrix} \Theta_{H_1\leftarrow H_1}(H) & \Theta_{H_1\leftarrow L_1}(H) & \cdots & \Theta_{H_1\leftarrow L_N}(H) \\ \Theta_{L_1\leftarrow H_1}(H) & \Theta_{L_1\leftarrow L_1}(H) & \cdots & \Theta_{L_1\leftarrow L_N}(H) \\ \vdots & \vdots & \ddots & \vdots \\ \Theta_{L_N\leftarrow H_1}(H) & \Theta_{L_N\leftarrow L_1}(H) & \cdots & \Theta_{L_N\leftarrow L_N}(H) \end{bmatrix} \quad \text{for } H = 4, 8 \quad (3.19)$$

where $K = 20$, the index H_i represents a high-frequency variable i.e. financial stress index and the L_i denotes a low-frequency variable i.e. GDP growth uncertainty, for country $i = \{1, 2, \dots, 10\}$.⁸ For instance, the (2×2) upper-left block in eq. (3.19) corresponds to a (4×4) upper-left block of MF-GFEVD matrix in eq. (3.17), as follows:

$$\Theta_{H_1\leftarrow H_1}(H) \equiv \begin{bmatrix} \theta_{1\leftarrow 1}(H) & \theta_{1\leftarrow 2}(H) & \theta_{1\leftarrow m}(H) \\ \theta_{2\leftarrow 1}(H) & \theta_{2\leftarrow 2}(H) & \theta_{2\leftarrow m}(H) \\ \theta_{m\leftarrow 1}(H) & \theta_{m\leftarrow 2}(H) & \theta_{m\leftarrow m}(H) \end{bmatrix}_{(m \times m)} \quad (3.20)$$

$$\Theta_{H_1\leftarrow L_1}(H) \equiv \begin{bmatrix} \theta_{1\leftarrow k_1}(H) \\ \theta_{2\leftarrow k_1}(H) \\ \theta_{m\leftarrow k_1}(H) \end{bmatrix}_{(m \times 1)}$$

⁷Also the individual elements of MF global connectedness matrix in (3.17) could be used directly to study the GCMs.

⁸Note that (H) stands for a forecast horizon and H_i for a high frequency variable for country i .

$$\Theta_{L_1 \leftarrow H_1}(H) \equiv \begin{bmatrix} \theta_{k_1 \leftarrow 1}(H) & \theta_{k_1 \leftarrow 2}(H) & \theta_{k_1 \leftarrow m}(H) \end{bmatrix}_{(1 \times m)}$$

$$\Theta_{L_1 \leftarrow L_1}(H) \equiv \theta_{k_1 \leftarrow k_1}(H)_{(1 \times 1)}$$

where for country $i = 1$ the $\Theta_{H_1 \leftarrow L_1}(H)$ ($\Theta_{L_1 \leftarrow H_1}(H)$) gathers together the elements measuring the contribution of the low-(high-) frequency variable to the H-step ahead FEVD of high-(low-) frequency variable. Similarly, the elements $\Theta_{H_1 \leftarrow H_1}$ ($\Theta_{L_1 \leftarrow L_1}$) represents the contribution of the high-(low-) frequency variable to itself.

More specifically, the elements in $\mathbb{C}_{AGG(MF)}^{(H)}$ eq. (3.19) are computed by aggregating the corresponding elements in $\mathbb{C}_{MF}^{(H)}$ eq. (3.17), as follows. The contribution from high-frequency variable (H_g) to low-frequency variable (L_i) for countries $i, g = (1, 2, \dots, 10)$ is given by:

$$\Theta_{L_i \leftarrow H_g}(H) = \sum_{j=1}^m \theta_{l \leftarrow j}(H) \quad (3.21)$$

where l is a low-frequency variable related to county i (i.e. $GDP_i(t)$) and $j = 1, 2, 3$ is a high-frequency variable related to country g (i.e. $CLIFS_g(t, j)$).⁹ Similarly, the contribution from a low-frequency variable (L_i) to a high-frequency variable (H_g) is given by:

$$\Theta_{H_g \leftarrow L_i}(H) = \frac{1}{m} \sum_{j=1}^m \theta_{j \leftarrow l}(H) \quad (3.22)$$

Moreover, the contribution from high-frequency variable H_g in country g to a high-frequency variable H_i in country i is given by:

$$\Theta_{H_i \leftarrow H_g}(H) = \frac{1}{m} \sum_{l,j=1}^m \theta_{l \leftarrow j}(H) \quad (3.23)$$

Finally, the elements $\Theta_{L_i \leftarrow L_g}(H)$ simply corresponds to $\theta_{l \leftarrow j}(H)$.

After aggregation, the $\mathbb{C}_{AGG(MF)}^{(H)}$ in eq. (3.19) and $\mathbb{C}_{CF}^{(H)}$ in eq. (3.18) have the same dimension ($K \times K$) and can be interpreted in the same way.

⁹Note that i may be equal to g .

Second stage aggregation

To estimate the GCMs across the countries, regions and groups-specific variables, I follow the block aggregation approach proposed by Greenwood-Nimmo et al. (2015). Firstly, the connectedness matrix in (3.19) is re-normalized as:

$$\mathbb{C}_{R-AGG(MF)}^{(H)} = K^{-1} \mathbb{C}_{AGG(MF)}^{(H)} \quad (3.24)$$

Therefore, the sum of all elements in matrix $\mathbb{C}_{R-AGG(MF)}^{(H)}$ is equal to one. This modification ensures that I may achieve a clear percentage interpretation of any desired block aggregation scheme (Greenwood-Nimmo et al., 2015).

Since the GFEVDs are invariant to the ordering of the variables in the system, I can re-order variables in Z_t into b groups. Then, the $\mathbb{C}_{R-AGG(MF)}^{(H)}$ can be expressed in block form as follows:

$$\mathbb{C}_{R-AGG(MF)}^{(H)} = \begin{bmatrix} B_{1 \leftarrow 1}^{(H)} & B_{1 \leftarrow 2}^{(H)} & \cdots & B_{1 \leftarrow b}^{(H)} \\ B_{2 \leftarrow 1}^{(H)} & B_{2 \leftarrow 2}^{(H)} & \cdots & B_{2 \leftarrow b}^{(H)} \\ \vdots & \vdots & \ddots & \vdots \\ B_{b \leftarrow 1}^{(H)} & B_{b \leftarrow 2}^{(H)} & \cdots & B_{b \leftarrow b}^{(H)} \end{bmatrix} \quad (3.25)$$

The blocks lying on the main diagonal of $\mathbb{C}_{R-AGG(MF)}^{(H)}$ (i.e. $B_{\alpha \leftarrow \alpha}^{(H)}$) contain all the within-group FEVD contributions. The total **within**-group FEVD contribution for the α -th group is:

$$\mathcal{W}_{\alpha \leftarrow \alpha}^{(H)} = e'_{K_\alpha} B_{\alpha \leftarrow \alpha}^{(H)} e_{K_\alpha} \quad (3.26)$$

where e_{K_α} is an $K_\alpha \times 1$ vector of ones. The cross-group transmission (directional spillover) is indicated by $B_{\alpha \leftarrow \beta}^{(H)}$ for $\alpha \neq \beta$. In particular, the spillover **from** group β to group α is estimated as:

$$\mathcal{F}_{\alpha \leftarrow \beta}^{(H)} = e'_{K_\alpha} B_{\alpha \leftarrow \beta}^{(H)} e_{K_\beta} \quad (3.27)$$

and the spillover **to** group β from group α as:

$$\mathcal{T}_{\beta \leftarrow \alpha}^{(H)} = e'_{K_\beta} B_{\beta \leftarrow \alpha}^{(H)} e_{K_\alpha} \quad (3.28)$$

In other words, $\mathcal{W}_{\alpha \leftarrow \alpha}^{(H)}$, $\mathcal{F}_{\alpha \leftarrow \beta}^{(H)}$ and $\mathcal{T}_{\beta \leftarrow \alpha}^{(H)}$ are equal to the sum of all elements in the related block $B_{\alpha \leftarrow \beta}^{(H)}$. By following these definitions, it is straight forward to obtain the

group connectedness matrix form:

$$\mathbb{B}^{(H)} = \begin{bmatrix} \mathcal{W}_{1\leftarrow 1}^{(H)} & \mathcal{F}_{1\leftarrow 2}^{(H)} & \cdots & \mathcal{F}_{1\leftarrow b}^{(H)} \\ \mathcal{F}_{2\leftarrow 1}^{(H)} & \mathcal{W}_{2\leftarrow 2}^{(H)} & \cdots & \mathcal{F}_{2\leftarrow b}^{(H)} \\ \vdots & \vdots & \ddots & \vdots \\ \mathcal{F}_{b\leftarrow 1}^{(H)} & \mathcal{F}_{b\leftarrow 2}^{(H)} & \cdots & \mathcal{W}_{b\leftarrow b}^{(H)} \end{bmatrix} \equiv \begin{bmatrix} \mathcal{W}_{1\leftarrow 1}^{(H)} & \mathcal{T}_{1\leftarrow 2}^{(H)} & \cdots & \mathcal{T}_{1\leftarrow b}^{(H)} \\ \mathcal{T}_{2\leftarrow 1}^{(H)} & \mathcal{W}_{2\leftarrow 2}^{(H)} & \cdots & \mathcal{T}_{2\leftarrow b}^{(H)} \\ \vdots & \vdots & \ddots & \vdots \\ \mathcal{T}_{b\leftarrow 1}^{(H)} & \mathcal{T}_{b\leftarrow 2}^{(H)} & \cdots & \mathcal{W}_{b\leftarrow b}^{(H)} \end{bmatrix} \quad (3.29)$$

Note that the dimension of the group connectedness matrix is $b^2 < K^2$. Then, using (3.29) I can define the **total from**, **to** and **net** connectedness of the α -th group as follows:

$$\mathcal{F}_{\alpha\leftarrow*}^{(H)} = \sum_{\beta=1, \beta \neq \alpha}^b \mathcal{F}_{\alpha\leftarrow\beta}^{(H)}, \quad \mathcal{T}_{*\leftarrow\alpha}^{(H)} = \sum_{\beta=1, \beta \neq \alpha}^b \mathcal{T}_{\beta\leftarrow\alpha}^{(H)} \quad \text{and} \quad \mathcal{N}_{*\leftarrow\alpha}^{(H)} = \mathcal{T}_{*\leftarrow\alpha}^{(H)} - \mathcal{F}_{\alpha\leftarrow*}^{(H)} \quad (3.30)$$

where $\mathcal{F}_{\alpha\leftarrow*}^{(H)}$ measures the total contribution from all other groups to group α , $\mathcal{T}_{*\leftarrow\alpha}^{(H)}$ is the total contribution to all other groups from group α and $\mathcal{N}_{*\leftarrow\alpha}^{(H)}$ measures the net connectedness of group α . Finally, the total connectedness (spillover) index, $\mathcal{S}^{(H)}$, and the total domestic connectedness (within-group) index, $\mathcal{D}^{(H)}$, in terms of the b groups is defined as follows:

$$\mathcal{S}^{(H)} = \sum_{\alpha=1}^b \mathcal{F}_{\alpha\leftarrow*}^{(H)} \equiv \sum_{\alpha=1}^b \mathcal{T}_{*\leftarrow\alpha}^{(H)} \quad \text{and} \quad \mathcal{D}^{(H)} = \sum_{\alpha=1}^b \mathcal{W}_{\alpha\leftarrow\alpha}^{(H)} \quad (3.31)$$

3.4 Data

The proxy of financial conditions in each EZ country is the *monthly* Country-Level Index of Financial Stress (CLIFS) provided by ECB (see Duprey, Klaus and Peltonen, 2017).¹⁰ The CLIFS is a composite index derived from data representing three financial market segments: the stock price index (*STX*) for the equity market, the 10-year government yields (*R10*) for the bond market, and the real effective exchange rate (*REER*) for the foreign exchange market. More specifically, the stress in each financial market segment is captured by two indices: realized volatility and maximum loss over two year period, and then they are aggregated by using a portfolio aggregation approach. The composite index captures the financial stress, which is reflected by (i) the uncertainty in market prices, (ii) sharp corrections in market prices, and (iii) the degree of commonality across the three

¹⁰The data is available at Statistical data warehouse, ECB: <https://sdw.ecb.europa.eu/>.

financial market segments.

Since I also focus on macro-uncertainty, I rely on a novel real economic activity uncertainty dataset computed by Rossi and Sekhposyan (2017). The authors provide *quarterly* series of uncertainty for GDP growth.¹¹ The GDP growth uncertainty index by Rossi and Sekhposyan (2017) builds on the point forecasts from the Survey of Professional Forecasters administered by the European Central Bank and it is based on comparing the realized forecast error with the unconditional distribution of forecast errors for that variable (proxied by the full sample of past forecast errors). If the realized forecast error is in the tail of the distribution, then the realization is very difficult to predict, thus, the macroeconomic environment is very uncertain. For each country, Rossi and Sekhposyan (2017) construct the overall as well as the positive (upside) and negative (downside) uncertainty indices.¹²

All the series are plotted in Appendix 3.A.1. Figure 3.1 presents the monthly CLIFS for the period from April 1997 to March 2015. Panel (a) shows the CLIFS for the core EZ countries (Austria, Belgium, France, Germany and Netherlands) and panel (b) for PIIGS countries (Greece, Ireland, Italy, Portugal and Spain). By the construction the CLIFS values varies between 0 and 1, where the large values indicate the high level of stress associated with the GFC and the Eurozone debt crisis. Furthermore, Figure 3.2 presents country-specific quarterly GDP growth uncertainty series from 1997:Q2 to 2015:Q1. Panel (a) plots the series for core EZ countries and panel (b) – for PIIGS countries. I focus on the overall index of output growth uncertainty, which, by the construction, varies between 0.5 and 1. While, before 2007, the degree of co-movement among core countries is higher than among peripheral countries, it increases for both groups of countries during the GFC and at the beginning of EZ debt crisis (between 2007 and 2010).

3.5 LR test of MF *vs* CF Global VAR

I assess whether aggregation of high-frequency information generates a loss of information through a LR statistics computed for each country-specific VARX model, that is a VAR augmented by the current and lagged values of the exogenous variable (capturing the impact of the foreign variables). More specifically, I follow Bacchiocchi et al. (2018), and

¹¹The data is available at: <http://www.tateviksekhposyan.org/>. The authors rely on the methodology developed by Rossi and Sekhposyan (2015). The Baker et al. (2016) index of economic policy uncertainty would be another suitable candidate for the analysis, but it is available only few Eurozone countries: France, Germany, Italy, Spain and the Netherlands.

¹²Positive (negative) uncertainty indicates that realized output growth is higher (lower) than expected.

I compare the log-likelihood of the unrestricted model (l^u , i.e. MF-VARX), with the one for the restricted model (l^r , i.e. CF-VARX). Table 3.2 shows the LR test statistics. I can observe that the null of equivalence between the traditional CF-VARX and the MF-VARX is strongly rejected. The results suggest that each of the estimated MF-VARX models provide more accurate results than the traditional CF-VAR. Therefore, aggregating the mixed-frequency data to a low-frequency generates a loss of information. However, for the purpose of comparing results, in Section 3.6 I will provide the results both for the MF Global VAR and for CF Global VAR.

3.6 Spillovers Analysis

I am interested in exploring whether there is a change in macro-financial uncertainty spillovers since the Eurozone sovereign debt crisis period onwards. For this purpose, I focus on a sub-sample period spanning from 1997:Q2 to 2009:Q4 and also on the full sample period spanning from 1997:Q2 to 2015:Q1.

In the empirical analysis I consider various block aggregation schemes. I start from the aggregate results across the ten countries and follow with the country-specific results. All the results in Tables 3.3 - 3.6 (which are percentages of the total system-wide FEVD), are presented for the full and the sub-sample periods, distinguish between two forecast horizons: $H = 4, 8$ quarters. The mixed-frequency GVAR model results are presented in panels (A) and the corresponding results for a common-frequency GVAR model are given in panels (B) of Tables 3.3 - 3.6.

3.6.1 Macro-financial connectedness

First, I estimate the aggregate macro-financial uncertainty spillovers in the Eurozone. For this purpose, I examine the interconnectedness between the GDP growth uncertainty and the financial distress in the Eurozone, by considering two blocks: (i) the *macro-uncertainty block*, (ii) and the *financial stress block*. The macro-uncertainty block is constructed by aggregating the 10 countries' FEVD of GDP growth uncertainty, while the financial stress block is constructed by aggregating the 10 countries' FEVD of financial distress. The connectedness measures between the two blocks are presented in Table (3.3). The results on the main diagonal show the within-group spillovers and the off-diagonal elements represent the cross-block (directional) spillovers (see eq. (3.29)).

Inspection of Table 3.3 panel (A) shows that, in line with the empirical findings of

Jurado et al. (2015) for the US, the Eurozone macro-uncertainty and financial stress (capturing uncertainty in financial markets) are relatively disconnected. More specifically, if I consider a forecast horizon equal to a year ($H=4$), I find that the sum of cross-block variance shares (off-diagonal elements of Table 3.3, panel (A)) account only for a quarter of the system-wide FEVD. Moreover, the total connectedness does not change when I shift the focus from the sub-sample to full sample analysis, which includes the period of Eurozone sovereign debt crisis. A similar pattern is observed if I consider a forecast horizon equal to two years ($H=8$). More specifically, the total connectedness between macro-uncertainty and financial stress accounts for 28% of the system's FEVD (in sub-sample and full sample analysis).

As for the directional spillover results, if I consider a forecast horizon equal to a year ($H=4$), then I observe that there is a decrease (from 15.99% to 10.74%) in the spillover from FSI on GDP uncertainty when I shift the focus from the sub-sample to the full sample analysis (which also includes the Euro sovereign debt crisis). Moreover, I observe an increase (from 9.97% to 14.52%) in the spillover from GDP uncertainty on FSI when I move the focus from the sub-sample to the full sample analysis. A similar pattern can be observed if I consider a forecast horizon equal to two years ($H=8$), since there is evidence of a decrease (from 18.49% to 12.85%) in the contribution from FSI on GDP uncertainty and an increase (from 9.68% to 14.93%) in the spillover from GDP uncertainty on FSI when I shift the focus from the sub-sample to the full sample analysis. My findings contrasts with the historical variance decomposition results of the study on the US by Caldara et al. (2016) which shows an important contribution of shocks to financial stress (proxied only by the excess bond premium) on economic uncertainty and not vice-versa.

I also compare the mixed-frequency results with the results obtained by using a common-frequency approach (see panel (B) of Table 3.3). The total connectedness (sum of the off-diagonal elements) between GDP growth uncertainty and FSI obtained by the common-frequency approach is slightly lower than the connectedness index obtained by MF approach (i.e. 23% for CF approach *vs* 25% for MF approach, at $H=4$). Moreover, my findings are in line with those by Hallam et al. (2017). The authors, by using a MF-VAR, analyse macro-financial spillovers in the US for the sample period running from 1975 to 2015, and they find that the index of total connectedness for the MF and CF models is equal to 24.79% and 16.38% respectively.

3.6.2 Regional connectedness

In the second step, I analyse spillovers between two blocks: *periphery* and *core*. The findings in Table 3.4 panel (A) suggest a decrease in the cross-regional connectedness (given by a sum of off-diagonal elements) from 31.42% to 25.41% (at $H=4$) once I move from the sub-sample period preceding the Eurozone sovereign debt crisis to the full sample. Similarly, if I consider a forecast horizon of two years ($H=8$), I observe a decrease in the cross-regional connectedness from 33.32% to 28.73% when I move the focus from the sub-sample to the full sample analysis. This finding is in line with the empirical studies of Cipollini et al. (2015), Ehrmann and Fratzscher (2017) and of Caporin et al. (2018) which find evidence of segmentation among Eurozone sovereign bond markets during the Eurozone sovereign debt market crisis period.

Moreover, in line with empirical findings of Antonakakis and Vergos (2013), Fernandez-Rodriguez et al. (2016), and of De Santis and Zimic (2018) I observe a shift in the origin of connectedness relationships since the beginning of the Eurozone sovereign debt crisis.¹³ In particular, while core countries are triggers of cross-regional connectedness in the sub-sample period, PIIGS are the countries driving connectedness in the full sample period. More specifically, if I consider a forecast horizon equal to a year ($H = 4$), and if I shift the focus from the sub-sample to the full sample analysis (which includes Eurozone sovereign debt crisis), then I observe a decrease in the spillover from core to periphery countries (from 19.92% to 11.35%) and an increase in the spillovers from periphery to core countries (from 11.50% to 13.88%). If the focus is on a horizon equal to two years, then spillovers from periphery to core countries tends to increase from 12.88% to 17.33% when I move from the sub-sample to full sample analysis.

Furthermore, in line with empirical findings of Fernandez-Rodriguez et al. (2016) and De Santis and Zimic (2017), I observe a decrease (from 38.5% to 36.12%) in the degree of connectedness within core countries (the upper-left element) when I shift the focus from the sub-sample to the full sample analysis. However, in line with Antonakakis and Vergos (2013) and conversely to Fernandez-Rodriguez et al. (2016) and to De Santis and Zimic (2018), I find an increase (from 30% to 38.5%) in the degree of connectedness within PIIGS countries when I move from the sub-sample to the full sample analysis.

¹³The Diebold and Yilmaz (2014) approach has been used to analyse connectedness within Eurozone by Antonakakis and Vergos (2013), Fernandez-Rodriguez et al. (2016) and by De Santis and Zimic (2017). While Antonakakis and Vergos (2013) and Fernandez-Rodriguez et al. (2016) focus on EZ sovereign bond yield spread and volatility, respectively, and they use the general impulse response approach suggested by Diebold and Yilmaz, De Santis and Zimic (2018) use a Structural VAR fitted to EZ sovereign bond yields identified through sign restrictions.

The results obtained by a common-frequency approach (see panel (B) in Table 3.4) indicate that the spillovers within both country groups (diagonal elements) increase once I move to the period including the Eurozone sovereign debt crisis. Moreover, the CF model suggests smaller directional spillovers than those obtained from Global MF VAR.

3.6.2.1 Core-periphery connectedness: the role of financial stress and macro-uncertainty

Further, I examine whether the main drivers of connectedness between core and periphery are financial stress or macro-uncertainty, and whether the role of these drivers has changed over the years. In particular, I concentrate on four blocks: (i) GDP growth uncertainty in core EZ countries, (ii) GDP growth uncertainty in PIIGS countries, (iii) financial distress in core EZ countries and (iv) financial distress in PIIGS countries. The results for the full sample and for the sub-sample (i.e. before the Eurozone sovereign debt crisis) are presented in Table 3.5.

I find the core-periphery spillovers are mainly occurring through financial stress (see panel A). More specifically, if I focus on Panel A.1, then I can observe that, for a forecast horizon equal to one year, core-periphery spillovers occurring only through financial stress are equal to 16.1% over the period preceding the Eurozone debt crisis and they decrease to 9.3% once I consider the full sample.¹⁴ The main trigger of the disconnect between core and periphery is the strong decline in the financial stress spillovers from core to periphery countries, from 11.5% to 4.0%. This finding confirms the empirical findings of Cipollini et al.(2015), Ehrmann and Fratzscher (2017) and of Caporin et al (2018) which find evidence of segmentation (during the Eurozone sovereign debt market crisis period) by focussing only on Eurozone sovereign bond markets.

The core-periphery spillovers occurring only through macro-uncertainty (sum of the elements in row 3, column 1 and in row 1, column 3 of each 4×4 matrix in panel A.1) are equal to 4% and to 4.6% in the sub-sample and in the full sample period, respectively.

It is also important to notice that Table 3.5 highlights the role played by the core countries to system wide risk through financial stress before the Eurozone debt crisis, given that they are net donors of financial stress spillovers (see sub-sample results, panel A.2 and A.4). In particular, I observe a decrease (from 10.5% to -5.1%, at $H=4$) in the net spillovers from the core EZ financial stress when I shift from sub-sample analysis

¹⁴The financial stress spillovers between core and periphery are the sum of two elements of each 4×4 matrix (see panel A.1): the first is in row 4, column 2 and the second one is in row 2, column 4.

to full-sample analysis. The peripheral EZ countries are net donors, both in terms of financial stress and real output growth uncertainty, during the period which includes the EZ sovereign debt crisis (see panel A.2 and A.4). In particular, the net spillover from the periphery macro-uncertainty and financial stress group increase (respectively, from -3.9% to 1%, and from -4.5% to 1.3%, at $H=4$, see panel A.2) ones I move from sub-sample analysis to the full sample analysis. These findings are in line with Fernandez –Rodriguez et al. (2016) and De Santis and Zimic (2017), who find a decline (increase) in directional connectedness from core (peripheral) to peripheral (core) countries during the sovereign debt crisis.

The common frequency model results in panel B of Table 3.5 suggest smaller directional spillovers than those obtained from mixed frequency data model. In particular, if I consider a full-sample analysis in panel B.1, I find the core-periphery connectedness occurring through financial stress is 5% lower than the connectedness index obtained by MF approach, while the core-periphery connectedness occurring through macro-uncertainty is around 0.5 percentage points lower for a common frequency model. Moreover, contrary to the MF results, the common-frequency model suggests that periphery countries are net donors in terms of financial distress before Eurozone debt crisis and they become net recipients once I consider also the Euro sovereign debt crisis (see panel B.2 and B.4).

3.6.2.2 Core-Periphery connectedness: country specific analysis

I also examine the role played by each country in driving connectedness between core and periphery and whether the role of these drivers is changing over time. Table 3.6 records the *within*, *from* and *to* connectedness among countries in the system for the full sample and sub-sample periods at forecast horizon $H=4, 8$.

The evidence in Table 3.6 confirms my findings associated with Table 3.4: since the start of the EZ sovereign debt crisis, the Eurozone global risk, proxied by the total connectedness index (see the total *from/to* connectedness in panel A.1 and A.2), has declined. More specifically, if I consider a forecast horizon of one year ($H=4$ quarters) the total connectedness index decrease from 57.6% to 48.1% (see panel A.1), when I move from the sub-sample to the full sample analysis. If the focus is on a forecast horizon equal to two years ($H=8$ quarters) I observe a decrease in total connectedness from 62.33% to 52.86% (see panel A.2), when I shift from sub-sample to full-sample analysis. This finding holds for the common-frequency approach (see panel B.1 and B.2) although the total *from/to* spillovers are smaller than those obtained through the mixed-frequency approach. In par-

ticular, the CF results in panel B.1 show the decrease in total connectedness index from 43.71% to 36.52% (for $H=4$) when I shift from the sub-sample to the full sample analysis.

Our MF results are in line with other empirical studies using the Diebold and Yilmaz (2012, 2014) forecast error variance decomposition analysis focussing only on sovereign debt markets. Evidence of bond market fragmentation due to Eurozone sovereign debt crisis is given by Fernandez-Rodriguez et al. (2016) and by De Santis and Zimic (2018) find evidence of a decrease in connectedness among Eurozone sovereign yields.

The total net spillovers across the five core and the five peripheral countries confirm the findings in Table 3.4 (see panels A.1-A.2), that is, before the Eurozone sovereign debt crisis, the main contributors to connectedness are core countries. More specifically, while Belgium, Netherlands and Germany all show positive net indices (pointing at their role as net donors), the net spillover indices for the five peripheral countries are all negative. Moreover, the total net spillovers across the five core and the five peripheral countries confirm that after the Eurozone sovereign debt crisis, the main contributors to connectedness are peripheral countries. More specifically, while Greece, Ireland and Spain all show positive net indices (pointing at their role as net donors), the only core country with a positive net spillover index is Germany. These results differ, to some extent, from those obtained by De Santis and Zimic (2018) which find evidence of sovereign bond yields spillovers only from Greece and Italy during the turmoil related to the Eurozone sovereign debt market crisis.

3.7 Conclusions

In this chapter I examine the macro-uncertainty and financial distress connectedness among Eurozone countries from 1997 to 2015, by using a GVAR model fitted to two endogenous variables sampled at different frequencies: a *monthly* Country-Level Index of Financial Stress (CLIFS) and a *quarterly* index of uncertainty about GDP growth. In particular, I extend a GVAR model by using the recent econometric developments by Ghysels (2016), that allows the use of mixed-frequency data directly in the VAR model rather than aggregating the high-frequency variable to low-frequency before the estimation. Total and directional connectedness are computed by using the methodology developed by Greenwood-Nimmo et al. (2015) which extends the Diebold and Yilmaz (2012, 2014) VAR based approach to estimate the Forecast Error Variance Decomposition, FEVD, to a Global Vector Autoregressive, GVAR model.

The empirical findings suggest that macro-uncertainty and financial stress are relatively disconnected in the Eurozone, since the spillovers across the two blocks account only for 25% of the total Eurozone system-wide FEVD at one year forecast horizon. Moreover, I find evidence of disconnect between core and periphery countries since the outbreak of Eurozone sovereign debt crisis. I also find that connectedness between core and periphery is mostly occurring through financial stress and it decreases during the Eurozone sovereign debt crisis, given a strong decline in the financial stress spillovers from core to periphery. Moreover, I show that, while core countries (in particular Germany, Netherlands and Belgium) are the triggers of the connectedness between macro-uncertainty and financial stress before the Eurozone sovereign debt crisis, periphery countries (in particular, Greece, Ireland and Spain) play an important role in driving connectedness once I consider the full sample period (including the Eurozone sovereign debt crisis). Finally, by comparing the result obtained through mixed-frequency and the common-frequency Global VAR I find that MF based indices of connectedness are larger than those obtained through CF approach.

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3.A Appendix

3.A.1 Figures

Figure 3.1: Country-Specific Indicators of Financial Stress (CLIFS)

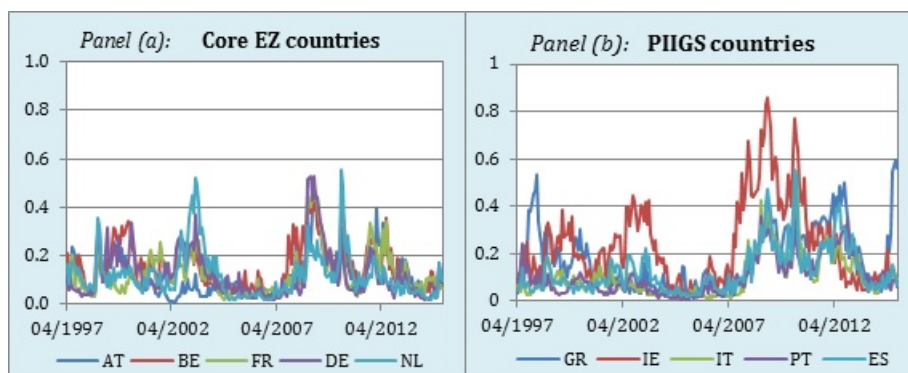
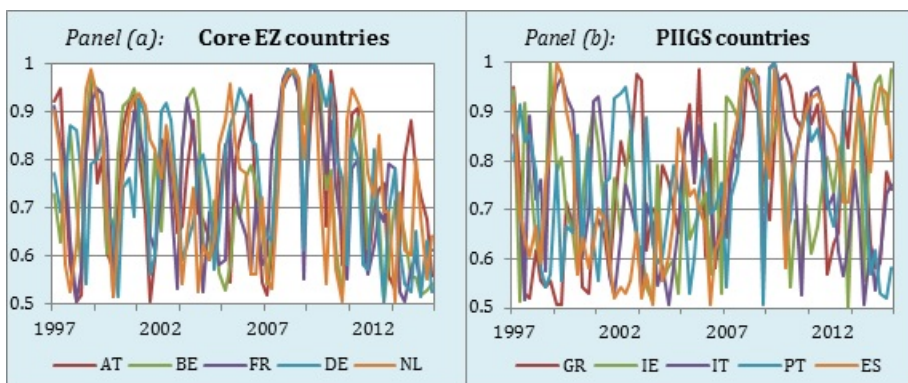


Figure 3.2: Country-Specific Output Growth Uncertainty Indices



Notes: horizontal axes show the forecast origin dates.

3.A.2 Tables

Table 3.1: Trade weights

w_{ig}	AT	BE	FR	DE	NL	GR	IE	IT	PT	ES
AT	0	0.054	0.091	0.6	0.068	0.004	0.009	0.125	0.008	0.04
BE	0.025	0	0.212	0.342	0.182	0.005	0.066	0.102	0.011	0.056
FR	0.031	0.135	0	0.398	0.096	0.005	0.019	0.166	0.022	0.13
DE	0.119	0.138	0.249	0	0.169	0.008	0.021	0.181	0.021	0.094
NL	0.03	0.175	0.149	0.436	0	0.006	0.021	0.105	0.014	0.061
GR	0.032	0.086	0.122	0.306	0.099	0	0.018	0.242	0.01	0.085
IE	0.032	0.131	0.167	0.342	0.135	0.006	0	0.102	0.013	0.072
IT	0.051	0.099	0.209	0.385	0.104	0.014	0.018	0	0.016	0.104
PT	0.017	0.054	0.142	0.239	0.069	0.004	0.012	0.105	0	0.358
ES	0.025	0.073	0.246	0.305	0.084	0.007	0.019	0.156	0.085	0

Table 3.2: LR test statistics for testing MF-VARX vs CF-VARX

Country	Sub-sample (1997-2009 Q4)	Full sample (1997-2016)
Austria	463.56	592.89
Belgium	429.62	575.87
France	482.74	624.66
Germany	414.91	590.64
Netherlands	465.9	622.12
Greece	407.19	529.8
Ireland	362.81	499.31
Italy	520.31	693.7
Portugal	512.22	651.22
Spain	516.74	675.92

Notes: The figures are the Likelihood Ratio, LR, statistics for testing the null of equivalence of MF-VARX with the traditional CF-VARX for each county $i = (\text{AT, BE, FR, DE, GR, IE, IT, NL, PT, ES})$, as suggested by Bacchiocchi et al. (2018). Rejection of the null hypothesis implies that aggregating the mixed-frequency series as in traditional CF-VARX generates a loss of information. The LR statistics is computed by comparing the log-likelihood of the unrestricted model, i.e. MF-VARX (l^u), with the one associated with the restricted model, i.e. CF-VARX (l^r). The test statistics $LR = -2(l^r - l^u)$ is asymptotically distributed as a χ^2 , with the degrees of freedom given by the number of restrictions (38 restrictions: twelve are imposed on Γ_i matrix, twelve on Λ_{i0} , twelve on Λ_i and two on c_i) on the MF-VARX coefficients. I report the LR test statistics in the table and p -values (available upon request) are close to zero, suggesting a strong rejection of the null hypothesis.

Table 3.3: Spillovers between financial stress and GDP growth uncertainty

Panel A: Mixed Frequency Approach									
Forecast horizon:		H=4				H=8			
		Sub-sample		Full sample		Sub-sample		Full sample	
		1997:Q2-2009:Q4		1997:Q2-2015:Q1		1997:Q2-2009:Q4		1997:Q2-2015:Q1	
From/To		GDP	FSI	GDP	FSI	GDP	FSI	GDP	FSI
	GDP	34.01	15.99	39.26	10.74	31.51	18.49	37.15	12.85
	FSI	9.97	40.03	14.52	35.48	9.68	40.32	14.93	35.07

Panel B: Common Frequency Approach									
Forecast horizon:		H=4				H=8			
		Sub-sample		Full sample		Sub-sample		Full sample	
		1997:Q2-2009:Q4		1997:Q2-2015:Q1		1997:Q2-2009:Q4		1997:Q2-2015:Q1	
From/To		GDP	FSI	GDP	FSI	GDP	FSI	GDP	FSI
	GDP	31.46	18.54	47.38	2.62	30.63	19.37	46.84	3.16
	FSI	4.39	45.61	20.48	29.52	5.65	44.35	23.22	26.78

Notes: Within-group connectedness indices are on the main diagonal and the off-diagonal elements show the *to/from* contributions. Total spillover index is estimated by summing the off-diagonal elements of (2×2) matrix.

Table 3.4: Regional spillovers

Panel A: Mixed Frequency Approach									
Forecast horizon:		H=4				H=8			
		Sub-sample		Full sample		Sub-sample		Full sample	
		1997:Q2-2009:Q4		1997:Q2-2015:Q1		1997:Q2-2009:Q4		1997:Q2-2015:Q1	
From/To		Core	Periphery	Core	Periphery	Core	Periphery	Core	Periphery
	Core	38.5	11.5	36.12	13.88	37.12	12.88	32.67	17.33
	Periphery	19.92	30.08	11.53	38.47	20.44	29.56	11.4	38.6

Panel B: Common Frequency Approach									
Forecast horizon:		H=4				H=8			
		Sub-sample		Full sample		Sub-sample		Full sample	
		1997:Q2-2009:Q4		1997:Q2-2015:Q1		1997:Q2-2009:Q4		1997:Q2-2015:Q1	
From/To		Core	Periphery	Core	Periphery	Core	Periphery	Core	Periphery
	Core	39.4	10.6	40.97	9.03	37.61	12.39	38.09	11.91
	Periphery	12.97	37.03	9.54	40.46	14.02	35.98	9.46	40.54

Notes: Within-group connectedness indices are on the main diagonal and the off-diagonal elements show the *to/from* contributions. Total spillover index is estimated by summing the off-diagonal elements of (2×2) matrix.

Table 3.5: Regional spillovers between financial stress and macro-uncertainty

Panel A: Mixed Frequency Approach								
H=4	Sub-sample (1997:Q2-2009:Q4)				Full sample (1997:Q2-2015:Q1)			
<u>Panel (A.1): Connectedness Table</u>								
	Core (GDP)	Core (FSI)	PIIGS (GDP)	PIIGS (FSI)	Core (GDP)	Core (FSI)	PIIGS (GDP)	PIIGS (FSI)
Core (GDP)	14.9	4.8	2.3	3	16.9	2.4	2.8	3
Core (FSI)	3.1	15.6	1.7	4.6	5.9	11	2.8	5.3
PIIGS (GDP)	1.7	3.5	15.1	4.7	1.8	2.5	17.8	2.8
PIIGS (FSI)	3.2	11.5	2	8.3	3.2	4	2.6	15.2
<u>Panel (A.2): Directional Connectedness Indices</u>								
	Within	From	To	Net	Within	From	To	Net
Core (GDP)	14.9	10.1	8	-2.1	16.9	8.1	10.9	2.7
Core (FSI)	15.6	9.4	19.8	10.5	11	14	8.9	-5.1
PIIGS (GDP)	15.1	9.9	5.9	-3.9	17.8	7.2	8.2	1
PIIGS (FSI)	8.3	16.7	12.2	-4.5	15.2	9.8	11.2	1.3
Total	54	46	46	0.0	60.8	39.2	39.2	0.0
H=8								
Sub-sample (1997:Q2-2009:Q4)				Full sample (1997:Q2-2015:Q1)				
<u>Panel (A.3): Connectedness Table</u>								
	Core (GDP)	Core (FSI)	PIIGS (GDP)	PIIGS (FSI)	Core (GDP)	Core (FSI)	PIIGS (GDP)	PIIGS (FSI)
Core (GDP)	12.53	6.38	2.69	3.39	14.94	2.90	3.42	3.74
Core (FSI)	2.60	15.61	2.02	4.77	5.07	9.76	3.76	6.41
PIIGS (GDP)	1.79	3.85	14.49	4.87	1.83	2.85	16.96	3.36
PIIGS (FSI)	2.55	12.24	2.51	7.70	2.60	4.12	3.50	14.78
<u>Panel (A.4): Directional Connectedness Indices</u>								
	Within	From	To	Net	Within	From	To	Net
Core (GDP)	12.5	12.5	6.9	-5.5	14.9	10.1	9.5	-0.6
Core (FSI)	15.6	9.4	22.5	13.1	9.8	15.2	9.9	-5.4
PIIGS (GDP)	14.5	10.5	7.2	-3.3	17	8	10.7	2.6
PIIGS (FSI)	7.7	17.3	13	-4.3	14.8	10.2	13.5	3.3
Total	50.3	49.7	49.7	0.0	56.4	43.6	43.6	0.0

Table 3.5: (Continued)

Panel B: Common Frequency Approach								
H=4	Sub-sample (1997:Q2-2009:Q4)				Full sample (1997:Q2-2015:Q1)			
	Panel (B.1): Connectedness Table							
	Core (GDP)	Core (FSI)	PIIGS (GDP)	PIIGS (FSI)	Core (GDP)	Core (FSI)	PIIGS (GDP)	PIIGS (FSI)
Core (GDP)	12.87	5.32	3.89	2.93	21.7	0.5	2.2	0.7
Core (FSI)	1.11	20.11	0.95	2.82	7	11.8	4	2.2
PIIGS (GDP)	4.92	4.82	9.78	5.48	1.9	0.7	21.7	0.7
PIIGS (FSI)	0.95	2.28	1.38	20.39	5	2	4.5	13.6
	Panel (B.2): Directional Connectedness Indices							
	Within	From	To	Net	Within	From	To	Net
Core (GDP)	12.9	12.1	7.0	-5.2	21.7	3.3	13.9	10.5
Core (FSI)	20.1	4.9	12.4	7.5	11.8	13.2	3.2	-10.0
PIIGS (GDP)	9.8	15.2	6.2	-9.0	21.7	3.3	10.6	7.3
PIIGS (FSI)	20.4	4.6	11.2	6.6	13.6	11.4	3.6	-7.8
Total	63.2	36.8	36.8	0.0	68.7	31.3	31.3	0.0
H=8	Sub-sample (1997:Q2-2009:Q4)				Full sample (1997:Q2-2015:Q1)			
	Panel (B.3): Connectedness Table							
	Core (GDP)	Core (FSI)	PIIGS (GDP)	PIIGS (FSI)	Core (GDP)	Core (FSI)	PIIGS (GDP)	PIIGS (FSI)
Core (GDP)	12.14	5.07	4.22	3.57	20.83	0.64	2.74	0.79
Core (FSI)	1.52	18.88	1.28	3.32	6.77	9.85	5.80	2.58
PIIGS (GDP)	5.81	4.69	8.46	6.05	2.00	0.85	21.28	0.88
PIIGS (FSI)	1.03	2.50	1.82	19.66	4.48	2.13	6.17	12.21
	Panel (B.4): Directional Connectedness Indices							
	Within	From	To	Net	Within	From	To	Net
Core (GDP)	12.1	12.9	8.4	-4.5	20.8	4.2	13.2	9.1
Core (FSI)	18.9	6.1	12.3	6.1	9.9	15.1	3.6	-11.5
PIIGS (GDP)	8.5	16.5	7.3	-9.2	21.3	3.7	14.7	11.0
PIIGS (FSI)	19.7	5.3	12.9	7.6	12.2	12.8	4.2	-8.5
Total	59.1	40.9	40.9	0.0	64.2	35.8	35.8	0.0

Table 3.6: Macro-financial spillovers among EZ countries

Panel A.1: Mixed Frequency Approach (H=4)								
	Sub-sample 1997:Q2-2009:Q4				Full sample 1997:Q2-2015:Q2			
	Within	From	To	Net	Within	From	To	Net
"AT"	4.39	5.61	4.69	-0.92	5.28	4.72	4.78	0.06
"BE"	4.12	5.88	9.76	3.88	3.9	6.1	4.57	-1.53
"FR"	3.7	6.3	5.19	-1.11	3.86	6.14	2.78	-3.36
"DE"	3.87	6.13	9.44	3.3	5.81	4.19	8.2	4.02
"NL"	4.9	5.1	8.37	3.26	5.33	4.67	3.13	-1.54
"GR"	6.4	3.6	3.43	-0.17	7.5	2.5	5.99	3.49
"IE"	4.1	5.9	5.72	-0.17	6.49	3.51	5.8	2.29
"IT"	2.7	7.3	2.7	-4.6	3.76	6.24	4.03	-2.21
"PT"	4.77	5.23	2.96	-2.27	5.13	4.87	1.73	-3.14
"ES"	3.43	6.57	5.36	-1.21	4.86	5.14	7.06	1.92
Total:	42.4	57.6	57.6	0	51.9	48.1	48.1	0
Total core:	21	29	37.4	8.4	24.2	25.8	23.5	-2.3
Total PIIGS:	21.4	28.6	20.2	-8.4	27.7	22.3	24.6	2.3

Panel A.2: Mixed Frequency Approach (H=8)								
	Sub-sample 1997:Q2-2009:Q4				Full sample 1997:Q2-2015:Q2			
	Within	From	To	Net	Within	From	To	Net
"AT"	3.77	6.23	4.07	-2.16	4.79	5.21	5.19	-0.02
"BE"	3.13	6.87	8.71	1.84	3.23	6.77	4.55	-2.22
"FR"	3.04	6.96	5.22	-1.74	3.15	6.85	2.40	-4.45
"DE"	3.87	6.13	13.46	7.33	5.09	4.906	8.16	3.25
"NL"	4.22	5.78	8.06	2.29	4.58	5.42	2.92	-2.50
"GR"	5.49	4.51	3.31	-1.20	7.30	2.70	5.65	2.94
"IE"	4.05	5.95	6.89	0.94	6.38	3.62	6.65	3.02
"IT"	2.36	7.64	2.89	-4.75	3.26	6.74	4.71	-2.03
"PT"	4.34	5.66	2.69	-2.97	4.57	5.43	1.65	-3.78
"ES"	3.40	6.60	7.02	0.42	4.81	5.19	10.97	5.78
Total:	37.67	62.33	62.33	0.00	47.14	52.86	52.86	0.00
Total core:	18.03	31.97	39.53	7.56	20.84	29.16	23.23	-5.93
Total PIIGS:	19.64	30.36	22.80	-7.56	26.31	23.69	29.62	5.93

Table 3.6: (Continued)

Panel B.1: Common Frequency Approach (H=4)								
	Sub-sample 1997:Q2-2009:Q4				Full sample 1997:Q2-2015:Q2			
	Within	From	To	Net	Within	From	To	Net
"AT"	6.16	3.84	4.89	1.05	6.44	3.56	4.32	0.76
"BE"	4.53	5.47	4.62	-0.86	4.73	5.27	2.18	-3.09
"FR"	5.14	4.86	5.23	0.37	5.34	4.66	1.96	-2.70
"DE"	5.41	4.59	5.87	1.28	7.28	2.72	8.04	5.33
"NL"	7.19	2.81	3.33	0.52	7.07	2.93	3.15	0.22
"GR"	6.01	3.99	3.78	-0.21	8.16	1.84	3.01	1.16
"IE"	4.58	5.42	2.77	-2.65	7.22	2.78	3.41	0.64
"IT"	6.35	3.65	7.20	3.55	5.24	4.76	3.39	-1.37
"PT"	6.46	3.54	1.93	-1.61	6.05	3.95	1.70	-2.24
"ES"	4.47	5.53	4.09	-1.45	5.96	4.04	5.34	1.30
Total:	56.29	43.71	43.71	0	63.48	36.52	36.52	0
Total core:	28.42	21.58	23.95	2.37	30.85	19.15	19.66	0.51
Total PIIGS:	27.87	22.13	19.76	-2.37	32.63	17.37	16.86	-0.51

Panel B.2: Common Frequency Approach (H=8)								
	Sub-sample 1997:Q2-2009:Q4				Full sample 1997:Q2-2015:Q2			
	Within	From	To	Net	Within	From	To	Net
"AT"	5.64	4.36	5.27	0.91	5.97	4.03	4.11	0.08
"BE"	3.77	6.23	4.22	-2.01	4.07	5.93	2.22	-3.71
"FR"	4.76	5.24	6.11	0.87	4.65	5.35	1.71	-3.64
"DE"	4.71	5.29	7.14	1.85	6.77	3.23	7.76	4.53
"NL"	6.65	3.35	3.36	0.01	6.60	3.40	3.69	0.30
"GR"	5.67	4.33	4.12	-0.20	8.05	1.95	2.98	1.04
"IE"	3.95	6.05	3.29	-2.77	6.96	3.04	3.82	0.77
"IT"	6.02	3.98	8.46	4.48	4.58	5.42	3.61	-1.81
"PT"	5.72	4.28	1.76	-2.52	5.26	4.74	1.67	-3.07
"ES"	4.12	5.88	5.27	-0.62	5.96	4.04	9.56	5.52
SUM:	50.99	49.01	49.01	0.00	58.87	41.13	41.13	0.00
Total core:	25.52	24.48	26.11	1.63	28.05	21.95	19.49	-2.45
Total PIIGS:	25.47	24.53	22.90	-1.63	30.81	19.19	21.64	2.45