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LINKING DISTRESS OF FINANCIAL INSTITUTIONS TO MACROFINANCIAL SHOCKS

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In 2014 all ECB publications feature a motif taken from the €20 banknote.

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Abstract

This paper links granular data of financial institutions to global macroeconomic variables using an infinite-dimensional vector autoregressive (IVAR) model framework. The approach taken allows for an assessment of the two-way links between the financial system and the macroeconomy, while accounting for heterogeneity among financial institutions and the role of international linkages in the transmission of shocks. The model is estimated using macroeconomic data for 21 countries and default probability estimates for 35 euro area financial institutions. This framework is used to assess the impact of foreign macroeconomic shocks on default risks of euro area financial firms. In addition, spillover effects of firm-specific shocks are investigated. The model captures the important role of international linkages, showing that economic shocks in the US can generate a rise in the default probabilities of euro area firms that are of a significant magnitude compared to recent historical episodes such as the financial crisis. Moreover, the potential heterogeneity across financial firms' response to shocks, which motivates an approach based on granular information, is investigated. By linking a firm-level framework to a global model, the IVAR approach provides promising avenues for developing tools that can explicitly model spillover effects among a potentially large group of firms, while accounting for the two-way linkages between the financial sector and the macroeconomy, which were among the key transmission channels during the recent financial crisis.

Keywords: Corporate Sector Credit Risk, Default Frequencies, Infinite-Dimensional VAR, GVAR
JEL Classification: C33, G33

Non-technical summary

The recent financial crisis has demonstrated the need to improve the effectiveness of macro-prudential tools for financial supervision. One challenge, which is often encountered in the context of macro stress test exercises for financial institutions, is how to integrate a large number of key variables endogenously into a single, consistent model. In stress test exercises, a set of macro-financial shocks is generated to assess the impact on financial indicators, such as capital ratios, at the firm level. Ideally, in such a set up, one can capture the particular linkages that exist both across firms and between firms and the macroeconomy. In particular, three features have shown to be highly relevant in the transmission of economic shocks. First, given the international operations of many of the larger financial institutions, the international exposures to economies beyond the domestic country can be important. Second, instability among one or more large and complex financial institutions can have negative repercussions for the macroeconomy, giving rise to negative feedback loops. Third, there exists significant heterogeneity among financial institutions, with large banks competing with non-bank financial companies who often perform similar functions subject to a different regulatory environment. Thus, it is important to account for this heterogeneity among financial institutions and possible spillover of risks between firms.

While these features of the relationship between financial institutions and the macroeconomy are rather well-known, it remains a challenge to incorporate them into a single model framework as doing so results in very large systems, whose parameters cannot be estimated directly. In practice, this problem is solved by using a separate model to generate an adverse macro scenario, which is then fed into another model to link the generated shocks to financial firms. This approach typically comes at the cost of exogenising parts of the model, which artificially restricts certain feedback effects.

This paper offers an alternative methodological approach that combines the infinite-dimensional vector autoregressive (IVAR) model framework, originally developed by Chudik and Pesaran (2011, 2013), with a global VAR (GVAR) model due to Pesaran et al. (2004) that can relate granular data at the firm level with a high-dimensional set of international macro-financial variables. The resulting system yields a large-scale VAR in which all variables are endogenous, thereby enabling a detailed analysis of international linkages and spillovers between the macroeconomy and individual firms.

Specifically, we apply the IVAR approach to the expected default probabilities of a set of euro area financial firms, and link these to a global set of macroeconomic variables. In contrast to other approaches, which first aggregate firm-level information at broad sectoral or country level before estimating two-way linkages with macroeconomic variables, the IVAR approach estimates these relationships at the firm level, thus accounting for potential heterogeneity of the firms' macrofinancial linkages. As this framework nests a GVAR model, we also capture the international transmission of shocks to the euro area financial sector. Given that all variables are endogenous, we can further quantify spillover effects across firms.

We apply this model to analyse two shocks. The first simulates a decline in US equity prices of a magnitude observed following the Lehman bankruptcy. The results show that an adverse shock to equity prices in the US has an adverse impact on the default probabilities of euro area financial firms that is not only statistically significant but also of an economically significant magnitude when considering recent historical episodes such as the financial crisis. The second shock simulates a rise in the default probabilities of the globally systemically important financial institutions in our sample. The spillover effects to the remaining euro area firms are found to be significant in the short term, showing that the model can capture contagion effects. The results also point to the existence of sizeable heterogeneity among the responses across firms, which motivates the use of firm-level data rather than using aggregate banking sector-level indicators.

This illustrative empirical exercise demonstrates that the methodological approach based on the IVAR framework can potentially sharpen the tools available to financial supervisors and policymakers in understanding the complex links across financial sector institutions and the macroeconomy. Enabling the inclusion of both firm-level data and a large set of macrofinancial variables provides a single framework, in which one can analyse a wide variety of adverse scenarios. Finally, as the model framework is rather general, it is straightforward to incorporate additional sectors of interest, such as, e.g., the non-financial sector to assess the spillover between financial and non-financial corporate sectors.

1 Introduction

In the wake of the financial crisis, financial supervisors re-evaluated the effectiveness of the macro-prudential tools at their disposal. In hindsight, better models were needed to anticipate financial imbalances and to understand the impact of their unwinding on the real economy. Over the past years, research on macroprudential theory and practice has increased substantially with the aim of identifying and containing risk in the financial system.[1] One key aspect in this literature pertains to systemic risk, which represents the risks that financial stability breaks down to the point that the functioning of financial institutions is impaired with significant adverse effects on the macroeconomy (ECB (2009)). Therefore, one underlying factor leading to the materialisation of systemic risk is financial contagion among institutions or markets, see, e.g., De Bandt and Hartmann (2000). Measuring the risk of contagion among financial institutions, in turn, requires tools that incorporate data at the individual firm level. Indeed, one of the more prominent macro-prudential tools to assess systemic risk are macro stress testing models. These models measure conditions in the banking sector against a range of shocks in the macro-financial system. As explained in Henry and Kok (2013), the accuracy of such stress tests depend on the degree of granularity in the data used as well as the range of interlinkages between banks and the macrofinancial environment considered.

However, one challenge that is often encountered in the context of macro stress test exercises for financial institutions, is how to integrate a large number of key variables endogenously into a single, consistent model.[2] For instance, when linking firm-level distress indicators to the macroeconomy, not only is the domestic economy relevant but also the macrofinancial variables from key trading partners and global financial market hubs. That is, international macrofinancial linkages are both significant and complex. Second, heterogeneity among financial institutions and possible spillover of risks between firms are essential in accounting for the connectedness of the financial system. Finally, possible feedback effects from financial instability to macrodynamics are important, as negative feedback loops between the financial sector and the macroeconomic environment were among the key challenges to policymakers during the financial crisis. While these features of the relationship between firms and the macroeconomy are well-known, it remains a challenge to incorporate these into a single model framework, as doing so results in very large systems that are subject to the curse of dimensionality.

The contribution of this paper is to combine the infinite-dimensional vector autoregressive (IVAR) model framework, originally developed by Chudik and Pesaran (2011, 2013), with a global VAR model due to Pesaran et al. (2004) to relate granular data at the firm level to a high-dimensional set of international macro-financial variables. The resulting system yields a large-scale VAR in which all variables are endogenous, thereby enabling a finely detailed analysis of international linkages

[1] See, e.g., the workstream of the European System of Central Banks Macro-prudential Research (MaRs) Network ECB (2012).

[2] For reviews of macro stress testing models, their objectives and challenges see, e.g., Alfaro and Drehmann (2009), Drehmann (2009), Foglia (2009) and Henry and Kok (2013).

and spillovers between the macroeconomy and individual firms. Specifically, we apply the IVAR approach to the expected default probabilities of a set of euro area financial firms, where the default probabilities have been derived from credit risk models, and build a panel consisting of both firm-level risk indicators and a global set of macroeconomic variables. In contrast to other approaches, which first aggregate firm-level information at broad sectoral or country level before estimating two-way linkages with macroeconomic variables, the IVAR approach estimates these relationships at the firm level, thus accounting for potential heterogeneity of the firms' macrofinancial linkages. As this framework nests a global VAR (GVAR) model, we also capture the international transmission of shocks to the euro area financial sector. Given that all variables are endogenous, we can further quantify spillover effects across firms. Allowing for differentiated responses among firms within fully endogenous macro-financial system represents an advancement over current approaches, where either the size of the system is reduced by considering aggregate banking systems (Gray et al. (2013) and Chen et al. (2010)) or where granular bank-level data is included at the expense of exogenising various model blocks such that feedback effects cannot be fully taken into account (Henry and Kok (2013)). A related approach is given by Gross and Kok (2013), which combine financial variables at the country level with bank-level data using a GVAR. Their approach does not include macroeconomic data and does not make use of the IVAR framework, which yields important differences in the model specification.[3]

In the empirical exercise, we consider two shocks. The first simulates a decline in US equity prices of a magnitude observed following the Lehman bankruptcy. The results show that the model can capture a significant rise in large firms' default probabilities that is up to half of the rise observed during the Lehman episode. Given that this exercise entails only a single shock to US equities, whereas a broad set of shocks materialised during the financial crisis, the resulting firm-level responses are economically significant. The second shock simulates a rise in the default probabilities of the globally systemically important financial institutions in our sample.[4] The spillover effects to the remaining euro area firms are found to be statistically significant in the short term, which provides further evidence for the importance of accounting for firm-level information.

The paper is structured as follows. Section 2 discusses the IVAR modelling approach and the link between firm-level and macroeconomic variables, and Section 3 describes the data used in the empirical application. Section 4 presents the specification of the model, its estimation and generalised impulse response functions for the two shocks mentioned above. Section 5 offers some concluding remarks and areas for future research.

[3]Specifically, Gross and Kok (2013) do not make use of the neighbour/non-neighbour differentiation that is essential to the theoretical coherence of the IVAR. Also, a different approach is used aggregating country- and bank-level data by using estimated weight matrices. See next section for further details.

[4]See Financial Stability Board (2013a) and Financial Stability Board (2013b) for the definition of global systemically important banks and insurers.

2 The infinite-dimensional VAR approach

In constructing a high-dimensional VAR in which financial stress indicators from a potentially large set of firms are combined with a comprehensive set of international macroeconomic variables, the resulting parameter space is too large to enable direct estimation of the system. The IVAR framework introduced by Chudik and Pesaran (2011, 2013) offers an empirical approach that facilitates the estimation of VARs with both, the cross section and time dimension, large. The IVAR framework is closely related to that of the more well-known GVAR approach. The standard GVAR as presented, e.g., in Dées et al. (2007) is motivated as an approximation to a global factor model that contains macrofinancial variables from a potentially large set of small open economies. The model allows for long-run relationships between the macrovariables, which are motivated by economic theory. Given the small open economy framework, the trade-weighted foreign variables are treated as weakly exogenous such that the system can be consistently estimated in country-by-country blocks.[5]

The IVAR approach has many similarities to that of the GVAR, but it is more general in the sense that it starts with an arbitrarily large set of units and motivates the modelling strategy as an approximation to a large-scale system. To illustrate this approach, assume the following N-dimensional VAR:

$$x_t = \Phi x_{t-1} + u_t.$$

In this system, there is no theory, a priori, how each unit i in x_t is related to the remaining units. Rather, it is assumed that an individual unit has relatively strong links to a finite (and typically small) number of other, so-called 'neighbouring', units, while the individual links to all other units, the so called 'non-neighbours', weaken as the number of variables in the system rises:

$$x_{i,t} = \phi_i x_{i,t-1} + \underbrace{\sum_{j \in \mathbf{M}_i^n} \phi_{ij} x_{j,t-m}}_{Neighbours} + \underbrace{\sum_{j \in \mathbf{M}_i^o} \psi_{ij} x_{j,t-m}}_{Non-neighbours} + u_{i,t}.$$

In this equation, the parameters ϕ_{ij} on the neighbours cannot be restricted. However, the coefficients related to the 'non-neighbouring' units tend to zero as the total number of units N in the system tends to infinity, such that

$$|\psi_{ij}| \leq \frac{K}{N} \text{ for } K < \infty \text{ and } \forall j \in \mathbf{M}_i^o,$$

for some constant K.

At the same time, even if the individual links to the non-neighbouring units need not be considered separately, these units can, in the aggregate, have a significant impact on $x_{i,t}$, such that

[5] See, e.g., di Mauro and Pesaran (2013) and Chudik and Pesaran (2014) for a comprehensive summary of empirical applications of the GVAR.

$$\lim_{N\to\infty}\sum_{j=1}^{N}|\psi_{ij}| < K.$$

This is the case if there exists strong cross-section dependence across the units in the system.[6] Chudik and Pesaran (2011) show that under a certain set of assumptions, such a high-dimensional VAR can be consistently estimated using unit-by-unit cross-section augmented regressions.[7] Here, the large number of non-neighbouring units is replaced by their cross-section average (CSA). This CSA can be interpreted as an estimate of an unobserved common factor that captures strong cross section dependence. The approach greatly reduces the number of parameters to be estimated, while, similarly to the GVAR framework, the original large-scale VAR can be recovered from the unit-level regression estimates. In addition to the potential inclusion of 'neighbours', Chudik and Pesaran (2013) also explicitly introduce so-called dominant units to the analysis. This is a unit that has direct contemporary links to every other unit in the system. Such a modeling approach can, for example, accommodate the dominant role of the US in international financial markets.

2.1 Modelling framework

In our model framework, there are two different types of 'units'. One set consists of default probabilities for 35 financial firms located in the euro area, denoted by the $M \times 1$ vector x_t. A second set of variables consists of macroeconomic time series for the euro area, collected in the $k \times 1$ vector y_t, and macro variables for 20 non-euro area economies, represented by the $(K - k) \times 1$ vector z_t. The aim is to estimate a high-dimensional VAR, where the firm-level and macrofinancial variables are all endogenous:

$$Q_0 \begin{bmatrix} z_t \\ y_t \\ x_t \end{bmatrix} = q_0 + q_d t + \sum_{l=1}^{p} Q_l \begin{bmatrix} z_{t-l} \\ y_{t-l} \\ x_{t-l} \end{bmatrix} + u_t. \tag{1}$$

In what follows, we will show how to use cross-section augmented regressions to estimate the high-dimensional system (1) in blocks. The structure of the sub-system in terms of z_t and y_t is very similar to that of a standard GVAR, and in this sense a GVAR is 'nested' in our model. The structure of the firm-level system in x_t will follow the IVAR approach outlined above.

2.2 Firm-level system

The firm-level model block for firm $i = 1, ..., M$, is estimated in first differences initially with the following specification:

$$\Delta x_{i,t} = \alpha_i + \sum_{m=1}^{p_i-1} \phi_{im}\Delta x_{i,t-m} + \sum_{l=0}^{q_i-1} \beta_{il}\Delta \bar{X}_{i,t-l} + \sum_{l=0}^{q_{iy}-1} \delta_{il}\Delta \tilde{y}_{t-l} + \varepsilon_{i,t} \tag{2}$$

[6] For more details on the concept of strong and weak cross sectional dependence see Chudik et al. (2011).

[7] See also Pesaran (2006).

where $x_{i,t}$ denotes the financial stress indicator for firm i, $\bar{X}_{i,t}$ is the firm i-specific cross section average (CSA) – defined further below – and $\tilde{y}_t$ is a vector containing km variables of the k available euro area macro variables, with $km \leq k$. The CSA for firm i is defined as a simple average of all firms, excluding firm i:

$$\bar{X}_{i,t} \equiv \frac{1}{M-1} \sum_{j \neq i \in \mathbf{M}} x_{j,t} \equiv s_i x_t \tag{3}$$

where s_i is a $1 \times M$ weighting vector, whose elements are given by $1/(M-1)$ and a weight of zero is placed on firm i. The choice of equal weights follows the specification adopted in Chudik and Pesaran (2011). Asymptotically, the choice of weights should not affect the results; yet in practice, it has been shown that the weights used in finite samples can have a sizeable impact on the parameter estimates and impulse response functions (see e.g., Eickmeier and Ng (2011)).

We then inspect the correlation matrix of the residuals from (2), $Corr\left(\hat{\varepsilon}_{i,t}, \hat{\varepsilon}_{j,t}\right)$ for $i \neq j$ to identify the neighbours.[8] This approach is similar to that of Bailey et al. (2013a), who also derive so-called neighbours based on the correlation matrix of residuals. The idea in Bailey et al. (2013a) is to first remove common effects from the data using the cross-section augmented regressions in (2) and use the remaining spatial dependence between units to identify neighbours. Intuitively, if two units display co-movement, even after controlling for common shocks, then these units must share other characteristics, unrelated to common effects, that induce these units to be jointly determined, i.e., to be neighbours. Specifically, in the empirical application, for each unit i, the unit j is identified as a neighbour if $Corr\left(\hat{\varepsilon}_{i,t}, \hat{\varepsilon}_{j,t}\right) > \tau$, where $0 < \tau < 1$ is a pre-specified threshold parameter. In addition, we classify all firms belonging to the same country as neighbours of firm i, grouped into a spatial average $\bar{X}^c_{i,t}$. The neighbours $x_{ij,t}$, $j \in \mathbf{M}^n_i$ will then be removed from the cross section average that now only holds non-neighbour units $j \in \mathbf{M}^o_i$, such that (2) is re-specified to give

$$\begin{aligned} \Delta x_{i,t} \quad = \quad & \alpha_i + \sum_{m=1}^{p_i-1} \phi_{im} \Delta x_{i,t-m} + \sum_{m=1}^{p_{in}-1} \gamma_{im} I^s_i \Delta x_{t-m} + \sum_{m=1}^{p_{in}-1} \gamma^c_{im} \Delta \bar{X}^c_{i,t-m} \\ & + \sum_{l=0}^{q_{io}-1} \beta_{il} \Delta \bar{X}^o_{i,t-l} + \sum_{l=0}^{q_{iy}-1} \delta_{il} \Delta \tilde{y}_{t-l} + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

where I^s_i is a $M \times M$ neighbour selection matrix, which selects all neighbours that are not already captured by $\bar{X}^c_{i,t}$, defined as

$$\bar{X}^c_{i,t} \equiv \frac{1}{M^c_i} \sum_{j \in \mathbf{M}^c_i} x_{j,t} \equiv s^c_i x_t,$$

where M^c_i is the number of country-related neighbours of unit i defined to reside in the same country. The non-neighbours are aggregated into the following cross-section average

$$\bar{X}^o_{i,t} \equiv \frac{1}{M - M^n_i - 1} \sum_{j \neq i \in \mathbf{M}^n_i} x_{j,t} \equiv s^o_i x_t,$$

[8] In a dynamic sense the lagged own values of the cross section units can also be viewed as a neighbour of that unit.

where M_i^n is the number of neighbours of unit i.

We combine the $M \times 1$ firm-specific weight vectors s_i^o and s_i^c into the $M \times M$ weight matrices s^o and s^c, respectively (and likewise for $\gamma_{im} I_i^s$), such that

$$\begin{bmatrix} s_1^h \\ \vdots \\ s_M^h \end{bmatrix} x_t = s^h\, x_t\,,\ h \in \{o, c\}; \quad \begin{bmatrix} \gamma_{1m} I_1^s \\ \vdots \\ \gamma_{Mm} I_M^s \end{bmatrix} x_t = \gamma_m\, x_t.$$

We can then stack the firm-level equations in (4) to obtain

$$\begin{aligned} \Delta x_t &= \alpha + \sum_{m=1}^{p-1} \phi_m \Delta x_{t-m} + \sum_{m=1}^{p_n-1} \gamma_m \Delta x_{t-m} + \sum_{m=1}^{p_n-1} \gamma_m^c s^c \Delta x_{t-m} \\ &\quad + \sum_{l=0}^{q_o-1} \beta_l\, s^o\, \Delta x_{t-l} + \sum_{l=0}^{q_y-1} \delta_l \Delta \tilde{y}_{t-l} + \varepsilon_t, \end{aligned} \tag{5}$$

where ϕ_m, γ_m^c and β_l are $M \times M$ diagonal matrices, such that e.g.,

$$\phi_1 = \begin{bmatrix} \phi_{11} & 0 & \cdots & 0 \\ 0 & \phi_{21} & & \\ \vdots & & \ddots & \\ 0 & & & \phi_{M1} \end{bmatrix}.$$

Expressing (5) in levels and combining terms, we obtain

$$x_t = \alpha + \sum_{m=1}^{\tilde{p}} \phi^m x_{t-m} + \sum_{l=0}^{q_o} \beta^l\, x_{t-l} + \sum_{l=0}^{q_y} \delta^l\, \tilde{y}_{t-l} + \varepsilon_t. \tag{6}$$

where $\tilde{p} = max(p, p_n)$, $\phi^1 \equiv I + \phi_1 + \gamma_1 + \gamma_1^c s^c$, and $\phi^m \equiv (\phi_m - \phi_{m-1}) + (\gamma_m - \gamma_{m-1}) + (\gamma_m^c - \gamma_{m-1}^c) s^c$.[9] To simplify notation, we write equation (6) as

$$\Xi\, x_t = A_0 + \sum_{m=1}^{p_m} A_m\, x_{t-m} + \sum_{l=0}^{q_y} \tilde{D}_l\, \tilde{y}_{t-l} + \varepsilon_t \tag{7}$$

where $p_m = \max(p, p_n, q_o, q_y)$ and

$$\begin{aligned} \Xi &= I - \beta^0\,;\ A_0 \equiv \alpha\,;\ \tilde{D}_0 = \delta_0 \\ A_1 &= I + \phi^1 + (\beta^1 - \beta^0)\,;\ \tilde{D}_m = (\delta_m - \delta_{m-1}) \quad \text{for } m = 1, ..., q_y - 1 \\ A_m &= (\phi^m - \phi^{m-1}) + (\beta^m - \beta^{m-1}) \quad \text{for } m = 2, \ldots, p_m - 1; \\ A_{p_m} &= -(\phi^{p_m - 1} + \beta^{p_m - 1})\,;\ \tilde{D}_{q_y} = -\delta_{q_y - 1}. \end{aligned}$$

[9] Similarly, we define $\beta^0 \equiv \beta_0\, s^o$ and $\beta^l \equiv (\beta_l - \beta_{l-1})\, s^o$.

2.3 Euro area VARX*

The model for the euro area follows the VARX* framework of Pesaran et al. (2000), which is also used in the standard GVAR model, except that the firms are allowed in the aggregate to have a direct impact on the macro economy, so as to capture the two-way feedback between the financial sector and the macrodynamics that was observed during the financial crisis. The VARX* for the euro area is specified as follows:

$$\begin{aligned} \Delta y_t &= \tilde{a}_0 + \tilde{d}t + \begin{bmatrix} \Pi_y & \Pi_{\bar{X}} & \Pi_{y^*} \end{bmatrix} \begin{bmatrix} y'_{t-1} & \bar{X}'_{t-1} & y^{*\prime}_{t-1} \end{bmatrix}' \\ &+ \sum_{m=1}^{p_{\text{EA}}-1} \tilde{b}_m \Delta y_{t-m} + \sum_{l=0}^{q_{\text{EA}}-1} \tilde{\Psi}_l \Delta y^*_{t-l} + \sum_{l=0}^{q_{\text{EA}}-1} \tilde{\Phi}_l \Delta \bar{X}_{t-l} + e_t \end{aligned} \tag{8}$$

where y_t is a $k \times 1$ vector of euro area macro variables, $\bar{X}_t$ is the cross section average of firm-level indicators, defined as $\bar{X}_t = s_y x_t$, where s_y is a $1 \times M$ weighting vector containing the elements $1/M$, and y^*_t is a $k^* \times 1$ vector of euro area-specific foreign variables, which are defined as trade weighted cross section averages of the non-euro area macroeconomic variables given by

$$y^*_t \equiv \tilde{w}_N \begin{bmatrix} z_t \\ y_t \end{bmatrix}.$$

Here, $\tilde{w}_N$ is a $k^* \times K$ matrix holding bilateral trade weights between the euro area and the other countries in $\begin{bmatrix} z_t\prime & y_t\prime \end{bmatrix}'$.[10] Consistent with the VARX* framework in Pesaran et al. (2000), the contemporaneous foreign variables y^*_t are assumed to be weakly exogenous with respect to the long-run parameters in (8).[11] The euro area macrovariables y_t and euro area-specific foreign variables y^*_t can be linked to the vector of all macroeconomic variables in the system using the relation

$$\begin{bmatrix} y_t \\ y^*_t \end{bmatrix} = w_N \begin{bmatrix} z_t \\ y_t \end{bmatrix},$$

where

$$w_N = \begin{bmatrix} \tilde{I}_N \\ \tilde{w}_N \end{bmatrix}$$

with

$$\begin{aligned} \tilde{I}_N &= \begin{bmatrix} \underset{k \times (K-k)}{0} & \underset{k \times k}{I} \end{bmatrix} \\ \tilde{w}_N &= \begin{bmatrix} \underset{k^* \times (K-k)}{\tilde{w}_N} & \underset{k^* \times k}{0} \end{bmatrix}. \end{aligned}$$

[10] For ease of notation, we assume that the euro area is ordered last among the countries $j = 1, ..., N$.

[11] In Section 4, we test the validity of this assumption.

We can then write equation (8) in terms of z_t and y_t, given by

$$\begin{aligned}
\Lambda_{0N}\, w_N \begin{bmatrix} z_t \\ y_t \end{bmatrix} &= a_{0N} + d_N t + \sum_{m=1}^{\bar{p}_{\text{EA}}} \Lambda_{mN}\, w_N \begin{bmatrix} z_{t-m} \\ y_{t-m} \end{bmatrix} \\
&\quad + \sum_{l=0}^{q_{\text{EA}}} \Phi_l x_{t-l} + e_t, \qquad (9)
\end{aligned}$$

where $\bar{p}_{\text{EA}} = max(p_{\text{EA}}, q_{\text{EA}})$ and the coefficient matrices are defined as

$$\begin{aligned}
a_{0N} &\equiv \tilde{a}_0;\; d_N \equiv \tilde{d};\; \Lambda_{0N} = \begin{bmatrix} I & -\tilde{\Psi}_0 \end{bmatrix}; \Lambda_{mN} = \begin{bmatrix} b_m & \Psi_m \end{bmatrix} \text{ for } m = 1, ..., p_{\text{EA}}; \\
b_1 &= \left(I + \Pi_y + \tilde{b}_1\right);\; b_2 = \tilde{b}_2 - \tilde{b}_1; ...;\; b_{p_{\text{EA}}} = -\tilde{b}_{p_{\text{EA}}-1}; \\
\Psi_0 &\equiv \tilde{\Psi}_0;\; \Psi_1 = \left(\Pi_{y^*} + \tilde{\Psi}_1 - \tilde{\Psi}_0\right);\; \Psi_2 = \tilde{\Psi}_2 - \tilde{\Psi}_1; ...; \Psi_{q_{\text{EA}}} = -\tilde{\Psi}_{q_{\text{EA}}-1}; \\
\Phi_0 &= \tilde{\Phi}_0 s_y; \Phi_1 = \left(\Pi_{\bar{X}} + \tilde{\Phi}_1 - \tilde{\Phi}_0\right) s_y; \Phi_2 = \left(\tilde{\Phi}_2 - \tilde{\Phi}_1\right) s_y; ...; \Phi_{q_{\text{EA}}} = -\tilde{\Phi}_{q_{\text{EA}}-1} s_y.
\end{aligned}$$

2.4 Non-euro area VARX*

The specification for the non-euro area VARX* is closely related to the euro area counterpart in equation (8) except that non-euro area macroeconomic variables are not modelled to have a direct link to euro area firms. In the empirical application, we will show that firms and international macro variables are still interlinked via the euro area variables. The VARX* for country $j = 1, ..., N-1$ is estimated in the following VECM form

$$\begin{aligned}
\Delta y_{j,t} &= \tilde{a}_{0j} + \tilde{d}_j t + [\Pi_{yj}\, \Pi_{y^*j}] \left[y'_{j,t-1}\, y^{*\prime}_{j,t-1}\right]' + \sum_{m=1}^{p_j-1} \tilde{b}_{mj} \Delta y_{j,t-m} \qquad (10) \\
&\quad + \sum_{l=0}^{q_j-1} \Psi_{lj} \Delta y^*_{j,t-l} + e_{j,t}
\end{aligned}$$

where $y_{j,t}$ denotes the $k_j \times 1$ vector of country j's domestic macro variables, the $k^*_j \times 1$ vector $y^*_{j,t}$ represents country j's foreign variables, which are defined as trade weighted cross section averages of the non-domestic macroeconomic variables, given by

$$y^*_{j,t} \equiv \tilde{w}_j \begin{bmatrix} z_t \\ y_t \end{bmatrix},$$

where $\tilde{w}_j$ is a $k^*_j \times K$ matrix holding bilateral trade weights between country j and the other countries in $\begin{bmatrix} z'_t & y'_t \end{bmatrix}'$. Similarly to the euro area VARX*, the country j-specific domestic and foreign variables $y_{j,t}$ and $y^*_{j,t}$ can be linked to all macroeconomic variables in the system using the relation

$$\begin{bmatrix} y_{j,t} \\ y^*_{j,t} \end{bmatrix} = w_j \begin{bmatrix} z_t \\ y_t \end{bmatrix} \qquad (11)$$

where

$$
\begin{aligned}
w_j &= \begin{bmatrix} \tilde{I}_j \\ \tilde{w}_j \end{bmatrix} \\
\tilde{I}_j &= \begin{bmatrix} 0 & \cdots & 0 & I & 0 & \cdots & 0 \end{bmatrix},
\end{aligned}
$$

where $\tilde{I}_j$ is a selection matrix picking out $y_{j,t}$ from z_t. Using (11), we can re-write equation (10) in levels as follows

$$
\Lambda_{0j} w_j \begin{bmatrix} z_t \\ y_t \end{bmatrix} = a_{0j} + d_j t + \sum_{l=1}^{\bar{p}_j} \Lambda_{lj} w_j \begin{bmatrix} z_{t-l} \\ y_{t-l} \end{bmatrix} + e_{j,t}, \tag{12}
$$

where $\bar{p}_j = max(p_j, q_j)$ and the coefficient matrices are similarly defined as for the euro area VARX* in (9).

2.5 Solving for the IVAR

We can now derive the initial large-scale VAR in (1) by combining the VARX*s for the non-euro area countries in (12) and for the euro area in (9) with the model block for the firm level equations in (7), to obtain

$$
Q_0 \begin{bmatrix} z_t \\ y_t \\ x_t \end{bmatrix} = q_0 + q_d t + \sum_{l=1}^{p_{max}} Q_l \begin{bmatrix} z_{t-l} \\ y_{t-l} \\ x_{t-l} \end{bmatrix} + u_t,
$$

where

$$
\begin{aligned}
q_0 &= \begin{bmatrix} a_0 \\ a_{N0} \\ A_0 \end{bmatrix}; q_d = \begin{bmatrix} \tilde{d} \\ d_N \\ 0 \end{bmatrix}; Q_0 = \begin{bmatrix} G_{zz} & G_{zy} & 0 \\ G_{yz} & G_{yy} & 0 \\ 0 & -D_0 & \Xi \end{bmatrix} \\
Q_m &= \begin{bmatrix} F_{zz}^m & F_{zy}^m & 0 \\ F_{yz}^m & F_{yy}^m & \Phi_m \\ 0 & D_m & A_m \end{bmatrix}, \text{ for } m = 1, ..., p_{max}; \\
u_t &= \begin{bmatrix} \epsilon_t \\ e_t \\ \varepsilon_t \end{bmatrix},
\end{aligned}
$$

and where ϵ_t are the stacked residuals from the non-euro area VARX*s in (12) such that $\epsilon_t = \begin{bmatrix} e'_{1,t} & \cdots & e'_{N-1,t} \end{bmatrix}'$. We restrict the number of lags p_{max} to be four in levels and the G and F matrices are combinations of estimated parameters and the trade weights used to construct the foreign variables

$$
G = \begin{pmatrix} \Lambda_{01} w_1 \\ \Lambda_{02} w_2 \\ \vdots \\ \Lambda_{0(N-1)} w_{N-1} \\ \Lambda_{0N} w_N \end{pmatrix}, \; F^m = \begin{pmatrix} \Lambda_{m1} w_1 \\ \Lambda_{m2} w_2 \\ \vdots \\ \Lambda_{m(N-1)} w_{N-1} \\ \Lambda_{mN} w_N \end{pmatrix}, \text{ for } m = 1, ..., p_{max}.
$$

3 Data

In the empirical application, we use monthly data over the sample period June 1999 to September 2012. As regards the macroeconomic data, we include the following variables for each country i: industrial production $(ip_{i,t})$, the rate of inflation, $(\pi_{i,t} = p_{i,t} - p_{i,t-1})$, the real exchange rate $(e_{i,t} - p_{i,t})$ and, where available, real equity prices $(eq_{i,t})$, short- and long-term interest rates $(\rho^S_{i,t}, \rho^L_{i,t})$ and the oil price $(poil_t)$ for 21 countries (see Table 1).
As in Dées et al. (2007), the macroeconomic variables are defined as follows:

$$\begin{aligned} &ip_{i,t} = \ln(IP_{i,t}),\ \ p_{i,t} = \ln(CPI_{i,t}),\ \ eq_{i,t} = \ln(EQ_{i,t}/CPI_{i,t}), \\ &e_{i,t} = \ln(E_{i,t}),\ \rho^S_{i,t} = (1/12) * \ln(1 + R^S_{i,t}/100),\ \rho^L_{i,t} = (1/12) * \ln(1 + R^L_{i,t}/100), \end{aligned} \tag{13}$$

where CPI_t is the consumer price index, EQ_t is the nominal equity price index, E_t is the bilateral exchange rate against the US dollar, and R^S_t and R^L_t are the annualised short and long rate of interest, respectively. The country-specific foreign variables $(ip^*_{i,t}, \pi^*_{i,t}, eq^*_{i,t}, \rho^{*S}_{i,t}, \rho^{*L}_{i,t})$ are constructed using fixed trade weights based on the period 2005-2007 (see Table 2). The time series data for the euro area is obtained by using cross section weighted averages of each variable for Germany, France, Italy, Spain, Netherlands, Belgium, Austria and Finland, using the average Purchasing Power Parity GDP weights over the period 2005-2007.

For the financial stress indicators of firms we employ 12-month ahead default probability measures obtained from the Kamakura Corporation. Kamakura Corporation (2011) estimates the firm-specific default probabilities using a Merton-type structural model, which measures financial distress with indicators on a given firm's market leverage as well as stock price volatility. While the default probabilities (DP) are defined on the interval $[0, 1]$, we use a log-odds transformation for each firm given by

$$x_{i,t} = \ln\left(\frac{DP_{i,t}}{1 - DP_{i,t}}\right),$$

such that the log-odds ratio for firm i $(x_{i,t})$ is defined on the interval $(-\infty, \infty)$.[12]

We use default probability data for 35 euro area firms, which were chosen based on size of assets as well as data availability. As Table 3 shows, the 35 firms capture more than three quarters of all assets in the Kamakura database for financial firms in the eight countries that we use to approximate the euro area. Figure 1 presents the log-odds ratios for all 35 firms in our sample. The data imply that the default probabilities of many firms peak towards the end of 2008, which corresponds to the period following the Lehman bankruptcy. At the same time, there is sizeable heterogeneity, with some firms experiencing stronger distress during the euro area sovereign tensions in early 2012, while other firms show high stress episodes in the early 2000s. Figure 2 shows the default probabilities for the largest five financial institutions by assets, all of which are classified as globally systemically

[12] While $x_{i,t}$ is not defined for $DP_{i,t}$ equal to 0 or 1, in practice a firm always has a positive default probability, and is in default before the probability estimated by Kamakura reaches 1.

important institutions (G-SIFIs) by the Financial Stability Board, and which display a high degree of co-movement, suggesting that these large financial institutions react to a similar set of shocks.

4 Empirical results

4.1 Model specification and estimation

As detailed in Section 2, the IVAR model nests a GVAR model, similar to the one developed in Dées et al. (2007). In this paper, the global model covers 28 countries, where 8 of the 11 countries that originally joined the euro on 1 January 1999 are grouped together, and the remaining 20 countries are modelled individually (see Table 1). All models include the country-specific foreign variables, ip^*_{it}, π^*_{it}, eq^*_{it}, ρ^{*S}_{it}, ρ^{*L}_{it} and the log of oil prices $(poil_t)$, as weakly exogenous, with the exception of the US model. For the US, oil prices are included as an endogenous variable, with $e^*_{US,t} - p^*_{US,t}$, $ip^*_{US,t}$, and $\pi^*_{US,t}$ as weakly exogenous. As in Dées et al. (2007), the US-specific foreign financial variables, $eq^*_{US,t}$, $\rho^{*S}_{US,t}$ and $\rho^{*L}_{US,t}$ are not included in the US model, owing to the important role of the US in global financial markets, such that weak exogeneity assumption does not hold for these variables. For the euro area, in addition to the country-specific foreign variables, the VARX* model also includes the cross-section average $(\bar{X}_t)$ of the 35 euro area firms' default probability data as a weakly exogenous variable, thereby capturing the potential impact of financial firm distress on the macroeconomy. The firm-level IVAR model block expresses the default probability of firm j as a function of the spatial average of its country neighbours, additional neighbouring firms (if any), the cross-section average across the non-neighbouring firms, euro area industrial production and euro area equity prices . Overall, the system includes 152 endogenous variables. All variables are treated as I(1) processes, which was tested with the weighted symmetric Dickey-Fuller test, following Park and Fuller (1995).

For the non-euro area countries, the lag order of the individual VARX*(p_j, q_j) models, where p_j is the lag order of the domestic variables and q_j the lag order of the foreign variables, is selected according to the Akaike information criterion. Given the available data sample, we impose the restriction on the maximum lag to be 4 in levels. We then proceed with the cointegration analysis, where the country-specific models are estimated subject to reduced rank restrictions. Table 4 gives the lag orders and the number of cointegrating relations for the 21 countries/regions. The final specification of the global model including the selection of the number of cointegration relationships is adjusted to ensure that the system is stable and that all long-run relations have well-behaved persistence profiles, which indicates that the effects of shocks on the long run relations are only transitory (Pesaran and Shin (1996)), see Figures 3 and Figure 4.

As a key assumption underlying the estimation strategy is the weak exogeneity of the foreign variables, we follow Dées et al. (2007) and provide in Table 5 the F-test statistic for the weak exogeneity test for all foreign variables, the oil price and, in the case of the euro area model block, the cross-section average of firm-level data. The weak exogeneity assumption is rejected for only 13 out of the 124 foreign variables that are assumed to be weakly exogenous. More importantly, the weak exogeneity of foreign variables, oil prices and the cross-section average of firm-level data are not rejected in the euro area model. The same applies to the foreign variables (y^*_{US}, π^*_{US}, $e^*_{US} - p^*_{US}$) included in the US model.

In the firm-level IVAR block, we calibrate the neighbour threshold parameter as $\tau = 0.3$. Hence, if the absolute value of the pair-wise correlation of the residual for firm i with firm j in equation (2) exceeds τ, then firm j is classified as a neighbour of firm i. This identification strategy is conceptually similar to that of Bailey et al. (2013a), who also focus on the pair-wise correlations of residuals based on the cross-section augmented regressions.[13] With the given value for τ, we identify 15 firms with neighbours that range in number from 1 to 4. By inspection, most neighbours identified through the correlation matrix approach were located in the same country as firm i, which indicates that this data-driven approach is able to identify neighbours based on common characteristics. The same-country neighbours are aggregated into the spatial averages $\bar{X}^c_{i,t}$, similar to Bussière et al. (2013). In three instances, the identified neighbours are located in a different country than firm i, and these were included separately in the equation for $x_{i,t}$, see Table 7.

Table 6 presents the main results for the estimation of the firm-level IVAR block. The model is estimated in first differences and the lag orders in the firm-level model are selected by the Akaike information criterion individually for the autoregressive component, the country neighbours $\bar{X}^c_{i,t}$, the cross section averages of the non-neighbour units and the euro area macrovariables. Again, in some instances, the lag orders needed to be further constrained to ensure stability of the model. Contrary to the VARX* model block, we do not include cointegrating relationships in the firm-level model as their is no a priori theory for long-run relations among firm-level default probabilities. The results also suggest that the response of the default probabilities tends to be significantly different from zero mainly in the short run. The coefficients of $\Delta\bar{X}^o_{i,t}$ are in all cases highly significant. Their value provides evidence that the default probability of a firm is linked to financial distress in the aggregate financial sector, confirming the existence of strong cross section dependence across firms. Table 7 shows the coefficient estimates of the neighbours that are not from the same country as firm i, and these are not all significant but we follow Bailey et al. (2013a) to include all of them in the estimation, in order to distinguish between the source of cross-sectional dependence arising from common factor dependence and spatial (neighbour) dependence. The coefficients of the macroeconomic variables do not always have the expected sign, and few coefficients are statistically significant (Table 6). This result may arise due to an identification problem as the cross section average may capture effects of the observed common component as well (see also discussion in Chudik and Pesaran (2013) on the identification issue).[14] The impulse response exercise will confirm that an adverse shock to US

[13]Note that Bailey et al. (2013a) derive their threshold parameter using a methodology developed in Bailey et al. (2013b), which is set up as a multiple-testing procedure that corresponds to a given overall size of the test.

[14]To the extent that an observed common factor leads to an increase in all units $x_{i,t}$, this necessarily also leads to a

equities will have the expected sign in terms of the macrofinancial impact on the default probabilities of firms. Overall, the adjusted R^2 tends to be higher for large firms, with values up to 0.8 and tends to decline as the firm size becomes smaller, which may be due to the fact that smaller financial institutions may be driven to a greater extent by local shocks.

Finally, in Table 8 we examine the average pair-wise cross section correlations among the firms. The first and second columns confirm that there is a rather strong co-movement among the default probabilities of the firms both in terms of levels and first differences, consistent with data shown in Figure 1. Importantly, when assessing the average pair-wise correlations of the residuals, we find that the cross-section average and the euro area variables together account for most of the co-movement in the data, such that the residuals of equation (4) are only weakly correlated across firms.

4.2 Generalised Impulse Response Functions

The large-scale VAR in (1) once estimated in its reduced form, can be used for impulse response analysis. In this section we consider the impact of a negative shock to US equity prices on the default probabilities of firms of the size as observed during the Lehman collapse. Specifically, we use generalised impulse response functions (GIRFs) due to Koop et al. (1996) and Pesaran and Shin (1998). GIRFs assess a shock to a given error of the reduced-form system and integrates out the effects of the remaining shocks based on their empirical distributions without making use of orthogonalisation as in Sims (1980). The advantage of this approach is that the GIRFs are invariant to the ordering of the variables, which is an essential property when simulating very large VARs as in this application.

4.2.1 Negative shock to US equity prices

The first set of results is related to US equity prices so as to assess the international transmission of shocks. As the empirical application here is similar in spirit to macroeconomic stress tests on banks, we consider shocks of a size that correspond to tail events, which are more severe than the usual one-standard deviation shocks commonly used to demonstrate the dynamics of a model. Specifically, we calibrate the size of the shock so as to replicate a decline in financial variables that are similar in size to what has been observed during the recent financial crisis. For this purpose we simulate a shock that leads to a decline by 20% in US equity prices, which is close to the decline in stock prices observed following the Lehman bankruptcy.[15]

The 20% decline in US equity prices has a strong spillover effect on the euro area economy (see Figure 5). Consistent with the results in Dées et al. (2007), euro area equity prices decline more than their US counterparts. The shock to US equities also affects real variables, with industrial production declining significantly both in the US and in the euro area by respectively 1.8% and 3.4%

contemporaneous increase in the cross section average $\bar{X}_{i,t}$, resulting in the identification problem of whether the observed rise in $x_{i,t}$ was driven by the observed common factor or the unobserved common component proxied by $\bar{X}_{i,t}$.

[15] Lehman Brothers filed for bankruptcy on 15 September 2008. In October 2008, the S&P 500 declined by 20.4% month-on-month.

after one year. Importantly, the adverse financial shock in the US has sizeable spillover effects on euro area financial institutions. In response to the decline in equity prices, Figure 6 shows that the default probabilities (in log-odds transformation) rise by up to 1.6 for G-SIFIs (peak impact after 3-4 months). The responses are significant in all cases for about one year. When comparing this result to the actual evolution of the default probabilities of the G-SIFIs, this captures up to half of the magnitude of the rise that was actually observed during the financial crisis, which is remarkable as we only consider a single shock in this scenario.[16] Figure 10 depicts the median impact for all 35 firms in our sample, and shows that there exists a relatively large heterogeneity in terms of responses across firms, which range between 0.2 and 1.6 with an average response of 0.8 (peak impacts).

Finally, we inspect the responses of other variables in the system. In Figure 11, we see that inflation in the US declines following the negative shock to equity prices, while the short and long rates also decrease significantly. When converting the interest rate responses back to annualised rates, short term rates decline by just over 40 basis points in the US, while oil prices fall significantly by over 20%, owing to the strong global spillover effect from US equities to stock prices in other countries and reflecting the dominant position of the US in global financial markets. Strong spillover effects to commodity prices have also been observed during the crisis, with Brent crude oil prices declining by well over 50% peak-to-trough in 2008.

Figure 12 shows the spillover effects to euro area inflation, interest rates and the exchange rate. The only statistically significant response is the decline in the euro area long-term rates, which is approximately of a similar size as the decline in the US, and is consistent with its relation to the short rate, which also falls over the horizon, notwithstanding a brief minor rise in the short-run of annualised 20 basis points. As the shock scenario does not involve a rise in fiscal expenditures, the fall in euro area long-term interest rates is consistent with historical co-movements in the data.

4.2.2 Shock to the default probabilities of G-SIFIs

The second set of results is related to a shock to the default probabilities of the nine G-SIFIs by one standard deviation. On impact the (log-odd ratio) default probabilities increase by 0.1-0.2 and peak after 1-2 months (see Figure 13). In most cases, the impact is significant for 6 months and up to one year for some institutions. The purpose of this exercise is to show the spillover of this shock to the other institutions. Figures 14, 15 and 16 show that the reactions of the other institutions are quite heterogenous. Some react similarly to the G-SIFIs, both in terms of magnitude and significance (e.g., Firms 10, 11, 14, 16 and 29). Others remain unaffected by the shock, with non-significant responses (e.g., Firms 18, 23, 24, 30, 34, 35). These results support our approach to study the firm-level

[16] Note that the relationship between a change in the log-odd ratio (LOR) and expected default probabilities (DP) is state-dependent. At the end of the sample period, the average default probability is about 0.6%. At this starting level, the change in the LOR and the DP is approximately 1 for 1, such that a rise by 1.6 in the LOR corresponds to a rise in the expected default probability of about 1.6 percentage points. Again, this is close to half the rise of what was observed during the peak of the financial crisis for the largest firms in our sample.

reponses in a disaggregated manner rather than modelling median responses like in Castrén et al. (2010) or Chen et al. (2010). Finally, although our framework allows for two-way feedback between financial and macroeconomic variables, the impact of the shock to the default probabilities of G-SIFIs on equities of industrial production remains non-significant. Although this result could be seen as surprising, it is worth pointing out first that in reality shocks to the default probabilities of financial institutions are accompanied by changes in equity markets or confidence shocks to consumers and firms, so that more complex scenarios combining various shocks should be designed to fully capture all non-modelled reactions. Moreover, some of the spillover channels may not be present in our model, such as spillovers via non-financial corporations and key non-euro area firms. However, our approach can easily accommodate these additional spillover channels by extending the system accordingly. We leave such extensions for future research.

5 Concluding Remarks

The macroprudential approach to financial supervision requires tools that provide quantitative assessments of the links between financial systems and the real economy, while accounting for spillovers and heterogeneity at the firm level. This paper shows that the IVAR modelling approach offers a way to capture the complex interactions between heterogenous agents. As the framework incorporates a large set of non-domestic macrovariables, it also accounts for the linkages between the firms and the global economy. This modelling approach therefore provides a flexible framework that could be further developed as a high-dimensional macro stress-testing tool. For such purposes, macroprudential policy instruments should be incorporated into the model. Also, a more detailed modelling of the various components of banks' balance sheet and profit and loss components is required. As the IVAR can accommodate a large set of time series, such additional explanatory variables could easily be introduced.

The results in this paper show that an adverse shock to equity prices in the US has an adverse impact on the default probabilities of euro area financial firms that is not only statistically significant but also of an economically significant magnitude when considering recent historical episodes such as the financial crisis. Moreover, the results show that the model can capture significant spillover between financial firms, which is an essential property for such a macroprudential tool. Finally, the evidence points to the existence of sizeable heterogeneity among the responses across firms, which motivates the use of firm-level data, rather than using aggregate banking sector-level indicators.

Further research could deepen the understanding of the role of aggregation in such a model. One extension of the present analysis could relate to a comparison of the responses of aggregated sectors to macroeconomic shocks under two different estimation strategies; namely estimation based on firm-level information as in the present paper and that is aggregated ex-post, and an estimation at the sectoral level, where the firm-level data is aggregated ex-ante. Such a comparative analysis could illustrate the value added of the IVAR approach that accounts for both two-way feedback as well as potential heterogeneity among financial firms in macro stress testing models. Another avenue for future research pertains to the spillover between the financial and non-financial sector, where the firm-level block could be expanded to include non-financial firms. This extension could be used to model the extent to which distress in the financial sector spills over into other productive sectors of the economy.

References

Alfaro, R., and Drehmann, M. (2009) "Macro stress test and crises: what can we learn?" *BIS Quarterly Review* December 2009.

Bailey, N., Holly, S., and Pesaran, M.H. (2013a) "A two-stage approach to spatiotemporal analysis with strong and weak cross-sectional dependence." *Cambridge Working Papers in Economics* No.1362.

Bailey, N., Pesaran, M.H., and Smith, L.V. (2013b) "A multiple testing approach to the regularisation of sample correlation matrices." unpublished manuscript.

Bussière, M., Chudik, A., and Mehl, A. (2013) "How have global shocks impacted the real effective exchange rates of individual euro area countries since the euro's creation?" *B.E. Journal of Macroeconomics* 13, 1-48.

Chen, Q., Gray, D., N'Diaye, P., Oura, H., and Tamirisa, N. (2010) "International transmission of bank and corporate distress" *IMF Working Paper* No. 10/124.

Castrén, O., Dées, S., and Zaher, F. (2010) "Stress-testing euro area corporate default probabilities using a global macroeconomic model" *Journal of Financial Stabilityl* 6, 64-78.

Chudik, A. and Pesaran, M.H. (2014) "Theory and practice of GVAR modeling" *Federal Reserve Bank of Dallas Working Paper* 180.

Chudik, A. and Pesaran, M.H. (2013) "Econometric analysis of high dimensional VARs featuring a dominant unit" *Econometrics Review* 6, 592-649.

Chudik, A. and Pesaran, M.H. (2011) "Infinite dimensional VARs and factor models" *Journal of Econometrics* 163, 4-22.

Chudik, A., Pesaran, M.H., and Tosetti, E. (2011) "Weak and strong cross-section dependence and estimation of large panels" *The Econometrics Journal* 14 (1), C45-C90.

De Bandt, O., and Hartmann, P. (2000) "Systemic risk: a survey" *ECB Working Paper* No. 35.

Dées, S., di Mauro, F., Pesaran, M.H., and Smith, L.V. (2007) "Exploring the international linkages of the Euro Area: a Global VAR analysis" *Journal of Applied Econometrics* 22, 1-38.

di Mauro, F., and Pesaran, M.H. (2013) "The GVAR handbook: structure and applications of a macro model of the global economy for policy analysis" Oxford University Press.

Drehmann, M. (2009) "Macroeconomic stress testing banks: a survey of methodologies" in Qualgliariello, M. (ed.) "Stress Testing the Banking System: Methodologies and Applications" Cambridge University Press.

European Central Bank (2012) “Report on the first two years of the macro-prudential research network’, ECB, October.

European Central Bank (2009) “The concept of systemic risk” *Financial Stability Review* Chapter IV.B, December.

Eickmeier, S. and Ng, T. (2011) “How do credit supply shocks propagate internationally? A GVAR approach” *CEPR Discussion Paper* No. 8720.

Foglia, A. (2009) “Stress testing credit risk: a survey of authorities approaches” *International Journal of Central Banking* 5, 9-45.

Financial Stability Board (2013a) “2013 update of group of global systemically important banks (G-SIBs)”, *http://www.financialstabilityboard.org/publications/r_131111.pdf*, 11 November 2013.

Financial Stability Board (2013b) “Global systemically important insurers (G-SIIs) and the policy measures that will apply to them”, *http://www.financialstabilityboard.org/publications/r_130718.pdf*, 18 July 2013.

Gray, D., Gross, M., Paredes, J. and Sydow, M. (2013) “Modeling banking, sovereign, and macro risk in a CCA global VAR” *IMF Working Paper* No. 13/218.

Gross, M. and Kok, C. (2013) “Measuring contagion potential among sovereigns and banks using a mixed-cross-section GVAR” *ECB Working Paper* No. 1570.

Henry, J. and Kok, C. (eds.) (2013) “A macro stress testing framework for assessing systemic risks in the banking sector” *ECB Occasional Paper* No. 152.

Kamakura Corporation (2011) “Kamakura Public Firm Models: Version 5, April.”

Koop, G. Pesaran, M.H. and Potter, S.M.. (1996) “Impulse response analysis in nonlinear multivariate models” *Journal of Econometrics* 74, 119-147.

Park, H.J. and Fuller, W.A.. (1995) “Alternative estimators and unit root tests for the autoregressive process” *Journal of Time Series Analysis* 16, 415-429.

Pesaran, M.H. (2006) “Estimation and inference in large heterogeneous panels with a multifactor error structure” *Econometrica* 74(4), 967-1012.

Pesaran, M.H., Schuermann, T., and Weiner, S.M. (2004) “Modeling regional interdependencies using a global error-correcting macroeconometric model” *Journal of Business and Economic Statistics* 22, 129-162.

Pesaran, M.H., and Shin, Y. (1998) “Generalised impulse response analysis in linear multivariate models” *Economics Letters* 58, 17-29.

Pesaran, M.H., and Shin, Y. (1996) "Cointegration and speed of convergence to equilibrium" *Journal of Econometrics* 71, 117-143.

Pesaran, M.H., Shin, Y., and Smith, R.J. (2000) "Structural analysis of vector error correction models with exogenous I(1) variables" *Journal of Econometrics* 97, 293-343.

Sims, C. (1980) "Macroeconomics and reality" *Econometrica* 48, 1-48.

6 Appendix

USA	**Euro Area**	**Rest of Asia**
China	Germany	Korea
Japan	France	Indonesia
UK	Italy	Philippines
	Spain	Malaysia
Latin America	Netherlands	Singapore
Brazil	Belgium	
Mexico	Austria	
	Finland	
Other developed economies	**Rest of Western Europe**	**Rest of the world**
Canada	Sweden	India
Australia	Switzerland	South Africa
New Zealand	Norway	Turkey

Table 1: Countries and regions in the IVAR model.

Country	usa	austlia	bra	can	china	india	indns	japan	kor	mal	mex	nzld	nor	phlp	sing	safrc	swe	switz	turk	uk	euro
USA	0	0.1372	0.2821	0.7567	0.2297	0.1811	0.1184	0.2661	0.1921	0.1921	0.7572	0.1497	0.0724	0.2398	0.1625	0.1320	0.0894	0.1075	0.0957	0.1593	0.2013
Australia	0.0120	0	0.0083	0.0043	0.0323	0.0438	0.0431	0.0468	0.0358	0.0321	0.0025	0.2565	0.0022	0.0172	0.0346	0.0277	0.0098	0.0062	0.0059	0.0123	0.0141
Brazil	0.0205	0.0059	0	0.0052	0.0202	0.0164	0.0090	0.0100	0.0131	0.0053	0.0133	0.0032	0.0067	0.0048	0.0047	0.0190	0.0075	0.0091	0.0081	0.0077	0.0248
Canada	0.2365	0.0146	0.0224	0	0.0223	0.0165	0.0109	0.0233	0.0165	0.0083	0.0300	0.0186	0.0372	0.0102	0.0058	0.0159	0.0096	0.0108	0.0084	0.0219	0.0189
China	0.1330	0.1585	0.1200	0.0474	0	0.1368	0.1057	0.2196	0.2457	0.1113	0.0401	0.1007	0.0317	0.1100	0.1183	0.1029	0.0354	0.0244	0.0701	0.0460	0.1093
India	0.0136	0.0322	0.0187	0.0040	0.0234	0	0.0350	0.0095	0.0184	0.0256	0.0036	0.0093	0.0035	0.0074	0.0316	0.0319	0.0082	0.0073	0.0139	0.0146	0.0207
Indonesia	0.0082	0.0306	0.0088	0.0024	0.0184	0.0306	0	0.0379	0.0317	0.0381	0.0018	0.0219	0.0013	0.0207	0.0896	0.0080	0.0034	0.0019	0.0080	0.0040	0.0091
Japan	0.0997	0.1816	0.0592	0.0326	0.1950	0.0497	0.2098	0	0.1793	0.1520	0.0304	0.1230	0.0211	0.2091	0.1077	0.1045	0.0258	0.0348	0.0267	0.0337	0.0610
Korea	0.0363	0.0670	0.0337	0.0111	0.1153	0.0432	0.0762	0.0844	0	0.0515	0.0214	0.0389	0.0124	0.0636	0.0558	0.0278	0.0091	0.0071	0.0252	0.0128	0.0254
Malaysia	0.0204	0.0356	0.0107	0.0043	0.0330	0.0348	0.0559	0.0376	0.0290	0	0.0087	0.0294	0.0023	0.0545	0.1895	0.0129	0.0045	0.0030	0.0076	0.0082	0.0132
Mexico	0.1448	0.0058	0.0359	0.0251	0.0098	0.0084	0.0033	0.0119	0.0141	0.0051	0	0.0097	0.0013	0.0033	0.0049	0.0032	0.0047	0.0046	0.0029	0.0038	0.0152
New Zealand	0.0026	0.0554	0.0007	0.0012	0.0031	0.0023	0.0053	0.0057	0.0039	0.0049	0.0009	0	0.0004	0.0050	0.0045	0.0024	0.0011	0.0010	0.0006	0.0027	0.0026
Norway	0.0044	0.0016	0.0064	0.0088	0.0033	0.0031	0.0010	0.0033	0.0044	0.0010	0.0005	0.0016	0	0.0007	0.0027	0.0025	0.1134	0.0040	0.0064	0.0359	0.0351
Philippines	0.0094	0.0072	0.0040	0.0019	0.0178	0.0039	0.0126	0.0222	0.0160	0.0227	0.0027	0.0114	0.0006	0	0.0290	0.0017	0.0011	0.0012	0.0013	0.0030	0.0053
Singapore	0.0194	0.0524	0.0115	0.0025	0.0348	0.0645	0.1647	0.0339	0.0400	0.1996	0.0049	0.0316	0.0065	0.1020	0	0.0118	0.0047	0.0087	0.0043	0.0140	0.0163
South Africa	0.0051	0.0117	0.0110	0.0016	0.0090	0.0192	0.0048	0.0103	0.0061	0.0044	0.0003	0.0054	0.0017	0.0016	0.0031	0	0.0056	0.0063	0.0131	0.0149	0.0164
Sweden	0.0079	0.0099	0.0120	0.0034	0.0069	0.0102	0.0051	0.0054	0.0044	0.0043	0.0025	0.0070	0.1190	0.0025	0.0032	0.0132	0	0.0116	0.0186	0.0258	0.0594
Switzerland	0.0131	0.0088	0.0182	0.0040	0.0066	0.0259	0.0039	0.0099	0.0055	0.0072	0.0036	0.0062	0.0083	0.0040	0.0097	0.0216	0.0141	0	0.0397	0.0229	0.0916
Turkey	0.0048	0.0029	0.0050	0.0014	0.0066	0.0089	0.0065	0.0027	0.0065	0.0032	0.0007	0.0021	0.0056	0.0011	0.0017	0.0097	0.0106	0.0130	0	0.0143	0.0378
UK	0.0467	0.0529	0.0336	0.0262	0.0287	0.0624	0.0180	0.0280	0.0226	0.0234	0.0069	0.0465	0.2085	0.0194	0.0301	0.1037	0.0995	0.0555	0.0874	0	0.2226
Euro Area	0.1616	0.1279	0.2978	0.0557	0.1838	0.2382	0.1107	0.1316	0.1149	0.1079	0.0682	0.1274	0.4571	0.1230	0.1111	0.3475	0.5423	0.6818	0.5560	0.5422	0

Table 2: Country weights (fixed weights based on the period 2005-2007).

Firm	Country	Cumulated Assets (%)	G-SIFI
1	DEU	10.23	**x**
2	FRA	19.56	**x**
3	ESP	25.65	**x**
4	FRA	31.64	**x**
5	NLD	37.48	**x**
6	ITA	42.13	**x**
7	FRA	45.62	**x**
8	DEU	48.86	**x**
9	DEU	52.08	
10	ITA	55.29	
11	ESP	58.31	
12	FRA	61.01	
13	ITA	63.16	**x**
14	NLD	64.89	
15	FRA	66.49	
16	BEL	67.78	
17	DEU	69.02	
18	FRA	70.14	
19	ITA	71.22	
20	AUT	72.26	
21	ESP	73.02	
22	DEU	73.58	
23	ESP	74.07	
24	ITA	74.46	
25	ITA	74.85	
26	ITA	75.14	
27	ESP	75.42	
28	ESP	75.69	
29	DEU	75.95	
30	ITA	76.20	
31	ITA	76.43	
32	FIN	76.65	
33	AUT	76.85	
34	ITA	77.04	
35	ITA	77.23	

Table 3: Summary of the financial institutions included in the IVAR model. The table presents for each firm the country of origin, the cumulative assets as a share of all euro area financial sector (as approximated by eight countries) assets contained in the Kamakura database. The final columns indicates whether the institution has been classified as a globally systemically important financial institution (G-SIFI) by the Financial Stability Board (2013a) and the Financial Stability Board (2013b).

Country	VARX*(p,q)	# of coint.relations
USA	(2,1)	2
Australia	(4,3)	3
Brazil	(2,1)	2
Canada	(2,2)	2
China	(3,1)	2
India	(2,1)	3
Indonesia	(3,1)	2
Japan	(2,1)	3
Korea	(4,1)	3
Malaysia	(3,1)	3
Mexico	(1,1)	1
New Zealand	(4,1)	2
Norway	(2,1)	4
Philippines	(2,1)	4
Singapore	(2,1)	2
South Africa	(1,1)	4
Sweden	(2,1)	3
Switzerland	(4,2)	1
Turkey	(3,1)	2
United Kingdom	(1,1)	3
Euro Area	(2,1)	3

Table 4: Country data description. The country-specific VARX* lag structure refers to the lag order in levels, with p being the lag for country-specific domestic variables and q the lag of country-specific foreign variables. We impose the restriction on the maximum lag to be 4 in levels. The last column refers to the number of cointegrating relations imposed by applying the cointegration trace statistics using the 95% critical value, some of which were set manually in order for the persistence profiles of the cointegrating relations to converge to zero over a 10 year horizon.

Country	F-test CV	ips	Dps	eqs	eps	rs	lrs	poil	firm CSA
USA	3.062	1.683	0.662		0.910				
Australia	2.720	1.082	0.083	1.461		0.602	2.500	0.349	
Brazil	3.063	3.247	5.614	1.716		0.148	0.836	1.870	
Canada	3.067	0.706	2.166	5.045		0.938	0.887	1.332	
China	3.068	0.665	0.038	0.582		2.045	1.063	0.917	
India	2.672	0.439	0.763	1.445		0.424	1.219	0.077	
Indonesia	3.068	0.571	7.859	3.037		0.070	2.068	0.109	
Japan	2.673	1.818	0.191	1.118		1.663	0.527	0.860	
Korea	2.698	0.354	5.126	1.351		1.192	0.588	0.436	
Malaysia	2.677	1.236	3.703	1.796		0.221	3.735	0.123	
Mexico	3.908	0.024	0.018	0.002		0.059	0.057	1.352	
New Zealand	3.089	2.300	2.356	1.407		0.267	0.329	0.508	
Norway	2.440	3.070	3.233	1.774		0.697	0.346	0.295	
Philippines	2.439	4.381	2.156	0.518		0.263	1.335	0.959	
Singapore	3.063	1.284	1.839	0.928		2.092	2.280	0.108	
South Africa	2.437	1.488	1.276	0.836		2.177	2.145	0.827	
Sweden	2.673	1.238	0.306	3.279		0.100	1.403	1.519	
Switzerland	3.943	0.249	7.876	0.078		0.009	0.037	0.454	
Turkey	3.068	0.172	2.151	0.355		2.417	0.571	0.215	
United Kingdom	2.670	0.577	2.754	0.730		0.815	0.992	0.185	
Euro Area	2.673	0.830	2.201	0.791		0.537	1.422	1.186	0.099

Table 5: Test for weak exogeneity at the 5% significance level. The table displays the F test specification with the critical value at a 5% significance level. The F test statistic is derived for all weakly exogenous (foreign) variables for all countries in the IVAR model. The number of F test statistics above the critical value represent 10.5% (i.e. 13 out of 124) of all variables tested.

Firm	Δ $\mathbf{x}_{t-1}$	Δ $\bar{X}^c_{t-1}$	Δ $\mathbf{CSA}_t$	Δ $\mathbf{ip}_t$	Δ $\mathbf{eq}_t$	($\mathbf{p}$,$\mathbf{q}_o$,$\mathbf{p}_n$,$\mathbf{q}_y$)	adj. $\mathbf{R}^2$
1	0.2095**		1.0968***	-1.2162	-0.7195*	(2,3,0,0)	0.66
2	0.2374***	0.4220***	1.1228***	-1.1611	0.0570	(2,3,1,1)	0.71
3	0.4242***		1.0369***	-0.0184	-0.5559**	(2,1,0,0)	0.78
4	0.2047**	0.2889**	1.1484***	1.8116*	-0.3472	(2,3,1,1)	0.77
5	-0.0651	0.3344***	1.4627***	-0.9074	-1.2594***	(2,3,1,3)	0.80
6	0.0109	0.4031***	1.2516***	3.2473***	-0.2209	(2,3,3,0)	0.76
7	-0.0466	0.1762	1.0968***	1.6605	-1.1155**	(2,3,2,3)	0.72
8	0.1724**		0.9996***	0.1673	-0.2560	(2,3,0,0)	0.55
9	0.3052***	0.1646	1.1056***	-0.8406	-1.0252***	(2,3,3,2)	0.77
10	0.2165***		1.0369***	1.1183	-0.3391	(2,3,0,1)	0.66
11	0.1644*	0.1571	1.0065***	-0.5007	-0.5601*	(2,0,1,1)	0.72
12	0.1489*		1.1651***	-0.1140	1.1300*	(2,3,0,0)	0.33
13	0.2058**		0.9087***	-0.5918	-0.0422	(2,3,0,0)	0.72
14	0.2723***		1.1208***	-0.0470	-1.0973**	(2,3,0,2)	0.69
15	0.0906	0.0400	0.4997***	-0.1910	0.2087	(2,0,3,0)	0.29
16	0.3496***		1.4802***	0.4081	0.5992	(2,3,0,3)	0.69
17	0.0925	0.0677	0.9693***	-1.8838	-0.8003**	(2,3,3,2)	0.69
18	0.0406	0.2143	0.4424***	-2.5168*	0.0068	(2,3,3,0)	0.26
19	0.2670***	0.4885***	0.7810***	1.9802*	0.4431	(2,3,1,0)	0.51
20	0.0465		0.9191***	-0.7388	0.1909	(2,3,0,2)	0.65
21	-0.1244	0.3942***	0.8049***	0.2695	0.0121	(2,3,1,0)	0.52
22	0.1342		0.5725***	1.3020	-1.2674***	(2,3,0,2)	0.49
23	0.3375***		0.3759***	-0.2336	0.0838	(2,0,0,0)	0.21
24	0.1518*	0.6146***	0.7104***	-0.6897	0.0864	(2,2,1,1)	0.26
25	0.0532		0.8541***	-0.4089	0.5842	(2,3,0,0)	0.29
26	0.0319		0.5412***	0.8954	-0.3022	(2,0,0,1)	0.28
27	0.2406***		0.8764***	-3.2902**	0.3200	(2,3,0,3)	0.48
28	-0.0192	0.4693***	0.9402***	-2.3117	0.1175	(2,1,3,3)	0.52
29	0.1494*		1.2113***	0.0877	-0.4854	(2,3,0,3)	0.61
30	0.1231		0.8888***	0.2236	0.3003	(2,3,0,1)	0.32
31	0.1368*		0.6102***	2.7059**	0.2776	(2,0,0,0)	0.42
32	-0.0455		0.7922***	0.7765	-0.1833	(2,3,0,0)	0.32
33	0.2667***		0.5476***	-0.6644	0.3072	(2,0,0,3)	0.28
34	0.0880		0.2785**	0.8557	-0.9329	(2,0,0,0)	0.08
35	-0.0128	0.7297***	0.4791***	2.0382	-1.1302**	(2,1,3,0)	0.25

Table 6: Parameter estimates for the firm-level block. The table also provides information on the lag specification (with p being the firm-specific lag of own lags, q_o of the cross section average, p_n of the neighbours imposed and q_y the lag of firm-specific euro area macrovariables. We impose the restriction on the maximum lag to be 4 in levels.) and adjusted R^2 for each firm. * indicates a 10% significance level, ** 5% significance level, and *** 1% significance level.

Firm/Neighbour	Firm 5	Firm 7	Firm 9	Firm 14
Firm 5		-0.0718		
Firm 7	-0.0447		0.3024***	0.2033*
Firm 9		-0.1597*		

Table 7: Coefficient estimates of the first lag for additional neighbours not incorporated in the country neighbour cross section average that exceed the threshold of 30% correlation for each firm in the firm-level block. * indicates a 10% significance level, ** 5% significance level, and *** 1% significance level.

	Levels	First diff.	Residuals
1	0.74	0.58	-0.03
2	0.77	0.58	-0.01
3	0.73	0.62	-0.01
4	0.77	0.61	-0.01
5	0.73	0.63	-0.02
6	0.77	0.62	-0.00
7	0.71	0.60	-0.01
8	0.71	0.51	-0.03
9	0.60	0.59	-0.02
10	0.74	0.58	-0.00
11	0.74	0.61	-0.00
12	0.58	0.40	-0.04
13	0.70	0.59	-0.01
14	0.69	0.58	-0.01
15	0.61	0.40	-0.03
16	0.73	0.56	-0.03
17	0.51	0.56	-0.02
18	0.44	0.34	-0.03
19	0.68	0.47	-0.01
20	0.70	0.55	-0.03
21	0.73	0.53	-0.01
22	0.50	0.49	-0.02
23	0.64	0.29	-0.03
24	0.56	0.32	-0.03
25	0.65	0.44	-0.01
26	0.61	0.43	-0.00
27	0.63	0.48	-0.02
28	0.64	0.51	-0.02
29	0.58	0.56	-0.01
30	0.67	0.44	-0.02
31	0.66	0.47	-0.03
32	0.68	0.41	-0.04
33	0.50	0.35	-0.04
34	0.49	0.24	-0.03
35	0.65	0.37	-0.02

Table 8: Average pairwise correlation of firms.

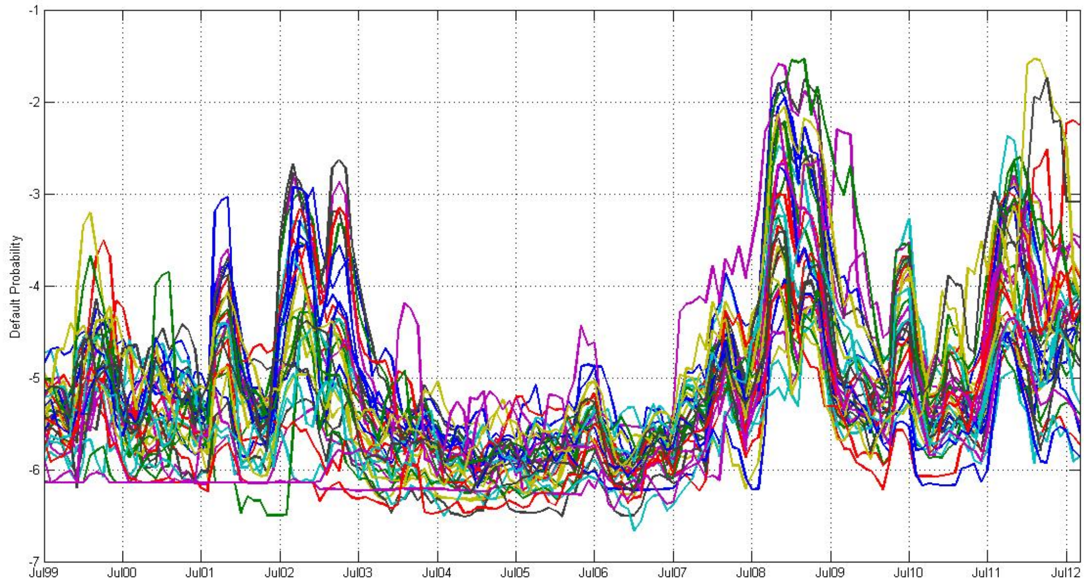

Figure 1: Default probabilities (in log-odd ratio transformation) for all 35 firms in the sample.

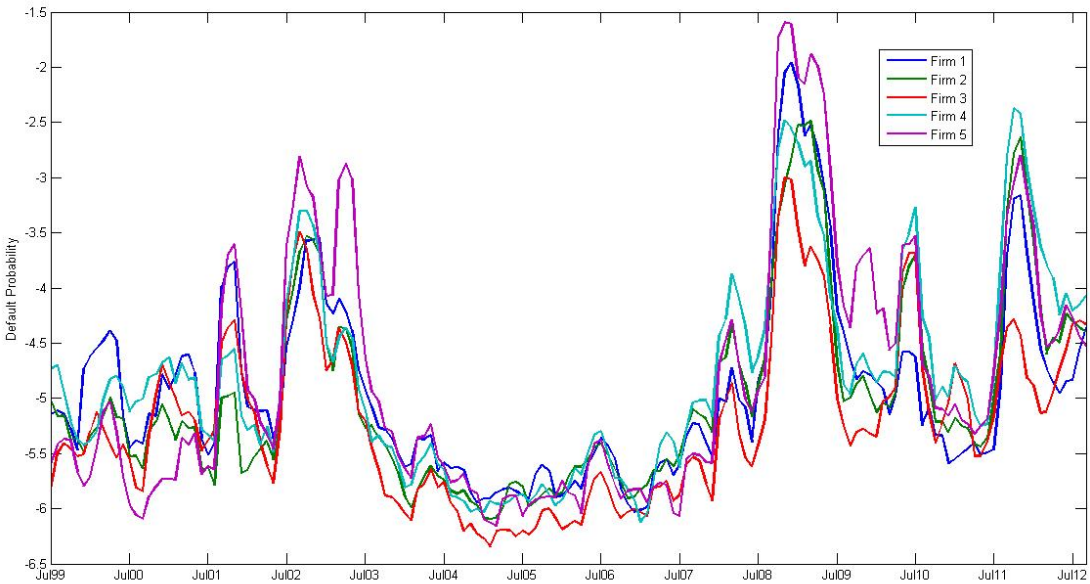

Figure 2: Default probabilities (in log-odd ratio transformation) for the largest five firms by assets.

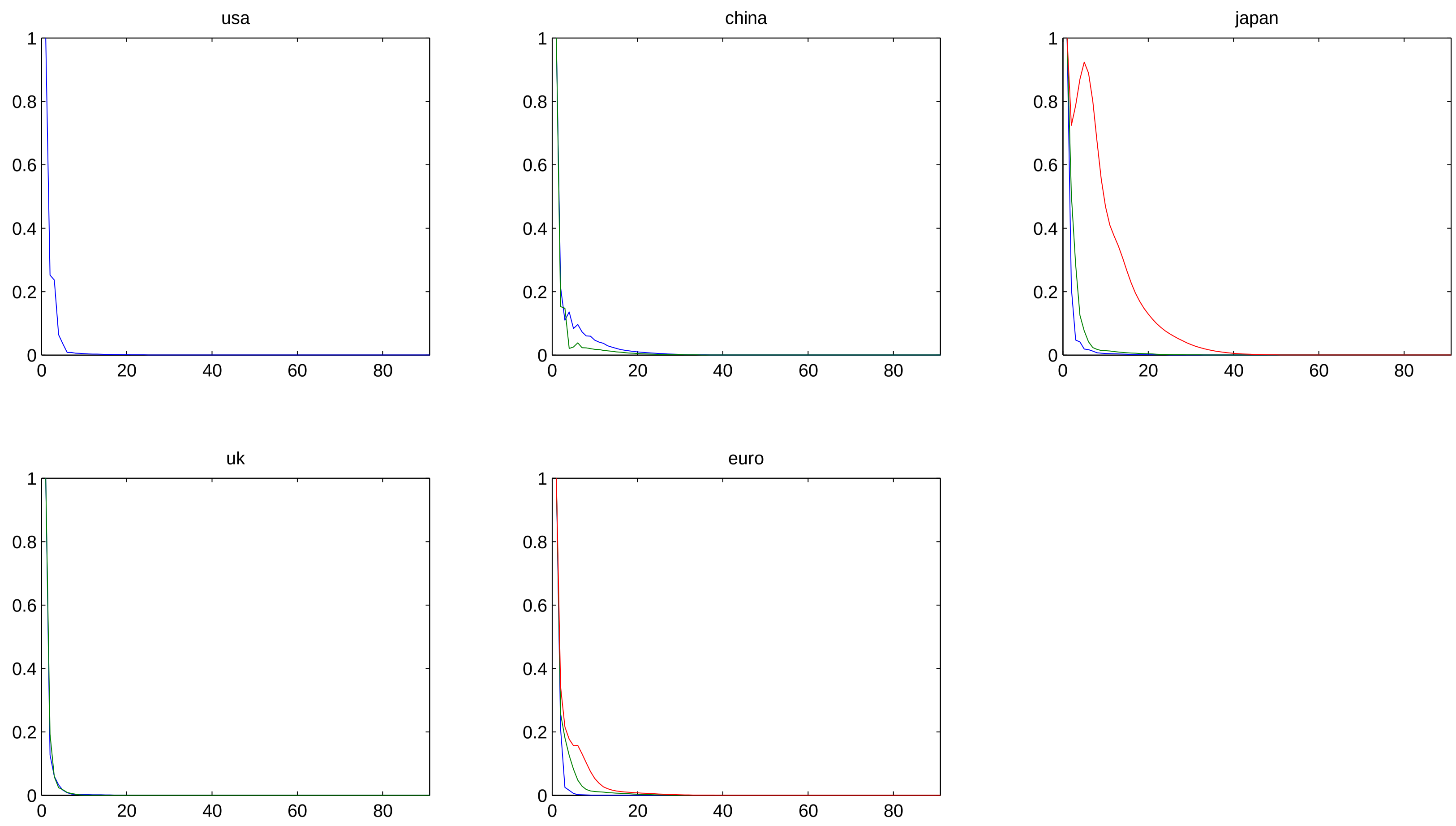

Figure 3: Persistence profiles for the USA, China, Japan, UK and the Euro Area.

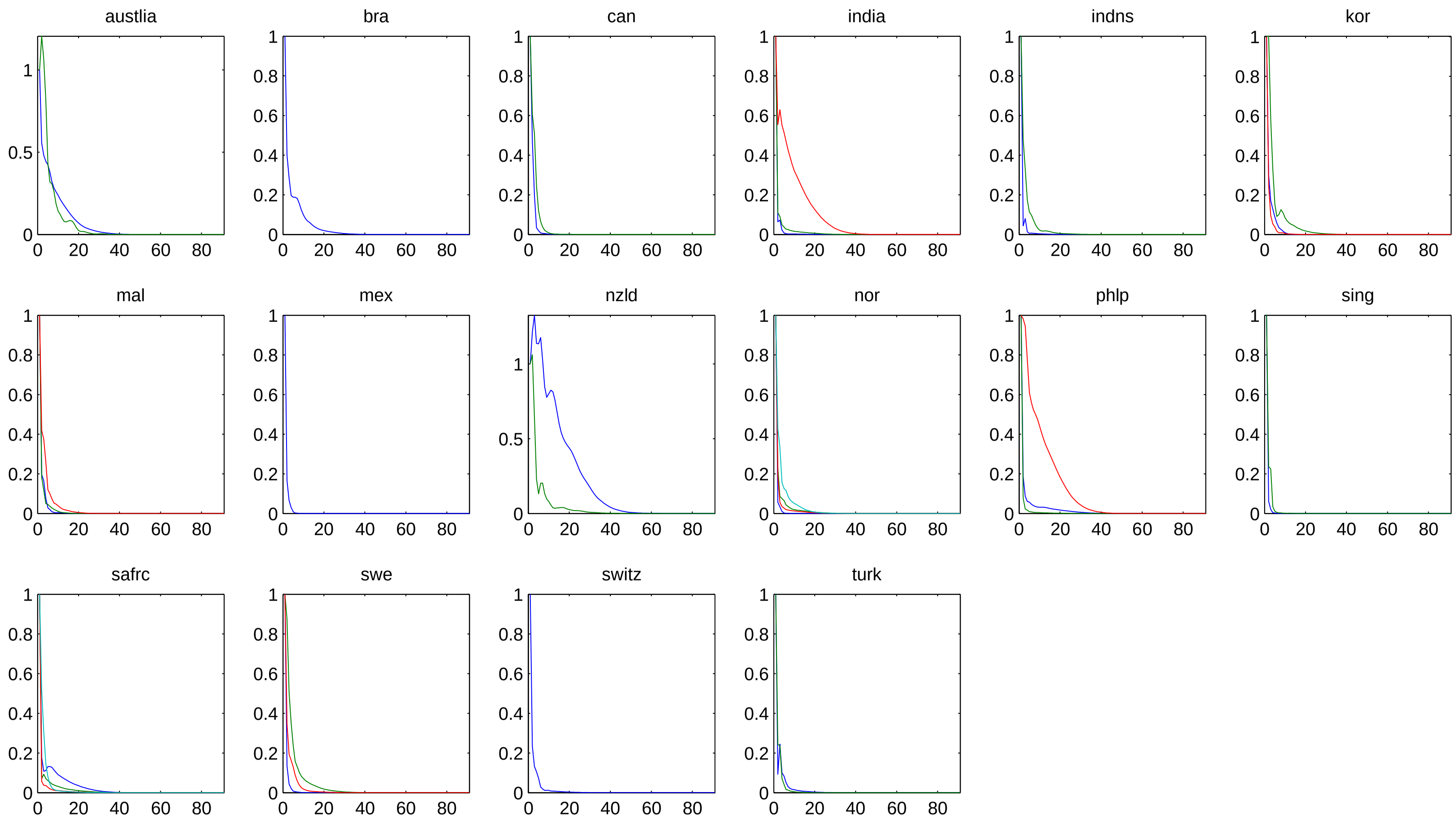

Figure 4: Persistence profiles for the remaining countries in the sample.

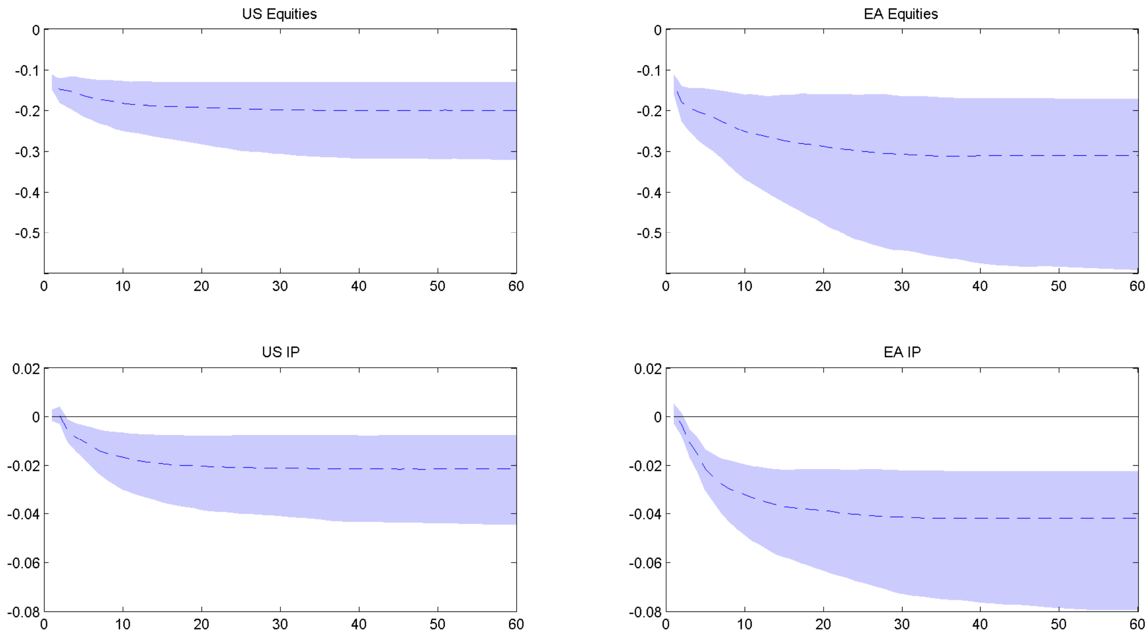

Figure 5: Negative US equity shock. Bootstrap median estimates with 90% confidence bands of the US and EA equity prices and industrial production.

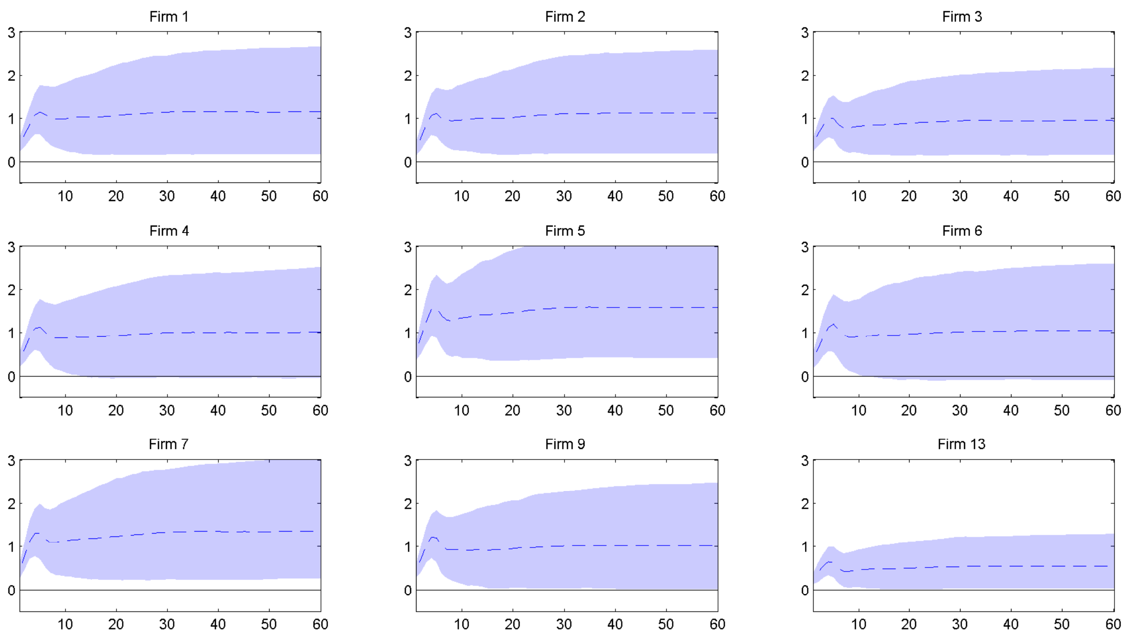

Figure 6: Negative US equity shock. Bootstrap median estimates with 90% confidence bands of the G-SIFIs in the sample.

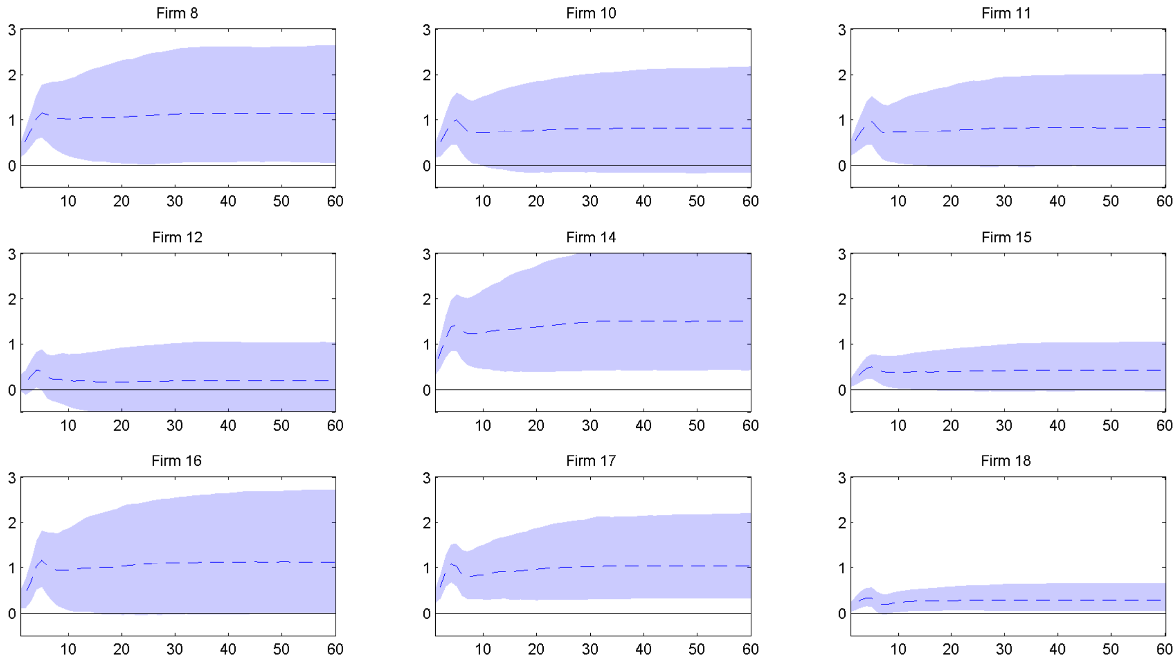

Figure 7: Negative US equity shock. Bootstrap median estimates with 90% confidence bands.

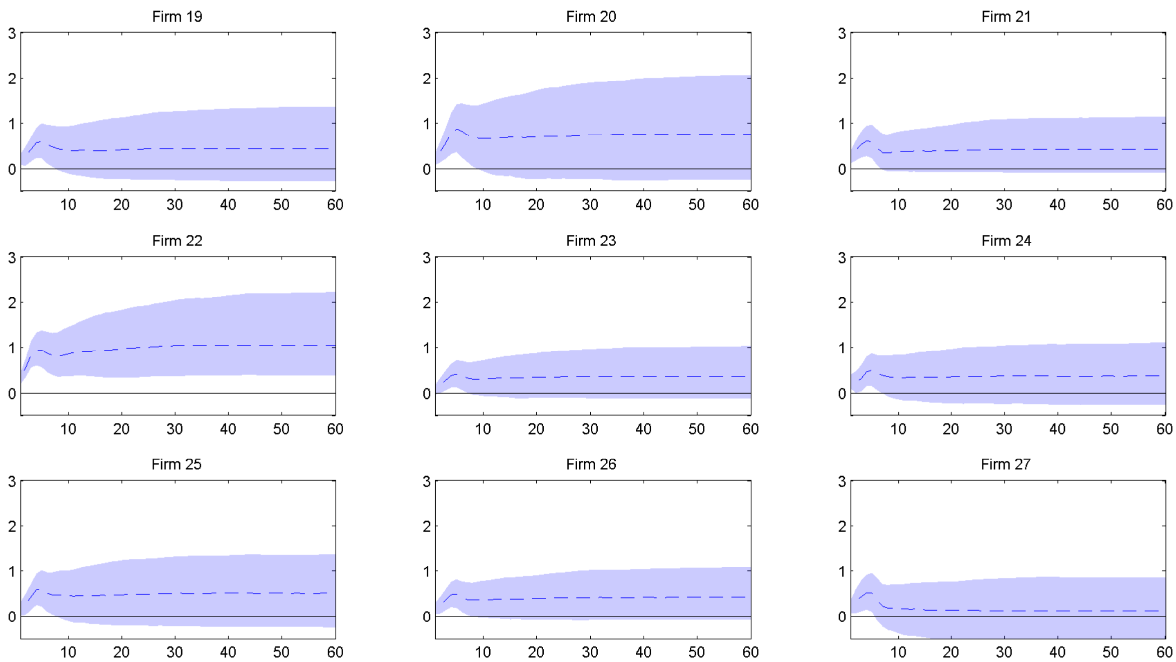

Figure 8: Negative US equity shock. Bootstrap median estimates with 90% confidence bands.

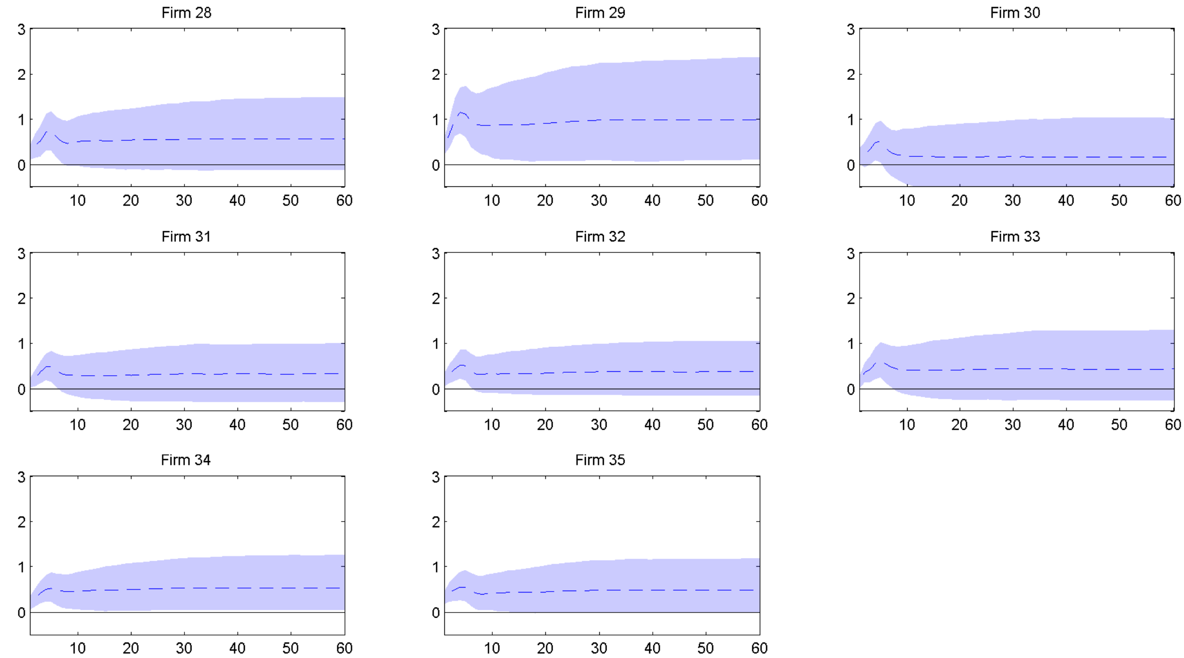

Figure 9: Negative US equity shock. Bootstrap median estimates with 90% confidence bands.

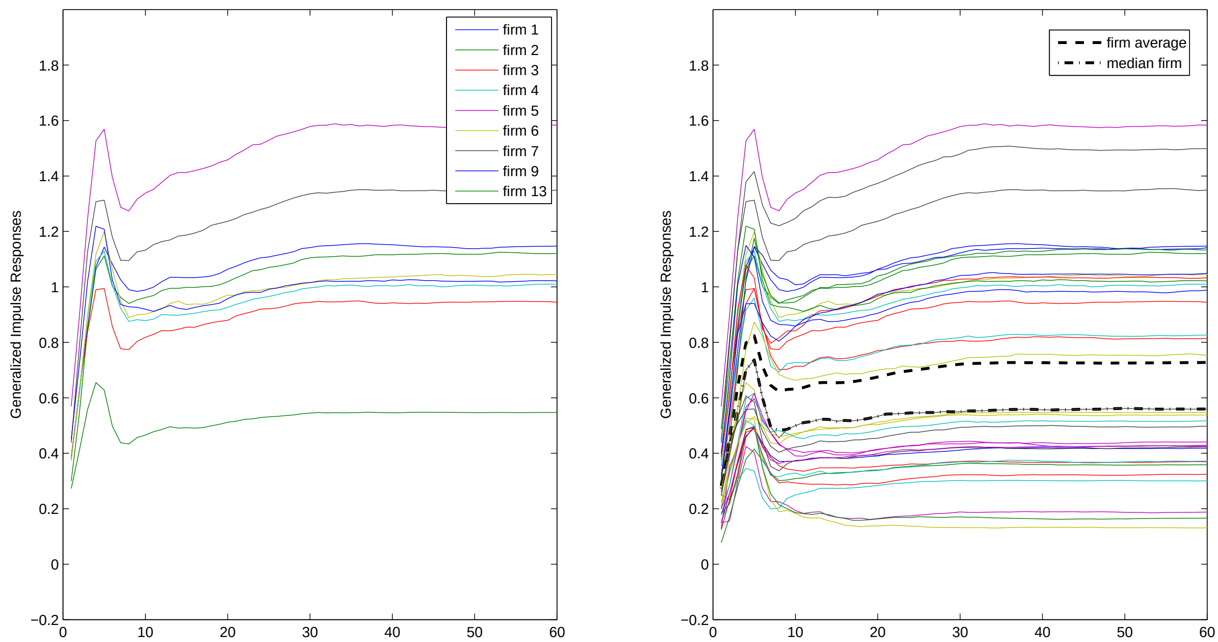

Figure 10: Negative US equity shock. Bootstrap median estimates of the G-SIFIs in the sample and of all firms along with the firm average and median firm responses.

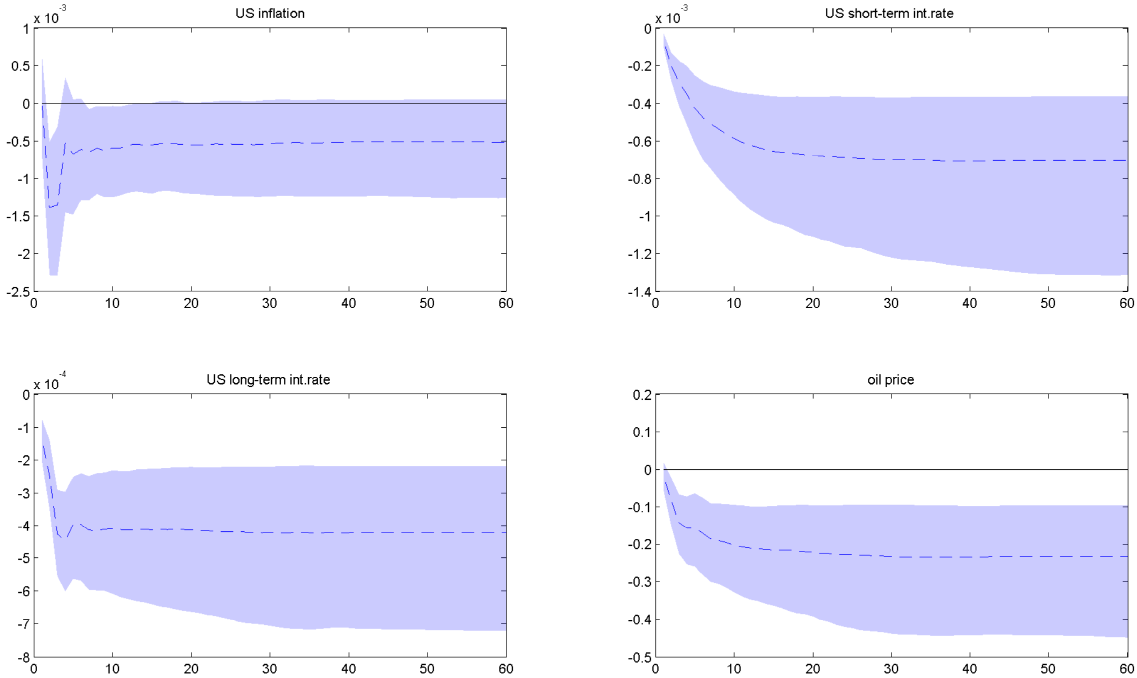

Figure 11: Negative US equity shock. Bootstrap median estimates with 90% confidence bands of the US inflation, short- and long-term interest rate and the oil price.

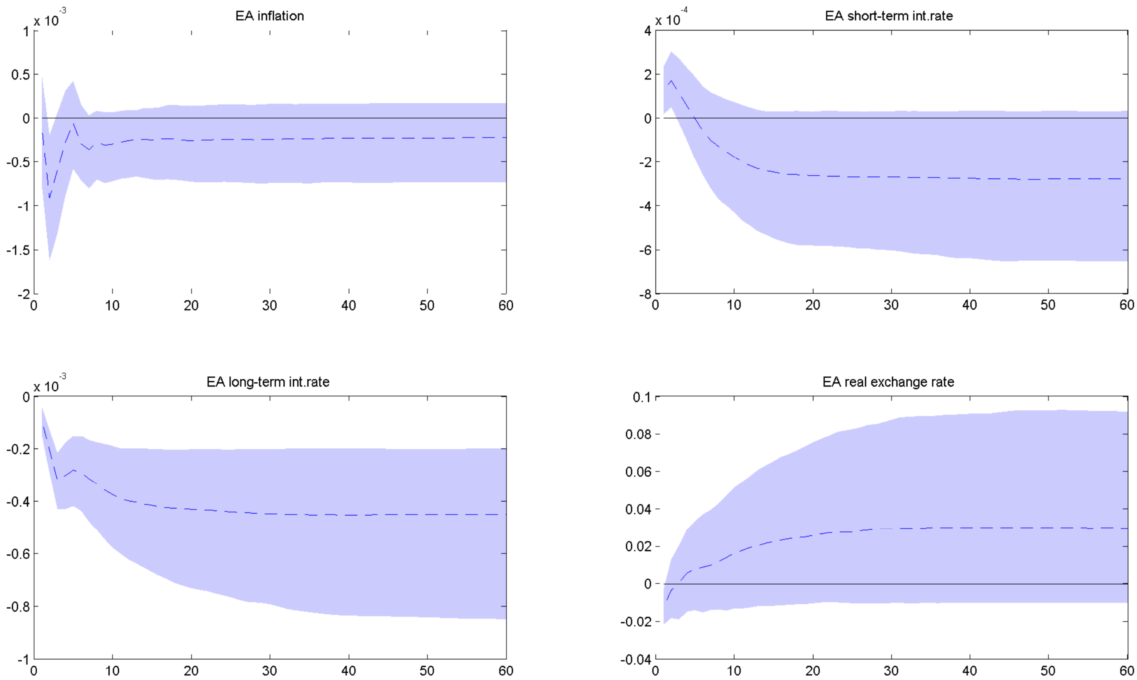

Figure 12: Negative US equity shock. Bootstrap median estimates with 90% confidence bands of the EA inflation, short- and long-term interest rate and the real exchange rate.

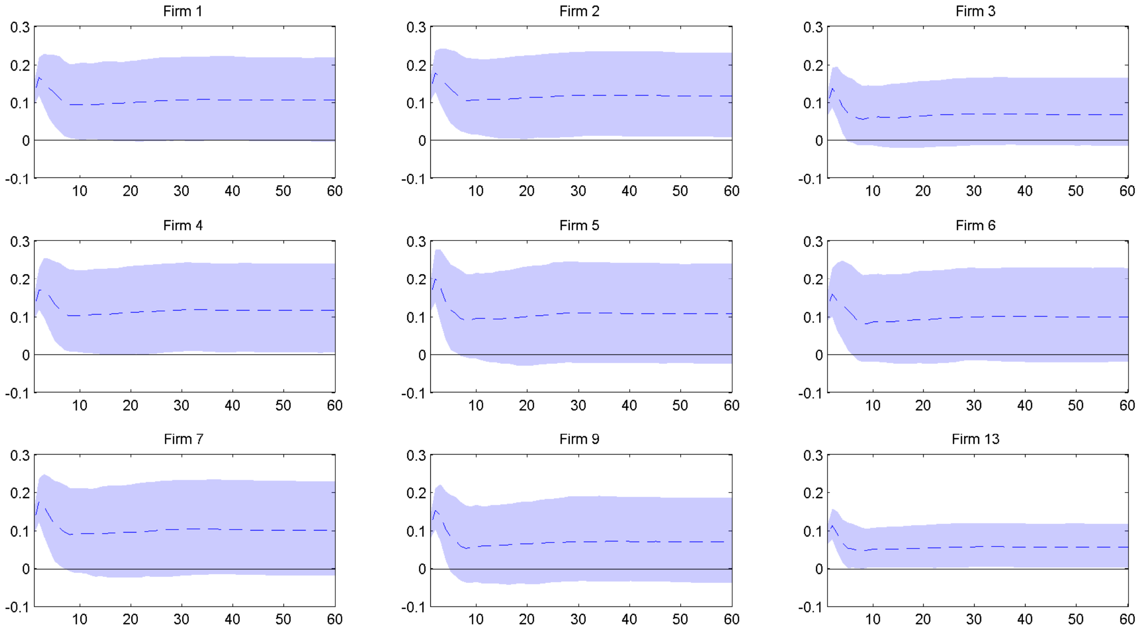

Figure 13: Positive shock to DP (log odd ratio) of G-SIFIs. Bootstrap median estimates with 90% confidence bands of the G-SIFIs in the sample.

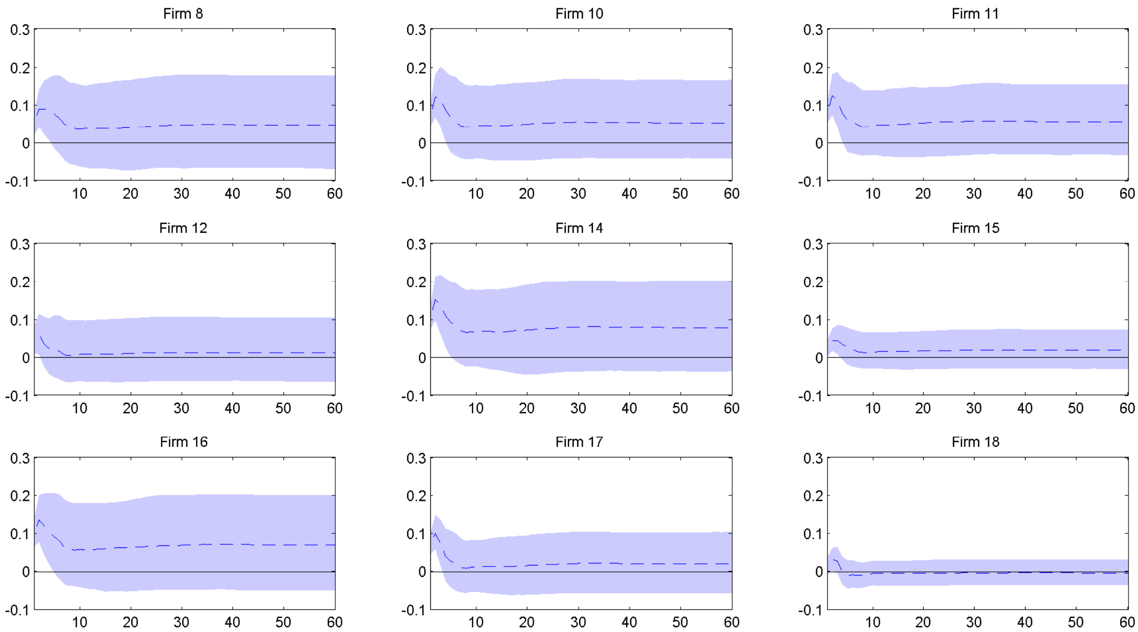

Figure 14: Positive shock to DP (log odd ratio) of G-SIFIs. Bootstrap median estimates with 90% confidence bands.

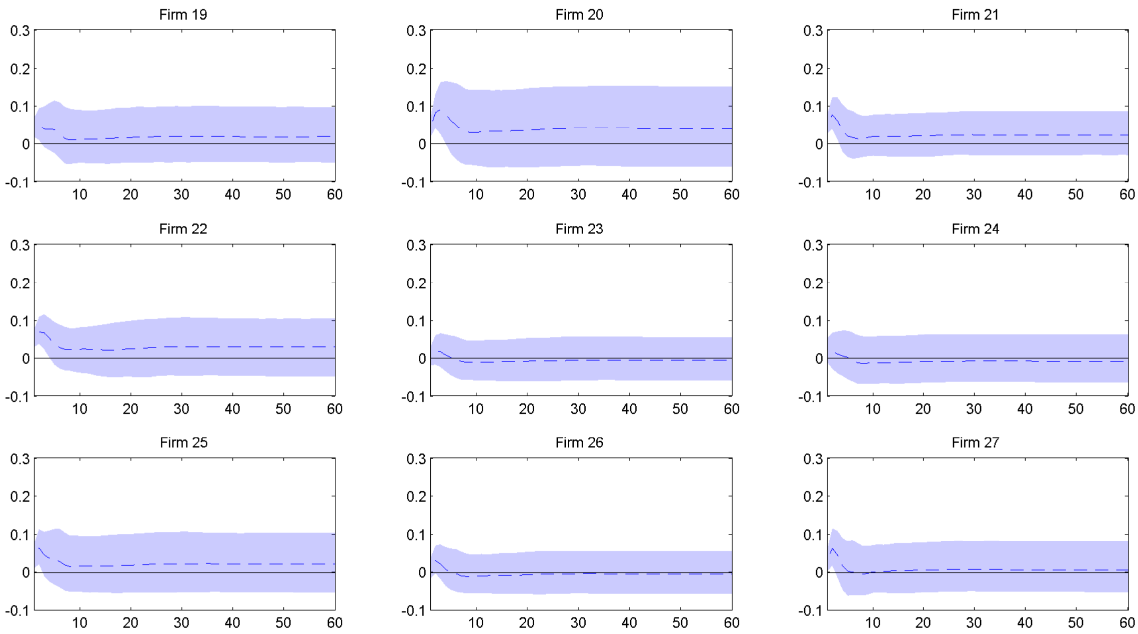

Figure 15: Positive shock to DP (log odd ratio) of G-SIFIs. Bootstrap median estimates with 90% confidence bands.

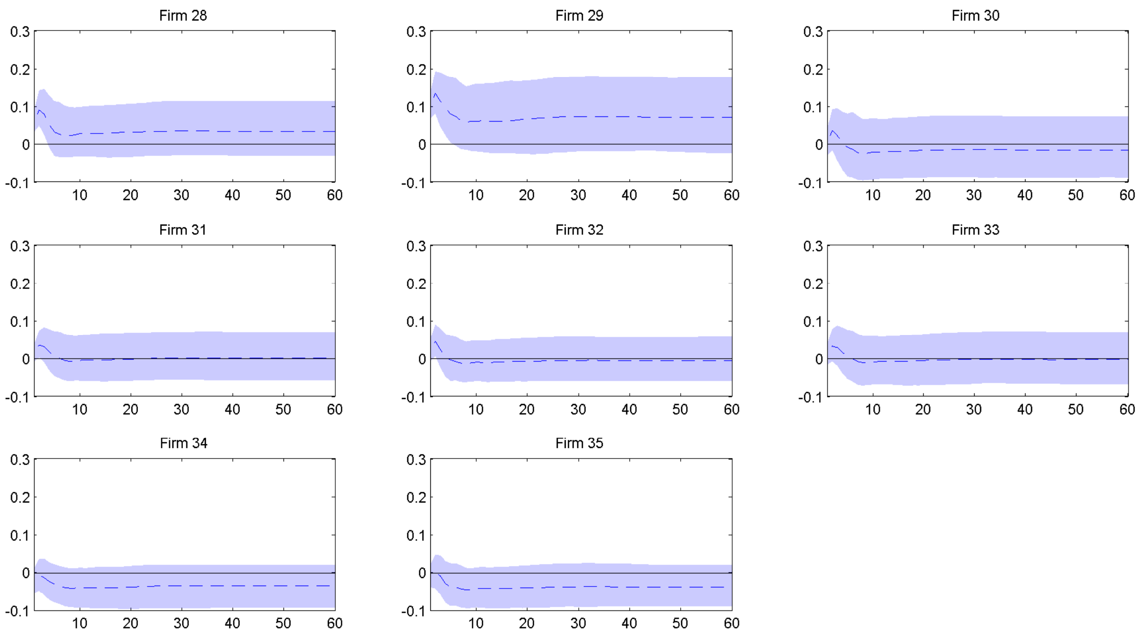

Figure 16: Positive shock to DP (log odd ratio) of G-SIFIs. Bootstrap median estimates with 90% confidence bands.