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The impact of bank capital on economic activity - Evidence from a Mixed-Cross-Section GVAR model

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Abstract

We develop a Mixed-Cross-Section Global Vector Autoregressive (MCS-GVAR) model for the 28 EU economies and a sample of individual banking groups to study the propagation of bank capital shocks to the economy. We conduct various simulations with the model to assess how capital ratio shocks influence bank credit supply and aggregate demand. We distinguish between *contractionary* and *expansionary* deleveraging scenarios and confirm the intuitive result that only when banks choose to achieve higher capital ratios by shrinking their balance sheets would economic activity be at risk to contract. The model can be used to establish ranges of impact estimates for capital-related macroprudential policy measures, including counter-cyclical capital buffers, systemic risk buffers, G-SIB buffers, etc., also with a view to assessing the cross-country spillover effects of such policy measures. We highlight the importance for macroprudential policy makers to give clear guidance to banks as to how certain macroprudential policy measures should be implemented — depending on what measure is considered, during which phase in the business cycle, and for what particular purpose.

Keywords: Macro-financial linkages, bank leverage, aggregate demand and supply, Basel III and capital regulation, macroprudential policy

JEL classification: C33, E51, E58

Non-technical summary

In this paper we explore how bank leverage via its impact on bank credit supply conditions influences business cycle dynamics both at the domestic level and across borders in the EU. We develop a Mixed-Cross-Section Global Vector Autoregressive (MCS-GVAR) model to examine how shocks to bank leverage — due for example to higher capital requirements — can propagate to the real economy, within and across borders. We estimate two versions of the model: one using individual bank balance sheet variables and the other using banking sector aggregates for the EU countries. Both model specifications offer valuable insights into the endogenous macro-financial linkages across the EU countries and banking systems. To our knowledge it is the first GVAR application that involves individual banks' balance sheet data.

The model can provide insights into the economic implications of macroprudential policy measures which are aimed at steering bank capital buffer requirements, such as the counter-cyclical capital buffer. We illustrate that the model is well-suited to simulate for instance the short-term cost in terms of lost output (under certain assumptions as to how banks react) and benefits in terms of lower bank distress arising due to higher capital buffer requirements. Importantly, the model setup allows for directly assessing also the cross-border spillover effects of such macroprudential policies.

At the bank-level we model loan volume growth, loan interest and deposit rates, capital ratios, and the banks' probability of default. At the country-level we model GDP, inflation, property price inflation, and long-term interest rates. The central bank cross-section contains short-term policy rates. In the MCS-GVAR model framework, channels of transmission are established between all these variables, both within and across cross-sections. It is a well-suited tool for assessing the multi-way linkages between the macroeconomic, financial, and central bank sphere, while accounting for cross-border spillover effects.

Concerning the simulations that we conduct with the model we distinguish between three types of behaviour of banks in response to higher required capital ratios. The first of two *polar cases* assumes that banks approach a higher capital ratio by reducing the size of their balance sheet while not raising capital (contractionary deleveraging). The opposite polar case assumes that banks raise equity capital or build up capital in a gradual manner by retaining earnings, to invest the additional funds in new assets (expansionary deleveraging). Along with the two polar cases, an unconstrained capital ratio shock scenario is meant to reveal how banks have been moving toward higher capital ratios on average historically. Depending on how the shocks are designed, the impact on aggregate demand is different. From a modelling perspective, the constrained leverage shocks are implemented by means of a sign restriction method.

The simulation results are intuitive in that they suggest that deleveraging shocks to individual banks tend to induce significant downward pressure on real activity if banks shrink the size of their balance sheet, i.e. reduce credit supply. If they delever by raising capital while not compressing the size of their balance sheets, economic activity is shown to expand in many countries. Under the unconstrained deleveraging shock mode, results are mixed (as expected), i.e. credit growth partly intensifies, partly falls, and in the sequel is either boosting or compressing GDP growth to some extent, while on average it is clearly downward skewed across banking systems and countries.

By distinguishing explicitly between contractionary and expansionary deleveraging we aim to raise the awareness that it matters how banks go about moving to higher capital ratios and that macropru-

dential policy makers ought to take into account and give concrete guidance depending on the context, i.e. on prevailing macroeconomic conditions and the purpose of the instrument. When imposing macroprudential capital buffer requirements during times of weak economic activity, a capital shortfall that banks may face should be filled rather by raising capital and not by further shrinking banks' balance sheet size. Compressing asset growth would imply the risk of dragging economic activity further as a result of falling bank credit supply and thus render recessions deeper. During times of expansion, on the other hand, shrinking the asset side rather than raising equity might be desired for achieving the macroprudential objective of dampening the financial cycle (e.g. using a countercyclical capital buffer).

1 Introduction

In this paper we explore how bank leverage via its impact on credit supply influences business cycle dynamics both at the domestic level and across borders in the EU. Using a Mixed-Cross-Section Global Vector Autoregressive (MCS-GVAR) approach we examine how shocks to bank leverage can propagate to the real economy within and across borders. We estimate two versions of the model: one using individual bank balance sheet variables and the other using banking sector aggregates. Both model specifications offer valuable insights into the endogenous macro-financial linkages across the EU countries and banking systems. In addition to providing diagnostics of how bank leverage fluctuations propagate to the economy, the model can provide valuable insights into the economic implications of macroprudential policy measures which are aimed at tightening or loosening bank capital requirements, such as the counter-cyclical capital buffer. We illustrate that the model is well suited to simulate for instance the cost in terms of lost output and benefits in terms of lower bank distress arising due to higher capital buffer requirements. Importantly, the model setup allows for directly assessing also the cross-border spillover effects of such macroprudential policies.

Credit cycles are a common feature of financial systems and tend to positively correlate with the business cycle, reflecting fluctuations in borrowers' demand for, and need of, financing; see Borio et al. (2001) and Brunnermeier and Shin (2009).[1] Cycles in credit developments and thereby implicitly in financial sector leverage (typically measured by asset-to-equity ratios) are exacerbated by the inherent pro-cyclical behaviour of financial intermediaries.[2] Experience from past financial crises indicates that the depth and length of crises tend to be stronger when they were preceded by credit booms (Reinhart and Rogoff (2009), Laeven and Valencia (2012)). This insight has led financial regulators around the world to consider counter-cyclical policy measures to help alleviate financial cycle fluctuations (Drehmann et al. (2011).

Our paper is related to the wealth of studies looking into the amplifying role of banks on macroeconomic fluctuations via their pro-cyclical provision of credit. A number of papers highlight the importance of credit constraints and highly leveraged banks for the amplitude of business cycle fluctuations. Bernanke and Gertler (1989) show how the financial accelerator effects can amplify the business cycle (via borrower net worth). As borrowers' net worth is typically pro-cyclical (because its underlying determinants, cash flows and collateral values, tend to be pro-cyclical) the external finance premium is counter-cyclical; a mechanism referred to as the financial accelerator.[3] Kiyotaki and Moore (1997) show that small shocks can be amplified due to credit constraints and give rise to substantial output fluctuations. Carlstrom and Fuerst (1997) demonstrated how the existence of asymmetric information between borrowers and lenders give rise to agency costs in the credit market that can amplify and alter business cycle fluctuations.

[1] See also Hiebert et al. (2014) for a recent analysis of the co-movements of financial and business cycles in the euro area.

[2] See Kiyotaki and Moore (1997), Bernanke et al. (1999), Allen and Gale (2004), Rajan (2005), Geanakoplos (2009), Adrian and Shin (2010), Schularick and Taylor (2012) and Claessens et al. (2012).

[3] See e.g. Stiglitz and Weiss (1981), Bernanke and Gertler (1995), Holmstrom and Tirole (1997) and Bernanke et al. (1999).

Also the net worth of the lender itself is likely to exert impact on the decision as to provide loans to finance firms and households. By way of their impact on bank balance sheets, valuations and overall bank profitability, business cycle fluctuations affect banks' capital position, thus inducing banks to adjust loan supply to meet targeted leverage and capital ratios, as well as regulatory capital requirements. The market for bank equity is imperfect in the sense that imperfect information, especially when financing conditions are more restrictive, makes it difficult, or costly, for banks to raise new equity.[4] Therefore, the macro-financial linkages via the credit market will depend on the liquidity and capital position of banks.[5] Diamond and Rajan (2000) show how the banks' capital structure decisions affect the provision of credit. They show that higher required capital creates a trade-off between lower liquidity creation and more resilient banks.[6]

At the same time, too low capitalisation levels may also be costly. Shleifer and Vishny (2010) present a model of unstable and leveraged banks operating in financial markets to explain the cyclical behaviour of credit and investment.[7] It has also been argued that higher capital induces banks to better screen borrowers (Coval and Thakor (2005)) and to more efficiently monitor them (Holmstrom and Tirole (1997), Mehran and Thakor (2011)). Moreover, building on Miller (1995) and the Modigliani-Miller capital structure irrelevance theorem, Admati et al. (2011) and Admati and Hellwig (2013) call for significantly higher capital ratios than those currently imposed on the banking sector. They suggest that the social costs related to such higher capital requirements would be negligible also in light of the resulting lower default probability for individual banks and the much safer financial system as a whole.[8]

Our study is also related to the literature on banks' capital buffer management.[9] Adrian and Shin (2010) show that banks tend to operate with a target leverage ratio. When deviating from their target due to an unforeseen shock, they can adjust their balance sheet in several ways to return to that target, e.g. by raising equity and/or adjusting the asset side. Such active balance sheet management can be achieved gradually and the speed may differ across different types of banks.[10]

A wide range of empirical bank-level studies documents the importance of bank capital on bank lending and real economic activity; see e.g. Hancock and Wilcox (1993), Hancock and Wilcox (1994), Berger and Udell (1994), Peek and Rosengren (1995), Kashyap and Stein (2000) and Peek et al. (2003) for some early US-based studies. Moreover, Bernanke and Lown (1991) using US State-level regressions document an important role for bank capital on loan supply during the late 1980s and early 1990s

[4]See Myers and Majluf (1984) and more specifically for the case of banks Van den Heuvel (2002), Bolton and Freixas (2006) and Kishan and Opiela (2006).

[5]See e.g. Bernanke and Lown (1991), Peek and Rosengren (1995), Kashyap and Stein (2000), Van den Heuvel (2002), Gambacorta and Mistrulli (2004), Kishan and Opiela (2006) and Den Haan et al. (2007).

[6]The role of banks as producers of liquidity is discussed extensively in the literature; for a few other seminal references see Gorton and Pennacchi (1990), Holmstrom and Tirole (1998) and Diamond and Rajan (2001). Van den Heuvel (2008) incorporates liquidity creating banks in a standard general equilibrium framework to analyse the welfare costs of higher capital requirements.

[7]See also related papers including fire sale effects related to forced deleveraging when banks need to restore solvency (and liquidity) positions when hit by adverse shocks, such as, Fostel and Geanakoplos (2008), Shleifer and Vishny (2011), Diamond and Rajan (2011) and Greenwood et al. (2012).

[8]See, however, DeAngelo and Stulz (2013) and Calomiris (2013) for a critique that refutes the relevance of the Modigliani-Miller theorem in the case of liquidity producing banks. Thakor (2014) on the other hand provides some empirical evidence in support of substantially higher capital levels in the banking system.

[9]For studies providing evidence that banks hold excess capital above regulatory minima, see e.g. Estrella (2004), Barth et al. (2006), Flannery and Rangan (2008), Zhu (2008), Acharya et al. (2011) and Repullo and Suarez (2013).

[10]Notably, Hancock and Wilcox (1993, 1994) first estimate banks' target capital ratio and secondly how they respond to deviations from those targets. Similar empirical approaches have been employed for European banks by Francis and Osborne (2009), Memmel and Raupach (2010) and Kok and Schepens (2013).

during the credit crunch in the US. More recent studies using bank-level data provide evidence of a strong role of capital for the supply of credit; see for instance Gambacorta and Mistrulli (2004) for a sample of Italian banks, Labonne and Lame (2014) for a sample of French banks, and two studies using UK bank samples; namely, Aiyar et al. (2014) and Bridges et al. (2014). The importance of bank loan supply effects on borrowers' access to bank financing has also been highlighted by studies using matched bank-firm data, such as Jimenez et al. (2010), Jimenez et al. (2014) and Amiti and Weinstein (2014).

These findings notwithstanding, other mainly US-based studies assign a much lower importance of bank capital on lending and economic activity. For instance, Aschcraft (2006) finds a very small elasticity of aggregate output to bank lending across US state banking markets. Also Berrospide and Edge (2010) argue that banks' capital position played only a minor role in the credit contraction observed during the 2007-9 financial crisis in the US, which the authors argue was mostly driven by demand-side effects. The authors thereby cast doubt on the assertion (by for example Adrian and Shin (2010)) that banks actively manage their assets on the basis of their capital positions. Pure bank-level analyses of the effects of bank capital on credit provision, however, suffer from the deficiency of not capturing well the feedback effects between banks' credit standards and the economy.[11]

Our study is also related to the recent strand of macroeconomic modelling in the context of dynamic stochastic general equilibrium (DSGE) models that explicitly analyse the financial accelerator mechanism operating via the feedback between (capital-constrained) banks and the economy. Some recent DSGE models with capital-constrained banking sectors include Dib (2010), Gerali et al. (2010), Christiano et al. (2010), Meh and Moran (2010), Darracq Paries et al. (2011), Gertler et al. (2011), Angeloni and Faia (2013), Hirakata et al. (2013), Benes et al. (2014) and Nikolov et al. (2015).

On the empirical side, there is a significant number of VAR-based studies that examine the relationship between bank credit variables and real output. Among the more recent ones, Lown and Morgan (2006) employ a VAR model to reveal the impact of change sin bank credit standards on business loans and output. Berrospide and Edge (2010) replicate the VAR approach of Lown and Morgan (2006) with a different sample (mainly large US banks) and find notably smaller effects of bank capital on loan growth and output. In contrast, applying a panel VAR approach, Ciccarelli et al. (2010), using information about the capital-related factors driving changes in banks' credit standards from the euro area Bank Lending Survey (BLS) and the US Senior Loan Officer's Survey (SLOS), provide evidence of substantial loan supply-driven amplification effects on the business cycle. See also Bassett et al. (2014) for a related study using US bank-level SLOS data to identify loan supply effects and demonstrate their importance for macroeconomic fluctuations using a standard VAR framework.[12] Similar findings are provided by other recent structural (S)VAR-based studies such as Peersman (2012) and Darracq Paries et al. (2014a).[13] In a recent study using a structural VAR approach based on UK supervisory data, Meeks (2015) provides evidence that increases in capital requirements lower lending to firms and households, reduce aggregate expenditure and raise credit spreads.[14]

Empirical analyses of macro-financial linkages have also recently been explored using factor-augmented

[11]See e.g. Hancock et al. (1995).

[12]Cappiello et al. (2010) and Hempell and Kok (2010) using country panel approaches have also provided evidence that capital constraints induced euro area banks to tighten credit standards during the financial crisis, while in a similar fashion Blaes (2011) and Del Giovane et al. (2011) use individual bank BLS data for Germany and Italy, respectively.

[13]In a methodological paper, Mumtaz et al. (2015) examine the ability of different SVAR approaches to identify credit supply shocks.

[14]See also Iacoviello and Minetti (2008), Musso et al. (2011) and Walentin (2014) for similar econometric approaches. The focus of these studies is, however, specific to the role of mortgage loan markets on real economic fluctuations.

VAR (FAVAR) models, along the lines of Bernanke et al. (2005) whereby a standard macroeconomic VAR model is extended with a set of factors summarising bank-level information. By combining macroeconomic variables with bank-level data, our paper is closely related to Buch et al. (2014) who, using a FAVAR approach, explore the impact on banks from macroeconomic shocks and document a role for capitalisation in the way banks respond to macroeconomic shocks. Jimborean and Mesonnier (2010) and Dave et al. (2013) use a similar micro-macro FAVAR framework to study the importance of the bank lending channel of monetary policy transmission. In a related study, Mesonnier and Stevanovic (2012) use US bank-level data to identify capital-related loan supply shocks and include those in a Factor-augmented Autoregressive Distributed Lag (FADL) model to assess their economic impact.

Our paper employs the Global VAR (GVAR) model structure as a basis. A useful entry point to the GVAR literature is a recent survey paper by Chudik and Pesaran (2014) who summarise all methodological and empirical developments in the field over the past decade. The initial methodological contributions by Pesaran et al. (2004), Pesaran and Smith (2006) and Dees et al. (2007) were followed by a meanwhile significant number of empirical applications. Recent examples include e.g. Galesi and Sgherri (2009), Chen et al. (2010), Chudik and Fratzscher (2011), Bussiere et al., Binder and Gross (2013), and Gray et al. (2013). Al-Hashimi et al. (2014) have developed an infinite-dimensional vector autoregressive (IVAR) model framework and include individual banks' probabilities of default (PD) for 35 financial institutions and link them to macroeconomic variables. The same Merton-model type PDs were included in the GVAR in Gray et al. (2013) and are also involved in the model that we present here. We use the Mixed-Cross-Section variant of the GVAR that was first developed by Gross and Kok (2013). It allows combining different cross-section types; e.g. countries with banks or banking systems, central banks, etc. While the application presented in Gross and Kok (2013) was focused on market price measures of risk for individual banks and sovereigns, we now combine individual bank balance sheet data in the bank cross-section with macroeconomic variables in the country and policy rates in the central bank cross-section. To the best of our knowledge it is the first GVAR application that involves individual bank balance sheet data. Related to our work is a paper by Eickmeier and Ng (2011) who develop a GVAR model for the assessment of how credit supply shocks propagate across countries. There are some differences to our GVAR setup that we shall highlight. First, Eickmeier and Ng (2011) use domestic credit as an endogenous model variable while acknowledging that they are unable to capture direct cross-border lending (p.8). We use aggregated credit as a basis instead which covers also direct cross-border lending.[15] Second, while Eickmeier and Ng (2011) employ variable-specific weights, such as BIS loan exposures, the way these weights are used is not ideal in our view. For example, it is not clear why domestic credit, which to a certain fraction is provided from some banks headquartered in another country, should be susceptible to changes to macro conditions in that other country (other than via the trade channel). This point relates to the Mixed-Cross-Section (MCS) feature of our model which is not only useful for individual bank model applications but also for banking system models. The MCS structure implies that weights are allowed to be *equation*-specific, not only variable-specific. A relevant example to highlight that point is to consider the aggregate loan growth variable. With the MCS feature, economic activity variables on the right hand-side of the loan growth equations are

[15] In the banking sector aggregated version of the model we do not yet capture the foreign operations via subsidiaries and branches (as we use the ECB's BSI statistics, i.e. a locational concept of monetary financial institutions). We compared the exposure profile (weights) based on the BSI statistics with the weights using consolidated banking data and they are broadly aligned. However, to fully capture the cross-border lending activity, the aggregated version of the model will need to be further extended and use the consolidated MFI groups, whereby individual MFIs are associated with their parents. This is work in progress. In the individual bank version of the model that we present we use publicly available consolidated banking data, which cover also the banks' foreign activities via branches and subsidiaries.

weighed based on banks' (or banking systems') exposure profiles, as they should, and not be based on trade.[16] For banks it is not relevant how much the country in which they are located trades with another country. What matters for the consolidated bank when assessing its susceptibility to macro developments in other countries is instead its own exposure to the other country.

In Section 2 we present the econometric modelling framework. In Section 3 we show the results from various leverage ratio shock simulations. Section 4 concludes.

2 The model

2.1 Model structure

The MCS-GVAR model comprises three cross-sections: a cross-section of $i = 1, ..., N = 28$ EU countries, a cross-section of financial institutions $j = 1, ..., M = 42$, and a central bank cross-section $l = 1, ..., B = 11$; the euro area and 10 non-EA EU national central banks.[17] The endogenous variables belonging to the three cross-sections are collected in the vectors $\boldsymbol{x}_{it}$, $\boldsymbol{y}_{jt}$, and $\boldsymbol{z}_{lt}$, respectively. For a given cross-section item at a point in time t, the three vectors are of size $k_i^x \times 1$, $k_j^y \times 1$, and $k_l^z \times 1$.

The model has the following form:

$$\begin{aligned}
\boldsymbol{x}_{it} &= \boldsymbol{a}_i + \sum_{p_0=0}^{P_0} \boldsymbol{\Theta}_{i,p_0} \boldsymbol{v}_{t-p_0} + \sum_{p_1=1}^{P_1} \boldsymbol{\Phi}_{ip_1} \boldsymbol{x}_{i,t-p_1} + ... \\
&\quad ... \sum_{p_2=0}^{P_2} \boldsymbol{\Lambda}_{i,0,p_2} \boldsymbol{x}^{*,C-C}_{i,t-p_2} + \sum_{p_3=0}^{P_3} \boldsymbol{\Lambda}_{i,1,p_3} \boldsymbol{y}^{*,C-B}_{i,t-p_3} + \sum_{p_4=0}^{P_4} \boldsymbol{\Lambda}_{i,2,p_4} \boldsymbol{z}^{*,C-CB}_{i,t-p_4} + \boldsymbol{\epsilon}_{it} \\
\boldsymbol{y}_{jt} &= \boldsymbol{b}_j + \sum_{q_0=0}^{Q_0} \boldsymbol{\Upsilon}_{j,q_0} \boldsymbol{v}_{t-q_0} + \sum_{q_1=1}^{Q_1} \boldsymbol{\Pi}_{jq_1} \boldsymbol{y}_{j,t-q_1} + ... \\
&\quad ... \sum_{q_2=0}^{Q_2} \boldsymbol{\Xi}_{j,0,q_2} \boldsymbol{x}^{*,B-C}_{j,t-q_2} + \sum_{q_3=0}^{Q_3} \boldsymbol{\Xi}_{j,1,q_3} \boldsymbol{y}^{*,B-B}_{j,t-q_3} + \sum_{q_4=0}^{Q_4} \boldsymbol{\Xi}_{j,2,q_4} \boldsymbol{z}^{*,B-CB}_{j,t-q_4} + \boldsymbol{\omega}_{jt} \\
\boldsymbol{z}_{lt} &= \boldsymbol{c}_l + \sum_{r_0=0}^{R_0} \boldsymbol{\Delta}_{l,r_0} \boldsymbol{v}_{t-r_0} + \sum_{r_1=1}^{R_1} \boldsymbol{\Gamma}_{lq_1} \boldsymbol{z}_{l,t-r_1} + ... \\
&\quad ... \sum_{r_2=0}^{R_2} \boldsymbol{\Psi}_{l,0,r_2} \boldsymbol{x}^{*,CB-C}_{l,t-r_2} + \sum_{r_3=0}^{R_3} \boldsymbol{\Psi}_{l,1,r_3} \boldsymbol{y}^{*,CB-B}_{l,t-r_3} + \sum_{r_4=0}^{R_4} \boldsymbol{\Psi}_{l,2,r_4} \boldsymbol{z}^{*,CB-CB}_{l,t-r_4} + \boldsymbol{\tau}_{lt}
\end{aligned} \tag{1}$$

The intercept terms $\boldsymbol{a}_i$, $\boldsymbol{b}_j$, and $\boldsymbol{c}_l$ are of size $k_i^x \times 1$, $k_j^y \times 1$, and $k_l^z \times 1$ respectively. Global exogenous variables can be collected in a $v \times 1$ vector $\boldsymbol{v}_t$, with its corresponding coefficient matrices in the three cross-sections — $\boldsymbol{\Theta}_i$, $\boldsymbol{\Upsilon}_j$, and $\boldsymbol{\Delta}_l$ — being of size $k_i^x \times v$, $k_j^y \times v$, and $k_l^z \times v$ respectively. All three equation

[16] A likelihood ratio test for the predictive performance of all equations for the banking system variables in our model — once using the country-country weights and once the banking system - country weights — suggest that indeed the MCS structure with banking system - country weights is superior to the traditional GVAR with variable-specific weights for the very majority of banking systems. The test results are available on request from the authors.

[17] In a future version of the model we plan to include the US, US banks, as well as Japan along with Japanese banks.

blocks contain a set of autoregressive terms — $(\mathbf{\Phi}_{i1}, ..., \mathbf{\Phi}_{iP_1})$, $(\mathbf{\Pi}_{j1}, ..., \mathbf{\Pi}_{jQ_1})$, and $(\mathbf{\Gamma}_{l1}, ..., \mathbf{\Gamma}_{lR_1})$ — which are of size $k_i^x \times k_i^x$, $k_j^y \times k_j^y$, and $k_l^z \times k_l^z$ respectively. The within- and across-cross-section dependence is then introduced via the star variable vectors. The corresponding coefficient matrices in the first equation block for the $\boldsymbol{x}_{it}$ — $(\mathbf{\Lambda}_{i,0,0}, ..., \mathbf{\Lambda}_{i,0,P_2})$, $(\mathbf{\Lambda}_{i,1,0}, ..., \mathbf{\Lambda}_{i,1,P_3})$, and $(\mathbf{\Lambda}_{i,2,0}, ..., \mathbf{\Lambda}_{i,2,P_4})$ — are of size $k_i^x \times k_i^{*x}$, $k_i^x \times k_i^{*y}$, and $k_i^x \times k_i^{*z}$. The corresponding coefficient matrices in the second equation block for the $\boldsymbol{y}_{jt}$ — $(\mathbf{\Xi}_{j,0,0}, ..., \mathbf{\Xi}_{j,0,Q_2})$, $(\mathbf{\Xi}_{j,1,0}, ..., \mathbf{\Xi}_{j,1,Q_3})$, and $(\mathbf{\Xi}_{j,2,0}, ..., \mathbf{\Xi}_{j,2,Q_4})$ — are of size $k_j^y \times k_j^{*x}$, $k_j^y \times k_j^{*y}$, and $k_j^y \times k_j^{*z}$. The corresponding coefficient matrices in the third equation block for the $\boldsymbol{z}_{lt}$ — $(\mathbf{\Psi}_{l,0,0}, ..., \mathbf{\Psi}_{l,0,R_2})$, $(\mathbf{\Psi}_{l,1,0}, ..., \mathbf{\Psi}_{l,1,R_3})$, and $(\mathbf{\Psi}_{l,2,0}, ..., \mathbf{\Psi}_{l,2,R_4})$ — are of size $k_l^z \times k_l^{*x}$, $k_l^z \times k_l^{*y}$, and $k_l^z \times k_l^{*z}$. The cross-section-specific shock vectors — $\boldsymbol{\epsilon}_{it}$, $\boldsymbol{\omega}_{jt}$, and $\boldsymbol{\tau}_{lt}$ — are of size $k_i^x \times 1$, $k_j^y \times 1$, and $k_l^z \times 1$ respectively. They have zero mean, are serially uncorrelated and have covariance matrices $\mathbf{\Sigma}_{ii}^x$, $\mathbf{\Sigma}_{jj}^y$, and $\mathbf{\Sigma}_{ll}^z$. A global matrix $\mathbf{\Sigma}$ shall cover the covariance structure of the combined set of residuals from all three equation blocks.

The weights which are needed to generate the star-variables are described in more detail in Annex A. In the Mixed-Cross-Section variant of the GVAR, not only one set of weights, but for three cross-sections up to nine sets of weights are needed.

There are ten variables involved, of which four are included in the country cross-section, five in the bank cross-section and one in the central bank cross-section. The country cross-section includes nominal GDP ($GDPN$), a GDP deflator ($GDPD$), nominal residential property prices (RPP) and long-term interest rates (LTN). GDP, the GDP deflator and house prices are modelled in quarter-on-quarter (QoQ) differences of natural log levels. Long-term interest rates are modelled in QoQ differences. For what concerns the banking sector-related variables, we include five variables: nominal credit (L), loan interest rates (I), deposit rates (D), a leverage multiple, defined as total assets over total equity (LEV) and the probability of default of the bank(s) (PD).

We estimate two versions of the model: (i) a version where the bank cross-section consists of 42 individual EU banks and (ii) a version where the bank cross-section consists of aggregate banking system data for the 28 EU countries. Tables 1 and 2 summarise the bank and banking system sample coverage. There are several reasons for operating with these two model variants.

On the one hand, estimating the model based on individual consolidated bank level data allows to better capture banks' heterogeneous responses to shocks. Different banks may respond differently to similar sized shocks depending on their balance sheet composition, capital buffers, etc. In addition, a model version based on individual bank-level data is useful for simulating macroprudential capital measures targeted at individual banks, or groups of banks, such as the systemic risk buffer and the G-SIB buffer. Furthermore, the use of consolidated banking group data allows for a precise mapping of prudential measures to the capital positions of the banks in our sample. The main disadvantage of using individual bank data, on the other hand, is that time series are relatively short for publicly available EU bank-level data and the sample of banks for which sufficiently long time series are available is small. Thus, for many EU countries the resulting individual bank sample is not fully representative. For this reason, we also estimate a version of the model using country aggregate banking sector data for which longer time series are available and which are by definition more representative of the EU banking system.

The loan volume variable L reflects either consolidated total loans at the bank-level from public data sources (SNL) or aggregated banking system loan volumes sourced from the ECB's Monetary Financial

Institutions (MFI) Balance Sheet Items (BSI) statistics.[18] For the latter, we include loans to the private sector (households and non-financial corporations).[19]

In the individual bank version of the model, the I variable is defined as the ratio of nominal interest income over income generating assets and serves as a proxy for loan interest rates. In the banking system version, aggregate loan interest rates are sourced from the ECB's MFI interest rate statistics. Likewise for the deposit rate measure D; it is defined as the ratio of nominal interest expense over expense generating liabilities in the individual bank version and sourced from the ECB's MFI interest rate statistics for the banking system model. The bank leverage variable (LEV) is based on consolidated banking data from SNL for the individual bank version of the model and from the ECB's BSI statistics for the banking system version. The PD variable reflects the probability of default of the bank which is a Merton model-based measure of expected default frequency.[20] The 42 banks in our sample are listed, i.e. the PD can be obtained for all of them. For the banking system version of the model, asset-weighted aggregates of the consolidated banking groups per country are included in the model. Concerning variable transformations, nominal credit is modelled in quarter-on-quarter (QoQ) differences of natural log levels. Loan interest rates, deposit rates, and the leverage ratio are modelled in QoQ differences. The PD variable is transformed by means of a logit function, of which quarter-on-quarter differences are then taken. The logit transformation is meant to guarantee that the PD responses under whatever scenario that will be simulated would never leave the [0,1] interval. The scenario responses that are presented later are transformated back to absolute differences by using the inverse logit (Sigmoid) function. In the central bank cross-section we include one variable, the short-term policy rate (STN) from the respective currency areas. The STN variable is modelled in QoQ differences.

The system of equations (1) will not be estimated in a fully unconstrained way. Exclusion restrictions for certain parts of the model are introduced. The rationale for doing so lies primarily in the fact that it would be hardly feasible to estimate the fully unconstrained model as even the GVAR model structure approaches its limits, with 10 model variables and relatively short time series (quarterly data over the 1999Q1-2014Q4 period). Imposing exclusion restrictions helps render the simulated scenario responses more precise, i.e. they will be surrounded by less uncertainty. This is of course conditional on the restrictions that are imposed being meaningful and not inducing omitted variable bias and moreover on some relationship that is estimated being significant after *ex ante* restrictions are being imposed. An additional gain in efficiency and parameter precision shall arise due to the fact that a number of equations can be estimated on a larger effective number of observations, if the time series length of certain model variables varies across countries. If for instance a house price series is very short for one country, but certain parts of the equation system do not include that house price variable, their effective sample length can be longer, adding to parameter precision. Finally, from a structural viewpoint, once

[18] The BSI statistics are residency based and hence not consolidated. This implies that business from subsidiaries of banks from country A operating in country B are included in the loan volumes for country B whereas business from foreign subsidiaries of banks from country B are not included in the credit aggregates of country B. Thus, when referring to, for instance, the Austrian banking system in the model, the system is composed not only of the Austrian-domiciled banks with their domestic and foreign operations (though not including the foreign operations of Austrian banking group's foreign subsidiaries), but also the foreign subsidiaries operating in Austria either domestically or cross-border. We do, however, add the direct cross-border lending of banks domiciled in Austria to other EU countries. In that sense, our loan volume measures are not purely locational. Details concerning the weights which reflect these direct cross-border exposures can be found in Annex A.

[19] In contrast to the banking system-level loan data, the individual bank loan data also includes the banking book exposures to sovereigns. The difference should not be material as banks' direct loan exposures to sovereigns are small compared to their private sector and interbank exposures.

[20] Sourced from Credit Edge, Moody's KMV. See Sun et al. (2012).

Table A: MCS-GVAR model structure

Cross-section type	Model variable		GDPN	GDPD	RPP	LTN	L	LEV	I	D	PD	STN
Countries	Nominal GDP	GDPN	2	2	2	2	2	0	2	2	0	2
	GDP deflator	GDPD	2	2	2	2	2	0	0	0	0	2
	Residential property prices	RPP	2	2	2	2	2	0	2	0	0	2
	Long-term interest rate	LTN	2	2	2	2	0	0	0	0	0	2
Banks	Nominal loan volumes	L	2	0	2	0	2	1	1	0	0	0
	Leverage (TA/E)	LEV	0	0	0	0	1	0	0	0	0	0
	Interest income / assets (or loan interest rate)	I	2	0	2	2	0	1	2	1	0	2
	Interest expense / liabilities (or deposit rate)	D	2	0	0	2	0	1	1	2	0	2
	Probability of default	PD	0	0	0	0	1	1	0	0	0	0
Central banks	Short-term policy rate	STN	2	2	0	0	0	0	0	0	0	0

a series of constraints is imposed on the equation system, the results of certain shock simulations can be corroborated more thoroughly by the underlying model structure. While the imposition of structural constraints is novel in the GVAR model context, it is a known feature that does characterise large scale equation systems used in particular at policy institutions.[21]

Table A provides an overview of the structure of the model. Channels are allowed to be *global* (2), i.e. are established by means of weights (following the traditional GVAR rationale, though also across different cross-section types — see Annex A), or *local* (1), meaning that a direct relationship is allowed to exist only for within a country, or within a bank or banking system. The third option is that a channel is *closed* (0), with the corresponding coefficients in the model being constrained to zero.

Aggregate economic activity, measured by nominal GDP, is allowed to be driven by all country cross-section variables, credit provided by banks, bank lending rates, the cost of funding of banks, as well as short-term interest rates.

The cross-country economic activity link is justified by the standard trade channel: a fall in aggregate demand in one country leads to lower imports from other countries, thereby compressing economic activity abroad. Similarly, the link via residential property prices and long-term interest rates is justified by wealth and discount rate effects, respectively.

The link through loan volumes reflects the role the financial sector, in particular banks, play in the economy by providing funds for investment and consumption, which in turn directly affect economic activity.[22]

The bank lending rate variable reflects the effective interest rates that households and firms pay for bank financing, while the funding cost measure is related to the effective interest rate that economic agents receive for depositing their money with the banks. The link with the economic activity variable is justified via at least two channels: First, higher interest rates, ceteris paribus, mean that fewer profitable projects can be financed and imply lower economic activity. In addition, existing projects can be discontinued, as financing costs exceed the average rate of return on the project. In an intertemporal set-up, higher interest rates will encourage households to postpone their consumption into the future and save more today, which also reduces current economic activity and affects the supply of deposits.

[21] Such as bank stress testing frameworks or large-scale macro models employed for developing macroeconomic projections.

[22] Bank credit is not the only source of financing for firms and households; although in most of Europe it remains the dominant source of external financing for the non-financial corporate sector as compared to the US where the role of market based corporate financing is more important.

While the literature suggests that bank leverage or bank PDs could impact the economic activity via loan supply (see, for instance, Bernanke and Lown (1991) and Hancock and Wilcox (1993)), we assume that if anything this can only work through indirect third channels to the extent that for instance they influence loan supply.

The channel for **aggregate nominal activity**, the GDP deflator, is open again for all variables in the country cross-section. The channels and argumentation is the same as for the aggregate economic activity above. Moreover, loan growth at the bank level is allowed to influence aggregate prices. We assume that excessive loan growth, if fuelled at times of strong expansion when firms operate close to their capacity constraints, may exert direct upward pressure on prices as firms cannot further satisfy demand by increasing production.

House prices are allowed to be driven by all macro variables in the country cross-section. The relation of house prices with macroeconomic variables is documented both by economic theory (see e.g. Hornstein (2009) and Treasury (2003) and the vast empirical literature (see e.g. Terrones and Otrok (2004), Tsatsaronis and Zhu (2004), Annett (2005), Egert and Mihaljek (2007). These empirical studies provide evidence that real disposable income, real interest rates, loan growth and other supply side factors all affect house price dynamics. Moreover, we allow for the link of residential property prices to loan growth and lending rates from the bank cross-section also because of the empirical evidence that loan growth is associated with the price increases in the residential property market (Hofmann (2003), Gelain et al. (2013), Cesa-Bianchi et al. (2015)).

Long-term interest rates are proxied by 10-year benchmark government bond yields. The justification for their link with macroeconomic variables in the cross-country section is provided in the above paragraphs. They are assumed not to be driven through any direct channel by bank variables.

Nominal credit at bank-level is allowed to be a function of nominal GDP, house prices, bank lending rates and bank leverage. Moreover, it is allowed to be a function of the weighted aggregate credit provision from the other banks in the system. For GDP, we allow a cross-country channel to be open, to reflect the fact that banks can have cross-border exposures and would be affected by changes in demand from the countries to whose residents they provide credit. Similarly, the house price link is also open in a cross country dimension to reflect the fact that boosting the value of housing collateral impacts bank lending via two wealth effect channels. First, since houses are used as a collateral, higher house prices strengthen households' borrowing capacity (Bernanke and Gertler (1989) and Kiyotaki and Moore (1997)). Second, in life cycle models higher value of household's wealth may increase lifetime consumption and impact today's demand for credit to smooth consumption over the life-cycle (Deaton (1992) and Muellbauer (1994)).

For bank leverage we assume that only the banks' own measure may be related to its own balance sheet structure. The bank lending rate is allowed to impact the loan volumes only at the bank level to reflect the fact that the demand for credit at the bank level can be steered by the bank by adjusting its credit margins.[23]

The **leverage** variable at bank-level is allowed to be a function of credit (only the bank's own measure), for the obvious reason that leverage is a mechanic function of its own assets.

Bank lending rates are allowed to be affected by GDP, house prices, long-term interest rates, bank

[23]See Freixas and Rochet (1999).

leverage, bank lending rates, the cost of funding, as well as short-term policy rates. For GDP the global channel is open, as the asset returns of banks that engage in cross-border business may be driven by macro conditions abroad. The channel through house prices is also allowed in a cross-country dimension as a change in property values may directly affect the loan interest rates to reflect changing collateral values and therefore risk. This is because residential property prices affect the value of bank's capital via the quality/value of mortgages secured by houses and therefore the price of credit (Chen, 2001). Finally, long-term rates in a jurisdiction where a bank operates will impact the interest rates on loans originated in these countries via the impact on the borrower net worth and thus its credit-worthiness (Bernanke and Gertler (1989)) and via its effect on bank funding costs (see also below). For leverage we assume that only the banks' own measures may impact their rates on loans. In turn, the cost of funding is allowed to impact the bank lending rates to reflect the empirical findings that banks, to a large extent, pass through the higher funding costs on their borrowers (Button et al. (2010), Deans and Stewart (2012), Darracq Paries et al. (2014b)). For bank asset returns themselves, a cross-bank channel is open as one bank may adjust its asset prices in response to asset price changes in other banks due to competitive pressures. Indeed, Gropp et al. (2014) and Van Leuvensteijn et al. (2013) find that competition among banks results in a faster bank interest rate pass-through.

The **cost of debt** (deposit rates in the banking system version) is allowed to be a function of GDP, long- and short-term interest rates, bank leverage, and the cost of funding of other banks. For GDP one may argue that banks are rather price setters of deposits and would thus be rather inelastic to changes in aggregate demand. While this argument has some merit, we nonetheless allow this channel to be present as the cost of funding, as we measure it, does not capture only the cost of deposits, but also that of wholesale funding instruments (for which banks tend to be rather price takers than setters). Empirical evidence tends to support this configuration: for internationally active banks, Babihuga and Spaltro (2014) find that factors such as global growth and implied market volatility as well as short-term interest rates and the slope of the yield curve are significant in explaining bank funding costs. Furthermore, the cost of funding is allowed to be driven by the cost of funding of other banks. This channel is a direct price spillover channel, which in particular during times of economic turmoil and recession is important as banks are at times observed to engage in 'deposit wars', where the cost of funding is, in a controlled manner, adjusted upward to attract depositors. This link is justified by the market power hypothesis, whereby banks can set the deposit rates depending on the scope of the competition in the deposit market (Hutchison (1995), Hutchison and Pennachi (2008)), for which the empirical literature provides evidence (see e.g. Kahn et al. (1999), Lago-Gonzales and Salas-Fumas (2005) and Van Leuvensteijn et al. (2013)). Craig and Dinger (2010) find evidence for the deposit market competition raises the optimal risk choice of the bank by raising the cost of bank liabilities. In general, the cost of funding can be expected to be correlated across banks on average over the business cycle. Finally, the cost of funding is allowed to be driven by leverage. Babihuga and Spaltro (2014), among others, document that bank funding costs are also influenced by bank capitalisation.

The **probability of default of a bank** is assumed to be a synthetic measure of the risk of the bank balance sheet, which given the current set of model variables is best represented by loan growth and leverage. Loan growth, which in this context can be considered a proxy for asset volatility, and leverage are the two main determinants of the probability of default; following a standard Merton model rationale.[24]

[24] In a future extension of the model we plan to include an asset volatility variable (Merton-model implied) in the bank cross section, to imply the distance to default and PD by leverage and asset volatility in a structural manner. Another option to better proxy asset volatility starting from the current version of the model would be to square the credit growth

The **short-term policy rates** for the various currency areas is included in both model variants, with a Taylor-rule rationale (Taylor (1993)) determining the shape of the short-term rate equation, i.e. for a direct link being established to GDP and the GDP deflator.[25]

In terms of model structure, we allow one autoregressive lag and the contemporaneous and first lag of all weighted cross-border and cross-bank variable vectors. The model is estimated based on data covering the 1999Q1-2014Q4 period (64 observations). Model residuals are all sufficiently free of serial correlation. It is partly unbalanced a panel as the time series for a few institutions and countries in the sample are shorter or not available. The individual equations are estimated by means of an Iteratively Reweighted Least Squares (IRLS) method, using a Cauchy weighting function.[26] The method is more robust to outliers than Ordinary LS and helps stabilise the dynamics of the global model. The global model is stable with its maximum modulus of the eigenvalues of the companion coefficient matrix being less than 0.7.

2.2 Global solution of the model

The equation system presented in equations (1) contains time-contemporaneous relationships, thus a combined system of these equations would not yet be ready for simulation purposes. The global model has therefore to be solved, i.e. the equations from all cross-sections need to be stacked and then reformatted in a way to contain only lagged relationships. This derivation can be summarised in four steps.

Step 1: Generate A-matrices. One starts by stacking the within-cross-section vectors along with the cross-cross-section weighted variable vectors in (here) three vectors $\boldsymbol{m}^x_{it}$, $\boldsymbol{m}^y_{jt}$, and $\boldsymbol{m}^z_{lt}$.

$$\begin{aligned}
\boldsymbol{m}^x_{it} &= \begin{pmatrix} \boldsymbol{x}_{it\prime} & \boldsymbol{x}^{*,C-C\prime}_{it} & \boldsymbol{y}^{*,C-B\prime}_{it} & \boldsymbol{z}^{*,C-CB\prime}_{it} \end{pmatrix}' \\
\boldsymbol{m}^y_{jt} &= \begin{pmatrix} \boldsymbol{y}_{jt\prime} & \boldsymbol{x}^{*,B-C\prime}_{jt} & \boldsymbol{y}^{*,B-B\prime}_{jt} & \boldsymbol{z}^{*,B-CB\prime}_{jt} \end{pmatrix}' \\
\boldsymbol{m}^z_{lt} &= \begin{pmatrix} \boldsymbol{z}_{lt\prime} & \boldsymbol{x}^{*,CB-C\prime}_{lt} & \boldsymbol{y}^{*,CB-B\prime}_{lt} & \boldsymbol{z}^{*,CB-CB\prime}_{lt} \end{pmatrix}'
\end{aligned} \tag{2}$$

The equation system can be re-written with these $\boldsymbol{m}$ vectors as follows.

$$\begin{aligned}
\underbrace{\begin{pmatrix} I_{k^x_i} & -\Lambda_{i,0,0} & -\Lambda_{i,1,0} & -\Lambda_{i,2,0} \end{pmatrix}}_{\equiv \boldsymbol{A}^x_{i0}} \boldsymbol{m}^x_{it} &= \boldsymbol{a}_i + \underbrace{\begin{pmatrix} \Phi_{i1} & \Lambda_{i,1,1} & \Lambda_{i,2,1} \end{pmatrix}}_{\equiv \boldsymbol{A}^x_{i1}} \boldsymbol{m}^x_{i,t-1} + \ldots + \boldsymbol{\epsilon}_{it} \\
\underbrace{\begin{pmatrix} I_{g^y_j} & -\Xi_{j,0,0} & -\Xi_{j,1,0} & -\Xi_{j,2,0} \end{pmatrix}}_{\equiv \boldsymbol{A}^y_{j0}} \boldsymbol{m}^y_{jt} &= \boldsymbol{b}_j + \underbrace{\begin{pmatrix} \Pi_{j1} & \Xi_{j,1,1} & \Xi_{j,2,1} \end{pmatrix}}_{\equiv \boldsymbol{A}^y_{j1}} \boldsymbol{m}^y_{j,t-1} + \ldots + \boldsymbol{\omega}_{jt} \\
\underbrace{\begin{pmatrix} I_{k^z_l} & -\Psi_{l,0,0} & -\Psi_{l,1,0} & -\Psi_{l,2,0} \end{pmatrix}}_{\equiv \boldsymbol{A}^z_{l0}} \boldsymbol{m}^z_{lt} &= \boldsymbol{c}_l + \underbrace{\begin{pmatrix} \Gamma_{l1} & \Psi_{l,1,1} & \Psi_{l,2,1} \end{pmatrix}}_{\equiv \boldsymbol{A}^z_{l1}} \boldsymbol{m}^z_{l,t-1} + \ldots + \boldsymbol{\tau}_{lt}
\end{aligned} \tag{3}$$

variable in the PD equation. These and similar extensions we plan to implement in the future.

[25]The central bank short-term rate equations do not have an exact Taylor rule structure of course, as they do not, for example, include any deviation from target measures for instance of inflation, and they include nominal instead of real GDP. Though they do in in terms economic rationale capture the link between short-term policy rates with real and nominal activity measures.

[26]The choice of the weighting function has no material impact at all on the results from the model.

Step 2: Generate L-matrices ("link" matrices). With a global, stacked variable vector $\boldsymbol{s}_t = (\boldsymbol{x}'_{1t}, ..., \boldsymbol{x}'_{Nt}, \boldsymbol{y}'_{1t}, ..., \boldsymbol{y}'_{Mt}, \boldsymbol{z}'_{1t}, ..., \boldsymbol{z}'_{Bt})$ at hand, the cross-section-specific variable vectors $\boldsymbol{m}^x_{it}$, $\boldsymbol{m}^y_{jt}$, and $\boldsymbol{m}^z_{lt}$ to $\boldsymbol{s}_t$ can be linked. The link matrices $\boldsymbol{L}^x_i$, $\boldsymbol{L}^y_j$, and $\boldsymbol{L}^z_l$ are used to map the local cross-section variables into the global vector, which involve the weights from the weight matrices $\boldsymbol{W}$.

$$\begin{aligned}
\boldsymbol{m}^x_{it} &= \boldsymbol{L}^x_i \boldsymbol{s}_t & \rightarrow \quad & \boldsymbol{A}^x_{i0}\boldsymbol{L}^x_i\boldsymbol{s}_t = \boldsymbol{a}_i + \boldsymbol{A}^x_{i1}\boldsymbol{L}^x_i\boldsymbol{s}_{t-1} + ... + \boldsymbol{\epsilon}_{it} \\
\boldsymbol{m}^y_{jt} &= \boldsymbol{L}^y_j \boldsymbol{s}_t & \rightarrow \quad & \boldsymbol{A}^y_{j0}\boldsymbol{L}^y_j\boldsymbol{s}_t = \boldsymbol{b}_j + \boldsymbol{A}^y_{j1}\boldsymbol{L}^y_j\boldsymbol{s}_{t-1} + ... + \boldsymbol{\omega}_{jt} \\
\boldsymbol{m}^z_{lt} &= \boldsymbol{L}^z_l \boldsymbol{s}_t & \rightarrow \quad & \boldsymbol{A}^z_{l0}\boldsymbol{L}^z_l\boldsymbol{s}_t = \boldsymbol{c}_l + \boldsymbol{A}^z_{l1}\boldsymbol{L}^z_l\boldsymbol{s}_{t-1} + ... + \boldsymbol{\tau}_{lt}
\end{aligned} \tag{4}$$

Step 3: Generate G-matrices. The equation-by-equation system can now be stacked into a global system.

$$\begin{aligned}
\boldsymbol{G}^x_0 &= \begin{pmatrix} \boldsymbol{A}^x_{10}\boldsymbol{L}^x_1 \\ ... \\ \boldsymbol{A}^x_{N0}\boldsymbol{L}^x_N \end{pmatrix}, \boldsymbol{G}^x_1 = \begin{pmatrix} \boldsymbol{A}^x_{11}\boldsymbol{L}^x_1 \\ ... \\ \boldsymbol{A}^x_{N1}\boldsymbol{L}^x_N \end{pmatrix}, ..., \boldsymbol{a} = \begin{pmatrix} \boldsymbol{a}_1 \\ ... \\ \boldsymbol{a}_N \end{pmatrix} \\
\boldsymbol{G}^y_0 &= \begin{pmatrix} \boldsymbol{A}^y_{10}\boldsymbol{L}^y_1 \\ ... \\ \boldsymbol{A}^y_{M0}\boldsymbol{L}^y_M \end{pmatrix}, \boldsymbol{G}^y_1 = \begin{pmatrix} \boldsymbol{A}^y_{11}\boldsymbol{L}^y_1 \\ ... \\ \boldsymbol{A}^y_{M1}\boldsymbol{L}^y_M \end{pmatrix}, ..., \boldsymbol{b} = \begin{pmatrix} \boldsymbol{b}_1 \\ ... \\ \boldsymbol{b}_M \end{pmatrix} \\
\boldsymbol{G}^z_0 &= \begin{pmatrix} \boldsymbol{A}^z_{10}\boldsymbol{L}^z_1 \\ ... \\ \boldsymbol{A}^z_{B0}\boldsymbol{L}^z_B \end{pmatrix}, \boldsymbol{G}^z_1 = \begin{pmatrix} \boldsymbol{A}^z_{11}\boldsymbol{L}^z_1 \\ ... \\ \boldsymbol{A}^z_{B1}\boldsymbol{L}^z_B \end{pmatrix}, ..., \boldsymbol{c} = \begin{pmatrix} \boldsymbol{c}_1 \\ ... \\ \boldsymbol{c}_B \end{pmatrix}
\end{aligned} \tag{5}$$

These cross-section-specific G matrices can be further combined to a set of global G matrices. The intercept vectors $\boldsymbol{a}$, $\boldsymbol{b}$, and $\boldsymbol{c}$ will be combined in a vector $\boldsymbol{d}$. That is,

$$\boldsymbol{G}_0 = \begin{pmatrix} \boldsymbol{G}^x_0 \\ \boldsymbol{G}^y_0 \\ \boldsymbol{G}^z_0 \end{pmatrix}, \boldsymbol{G}_1 = \begin{pmatrix} \boldsymbol{G}^x_1 \\ \boldsymbol{G}^y_1 \\ \boldsymbol{G}^z_1 \end{pmatrix}, ..., .\boldsymbol{d} = \begin{pmatrix} \boldsymbol{a} \\ \boldsymbol{b} \\ \boldsymbol{c} \end{pmatrix} \tag{6}$$

Step 4: Generate H-matrices. The global system can now be pre-multiplied by the inverse of $\boldsymbol{G}_0$. The system is now ready to be used for shock simulation and forecast purposes.

$$\boldsymbol{s}_t = \underbrace{G_0^{-1}d}_{\equiv H_0} + \underbrace{G_0^{-1}G_1}_{\equiv H_1}\mathbf{s}_{t-1} + ... + \boldsymbol{G}_0^{-1}\boldsymbol{\varphi}_t \tag{7}$$

Since the weights are time-varying, a choice has to be made as to the reference point in time as of which the weights are taken to solve the global model. The shock simulations that are presented in this paper take the end-sample (2014Q4) weight sets as a basis for deriving the global solution.

3 Shock simulations

3.1 Sign constraints and shock size calibration

We consider three types of negative bank leverage (positive capital ratio) shocks. The three types all start from the same negative percentage point shock ΔLEV. The following description of the shock setting applies to both the individual bank and the banking system version of the model.

Type 1: A negative credit supply shock. It is assumed that the capital ratio shock translates fully into asset side deleveraging, under the assumption of constant equity capital. Outstanding debt is assumed to shrink correspondingly.

Type 2: A positive credit supply shock. It is assumed that the capital ratio shock translates into an amount of equity capital that banks raise to extend the corresponding amount into loans, under the assumption of constant debt.

Type 3: The capital ratio shock is not translated into credit supply shocks but taken directly as a starting point for the shock simulation without any constraints on the adjustments of banks' balance sheet.

The Type 1 and 2 shock sizes are calibrated based on the formulas in equation 8 and 9, with E_0, A_0, and Δ denoting capital, total assets, and the capital ratio shock respectively:

$$shock^{Type1} = \ln\left(\frac{E_0}{\frac{E_0}{A_0} + \Delta}\right) - \ln\left(A_0\right) \tag{8}$$

$$shock^{Type2} = \ln\left(A_0 - E_0\left(\frac{\left(\Delta + \frac{E_0}{A_0}\right)\left(A_0 - E_0\right)}{E_0\left(\Delta + \frac{E_0}{A_0} - 1\right)} + 1\right)\right) - \ln\left(A_0\right) \tag{9}$$

The respective first terms in the two equations reflect the total asset values after the capital ratio shock Δ is applied. The shocks are the log difference between total assets post- and pre-shock. We assume that this log percent shock computed based on capital and total assets applies to the loan stock of a country (or a bank).

The first two shock types, which can be thought of as *polar cases*, are implemented by means of a sign restriction methodology.[27] Under Type 1, the assumed drop in credit growth is combined with a positive sign constraint on loan interest rates on the same banking system, while in the case of the positive credit supply shock (Type 2) loan rates are assumed to fall. Hence, in each case the sign constraint is meant to identify the impulse as a credit supply shock. The sign constraints are imposed only in the first period in which the shocks arrive.[28]

[27]As an entry point to the literature about sign restricted SVARs see Faust (1998), Canova and Nicolo (2002), and Uhlig (2005).

[28]Importantly, this identification scheme ignores the fact that while banks having raised fresh equity should be in a position to supply more credit for a given loan demand, hence pushing lending rates down, the new equity raised will also imply a dilution of existing shareholders and reduce the Return on Equity (RoE). This could be expected to induce banks to increase lending margins in order to reinstall their desired ROE target. Indeed, by only imposing the sign restriction in the first period our simulations allow for such rent seeking behaviour in subsequent periods. We shall, moreover, note

Figure 1 shows the magnitude of shocks — expressed in parallel as leverage multiple and capital ratio shocks — for the individual banks and the banking system aggregates. They reflect a 1-standard deviation of the residuals from the two versions of the MCS-GVAR model. Figure 4 shows the corresponding loan supply shocks under Type 1,2 and 3. As mentioned, for Type 3 the loan growth variable responds endogenously, i.e. there are no shock sizes to be pre-defined. For the individual bank-based model, shocks are applied to all banks from a banking system simultaneously. The sign constraint on the loan interest rate variable is imposed on the weighted aggregate (loan volume weighted) of the individual banks' responses in $T = 1$ and is combined with the constraint that any individual loan interest rate from the group of banks in a country is positive under Type 1 and negative under Type 2.

The size of $T = 1$ shocks is scaled such that the shock sizes reported in Figure 4 are met over a cumulative 3-year horizon. For the Type 1 and Type 2 simulations this scaling is based on the implied loan supply shocks, while under Type 3 the scaling is done with regard to the underlying capital ratio shocks directly.[29]

Shock correlations across countries or banking systems are assumed to be zero in $T = 1$. The pair-wise cross-cross-section residual correlation is small (0.05 on average, see the robustness section for more details) and the simulation results that we present are robust to allowing the cross-country correlations to be non-zero. A contemporaneous reaction to shocks in the country or banking system where the shock originates are allowed to be non-zero, for both macro and bank or banking system variables.

3.2 Results

The results from the shock simulations are collected in Figures 2-6. The figures show the 3-year cumulative scenario responses for five model variables: real GDP and house prices from the country cross-section as well as nominal loan growth, loan interest rates, and probabilities of default from the bank cross-section.[30] Real GDP responses are computed by subtracting the GDP deflator responses from nominal GDP responses.

Each figure contains two result sets, reflecting the banking system model and the individual bank model results. Both the domestic responses as well as the weighted cross-border responses are displayed in the same charts (for each country or bank/banking system in two columns next to each other). The cross-border dimension in the second column is compressed by computing weighted average responses, with the weights being the banks' or banking systems' loan exposure profiles as of 2014. Also for the macroeconomic responses, the loan exposure-based weights are employed, with the argument being again that for banks trade exposures do not matter directly, whereas the cross-border lending activity of banks should constitute the more relevant direct shock propagation channel.[31]

that the Type 2 behaviour of banks does not only reflect equity raising activities but as well a gradual rise in capital levels by retaining earnings.

[29] While the overall capital ratio is under control as it is included in the model and assigned a specific target post-shock in all three simulation types, there is only a partial control over how assets adjust, as we include only credit, and no assets other than credit. The fact that this non-credit residual is not included in the model means that the amount of debt to make the balance sheet actually balance is not explicitly quantifiable or controllable (just as the amount of total assets).

[30] A full catalogue showing all dynamic response profiles is available on request from the authors.

[31] Indeed, when using trade weights instead of exposure weights for the purpose of an *ex post* aggregation of e.g. the GDP responses, the weighted responses tend to be systematically smaller.

Related to the real GDP responses (Figure 2), two additional summary measures are provided: Figure 7 shows the real GDP to nominal loan growth shock long-run multipliers.[32] Figure 8 reports the ratio of weighted foreign GDP responses to domestic GDP responses.

The estimates of the impact of shocks on real GDP (Figure 2) suggest that Type 1 responses fall systematically below Type 2 and 3 responses and are sizeable from an economic point of view. Full asset side deleveraging exerts, as expected, the strongest downward pressure on real activity. Real GDP to loan growth multipliers (Figure 7) are large for many countries, with ratios exceeding 0.5 based on the banking system model for Austria, Germany, Finland, Slovakia, and a few more countries whose ratios range around 0.4. The GDP to loan growth shock multiples reflect a primary impact of domestic loan supply as well as an additional amplifying effect through the provision of loan supply of banks across borders, which have indirect trade spillover effects back to the domestic economy. Apart from the cross-border amplification effects which is a key feature of our model, the relatively sizeable GDP-loan multipliers are consistent with other findings from VAR-based studies though somewhat larger than those normally found using more structural and dynamic general equilibrium models.[33] The individual bank model responses are of systematically smaller magnitude compared to the banking system version of the model, reflecting the fact that the individual bank sample covers only a fraction of the total banking systems. The Type 3 simulation results suggest that the GDP impact lies in between the two polar simulations Type 1 and 2.[34]

The cross-border to domestic effects ratios (Figure 8) suggest that shocks to banking systems have sizable cross-border effects. For instance, the ratio for the German banking system is estimated at about 0.6, the maximum across all banking systems. It should be noted that these ratios reflect again two combined channels of transmission: the cross-border credit supply of banks that are active abroad and the cross-border macroeconomic feedback effects arising through bilateral trade channels.

House price responses (Figure 3) fall into reasonable ranges relative to the GDP impact estimates, with Type 1 effects being the most adverse for the majority of countries whose banking systems are shocked. Type 3 responses are not in all cases falling half-way in between Type 1 and Type 2 estimates; see for instance France for which the unconstrained Type 3 house price response comes close to the Type 1 response of about -2pp. In a few cases, Type 3 responses also fall outside the polar Type 1 and 2 impact estimates (e.g. GB, LT, SE). The responses from the individual bank-based model suggest, just like for GDP, that the direction of the impact estimates across the three simulation types is robust compared to the banking system version, yet is of somewhat smaller magnitude across all the countries.

The consolidated loan growth deviations (Figure 4) reflect, as mentioned, the exogenous shocks for the Type 1 and Type 2 simulations, and the endogenous response for Type 3, which for all banking systems fall in between the Type 1 and Type 2 bounds. The magnitude of the shocks under Type 1 and Type 2 are a function of two features of the banks and banking systems: the size of the shocks to the capital ratios (model residual-based) and the initial capital ratio of a bank or banking system at the outset of the simulation horizon in 2014. For example, for two banks with an (assumed) equal residual standard deviation for their leverage variable from the model, the bank with a higher initial leverage multiple (lower capital ratio) would be assigned a more pronounced fall in asset growth under

[32] They are the same under the Type 1 and 2 simulation schemes.

[33] See e.g. BCBS (2010) for a discussion of the macroeconomic impact of capital requirements across a wide range of macro models incl. VAR models and why their outcomes may differ.

[34] Note that we do not impose any restrictions in this regard. In principle, the Type 3 impact could lie outside the polar bounds.

the Type 1 simulation, reflecting the higher leverage of its balance sheet compared to the other bank.

To visualise that effect, Figure 9 shows a scatter of the residual standard deviation-implied loan supply shocks against the initial leverage multiple (upper left scatter) and the initial capital ratio (lower left scatter). In addition, the two scatter plots in the middle column and the two in the right column are based on the loan supply shocks that would result from uniform +1pp shocks to capital ratios for all banking systems, instead of the residual-based ones. In this case, the mechanic relation between initial leverage and implied loan supply shocks is very visible, with higher leverage (lower capital) at the outset meaning that the required asset size reduction (Type 1) would be more substantial compared to banks with lower leverage. The fact that the scatters based on the actual shock sizes that are used for the simulations (first columns) are more evenly distributed (after removing visually the Greek and Cypriot banking systems), reflects that residual-based leverage ratio shock sizes tend to increase, i.e. get more negative, with higher initial leverage. Cyprus and Greece stand out as they are having comparably low leverage (high capital ratio) starting points and nonetheless sizable residual-based shocks.

Loan interest rate responses (Figure 5) attain positive signs in the long-run for Type 1 in many cases. Recall that the T=1 responses were constrained to be positive under Type 1 and negative under Type 2. In some banking systems, the responses revert their sign in the long-run, but stay close around zero in most of the cases. Type 3 responses in general fall in between the two polar scenarios. Individual bank-based model results are again generally somewhat smaller in magnitude compared to the banking system model results.

Turning to the impact on banks' probability of default (Figure 6), two aspects need to be seen as the driving forces whose net effect can either be positive or negative. On the one hand, the PD of a bank falls mechanically the moment its leverage decreases (capital ratio increases), all else, meaning in particular asset volatility, equal. Thus, all three scenario types should imply this downward pressure on PDs. On the other hand, banks' PDs may increase as a result of the feedback through economic activity which in particular under the Type 1 simulation is seen to contract significantly. This drop in activity would imply higher asset volatility (reflecting for instance higher loan loss provisioning needs) which implies upward pressure on the PD of a bank. It is an empirical question which of the two effects dominate.

For banking systems such as Austria, Belgium, Germany, Finland, Greece, Ireland, Italy, Netherlands, and Sweden (to list the more clear-cut cases) the estimated net effect on bank PDs is negative under Type 1, i.e. the macro feedback effect on banks' PDs seems to be limited. By contrast, in other banking systems, such as Spain and France, the macro feedback effects appear to dominate, resulting in higher bank PDs under the Type 1 simulation. Notably, many of the banking systems that fall into the first category (i.e. negative net effect on bank PDs) are characterised by having relatively low capital ratios; specifically, Belgium, Germany, Finland, Netherlands, and Sweden. It appears that more highly leveraged banking systems gain more in terms of lowering of bank PDs from the mechanic reduction of leverage, with macro feedback effects not being sizable enough to outweigh that gain. This may suggest that the benefits of increasing the level of bank capital measured in terms of higher bank resilience (here proxied by bank PDs) are largest when capital ratios are initially low, whereas the beneficial effects may abate somewhat for higher initial capital ratios.[35]

[35] This finding is consistent with the non-linear benefits of higher capital requirements documented in the BCBS/FSB 2010 study on the long-term economic impact (the LEI report), whereby the estimated benefits of raising capital requirements declined for higher starting point capital ratios.

A general observation across all model variables is that the two polar cases result in asymmetric bounds in terms of impact ranges. The first polar case, following a Type 1 simulation (asset side deleveraging), results in more negative responses compared to the magnitude of positive responses under the upper polar case, following a Type 2 simulation (equity raising). This asymmetry is mechanically driven by the effect of levered balance sheets, whereby the same capital ratio shock if translated into an asset side reaction is more pronounced than when raising equity capital.

This asymmetry has also important policy implications. In order to counteract the adverse economic response to an introduction of higher capital requirements, the macroprudential authority could decide that the new capital requirements must be met by raising capital by a certain target minimum amount or set a RWA floor on deleveraging. In fact, Msonnier and Monks (2014) found empirical evidence that banks that had to increase its capital in the context of the context of the EBA 2012 Capital Exercise tended to have annualized loan growth that was lower than for banks that did not have to increase their capital ratio. It is important to highlight that the capital exercise, unlike the EBA stress test exercises, did not require banks to raise capital but allowed them to meet the new capital requirements also through deleveraging.

3.3 Policy applications

In this section, an illustration of how the model can be applied for the purpose of assessing the macroeconomic impact of specific macroprudential buffer requirements on specific banks, or a group of banks (for example, all banks in a country) is presented.[36]

Instead of starting from model residual-based shocks to leverage (capital) ratios, we now start from a +1pp shock to the capital ratio of a specific bank. Conceptually the simulation method is otherwise no different from the application presented in the previous section. The +1pp shock could be thought of as resulting from the imposition of an extra capital buffer, which is assumed for simplicity to be binding. The shock size calculations that precede the simulation with the model would in practice take proper account of where the various regulatory and extra buffer requirements stand prior to the capital buffer shock and compare to the actual capital ratio of a bank, to see whether the bank would effectively face a shortfall after the imposition of a buffer and therefore take action to attain a higher capital ratio.[37]

For the sake of illustration, we take Santander Group (headquartered in Spain) and the Spanish banking system as a starting point for two simulations, again distinguishing between the Type 1, 2, and 3 reactions. We show the dynamic response profiles of real GDP in Spain in Figure 10, the responses of bank PDs in Figure 11, and the response of Portuguese real GDP in Figure 12. Portugal is chosen as an example for the response of another country as Santander and the Spanish banking system overall have significant exposures to Portugal.

Under the Type 1 simulation, the domestic real GDP effects in Spain (Figure 10 suggest that the response to the banking system shock is somewhat more pronounced than the Santander-specific shock

[36]Depending on the purpose, macroprudential capital buffers may be imposed on individual banks (e.g. G-SIB buffer), groups of banks (e.g. systemic risk buffer) or entire banking systems (e.g. countercyclical capital buffer).

[37]More nuanced shock size calibrations may also take into account some extra capital buffer that banks choose to hold voluntarily above the thresholds implied by regulators, including extra buffers. Thus even if the combined capital requirements including an assumed extra buffer would not be implying a shortfall for the bank, it may take action to increase its capital ratio in order to return to its desired excess capital buffer.

(-1.4pp versus -1.0pp long-run deviation from baseline growth). Under Type 2, the responses are slightly positive, though insignificant, at around +0.1/0.2pp. The unconstrained Type 3 responses are negative, at -0.7pp and -1.0pp for the Santander-specific and banking system wide shock, respectively.

The banks' PD responses (Figure 11) are in line with the GDP responses in the sense that the PD of the aggregate banking system increases slightly more than Santander's own PD under the Type 1 simulation. Under Type 2, the net response of PDs is slightly negative, while significant from a statistical viewpoint for Santander only for a short while after the 4-th quarter. For the the banking system, the response is more visibly significant from quarter 3-8, with PDs falling by about -0.2pp below baseline long-run changes. Under the unconstrained Type 3 simulation, neither Santander's PD nor the system-wide aggregate PD for the Spanish banking system respond significantly.

Portuguese real GDP responses (Figure 12) are significant, though less pronounced than in Spain. Under the Type 1 simulation, the shock to the total Spanish banking system implies a -0.8pp long-run deviation of real GDP from baseline growth in Portugal. A shock to only Santander halfs that response to -0.4pp. The Type 2 responses range near around zero. Type 3 results suggest a still significant response when the total Spanish system was shocked, with real GDP in Portugal falling by about -0.4pp in the long run.

3.4 Further model diagnostics and robustness checks

The additional model diagnostics that we report in this section concern, first, the properties of the model residuals from the GVAR in its two variants. Durbin Watson (DW) statistics are collected in Figures 13 and 14. They confirm that all equations' residuals are sufficiently free of serial correlation in both models.[38]

In addition to assessing remaining serial dependence in the residuals, we examine their remaining cross-section dependence. By operating with weighted foreign variable vectors in the GVAR, and multiple cross-section weighted vectors in the MCS-GVAR, these should serve as common global factors and compress the amount of remaining cross-equation residual correlation. Tables 4 and 5 show the average pair-wise cross-correlation estimates based on the raw data (in the format as included in the model, i.e. in differences of levels or log levels) as opposed to the residuals. We report the average cross-section correlations for the total group of countries and separately from the perspective of the largest five euro area countries and all central banks in the model. The estimates suggest that the model, in both variants, manages well to capture the within and across cross-section dependencies. The residual correlation estimates fall with a few exceptions into a narrow -5/+5% interval.[39]

We now aim to assess the robustness of the model and its simulation results which is important as it is a relatively large scale model, involving a number of assumptions as to the structure that we impose, as outlined in sub-section 2.1. As mentioned before, we do not estimate a fully unconstrained model for two reasons: it would exhaust the degrees of freedom for the model to practically not be estimable

[38]We shall note that DWs close to 2 do of course not exclude the possibility that additional lags of local endogenous or weighted foreign variables could have additional predictive content, which we cannot, however, consider due to the aforementioned reasons about exhausting the degrees of freedom due to a significant number of variables.

[39]We did also, as is commonly done, compute the cross-correlations based on the residuals from a model in which the weighted foreign variable vectors were lagged only, instead of being included contemporaneously (along with the lags). The correlation estimates fall about half way in between the ones reported based on the 'data' and the 'residuals' in Tables 4 and 5. We do not report these additional estimates to not overload the tables.

anymore; moreover, we wish to keep a structure in the equations to reflect certain economic rationales. We, however, test three specific alternative specifications to gauge how sensitive the scenario responses presented in sub-section 3.2 are.

The three alternative specifications which we think could have some merit are (see Table A for comparison): i) to allow interest and deposit rates to exert a direct impact on the GDP deflator, using a global channel; ii) to allow the GDP deflator to exert a direct impact on banks' prices for loans and deposits, with a global channel; and iii) to allow loan volumes at bank or banking system level to influence directly the loan interest and deposit rate measures, using once again a global channel.

We re-simulate all the scenarios, i.e. Type 1, 2, and 3 for the banking system-based model to first obtain the cumulative responses of all model variables from the three alternative global models. Then we compute the ratio between the cumulative responses for all countries and variables to the responses from the 'base model' as presented in the previous section, for only the subset of responses that were significant at least at a 20% level in the base model. Table 3 presents some moments of the cross-country distribution of the ratios, distinguishing between domestic and foreign responses, the model variables, the three alternative model variants, and different moments of the distribution. Only a very small portion (less than 3%) of the significant cumulative responses, with regard to both domestic and cross-border responses, under the base model change their sign under the alternative model variants. These were excluded for the purpose of reporting the multiples and the corresponding statistics in Table 3. The multiples suggest that the cumulative responses are very close on average, with median multiples equalling merely 1.02 across variables. Another observation is that cross-border deviations are systematically a bit larger in magnitudes (see last column in the table), although they are not quite sizable on average either.

A final aspect to address is the choice of the number of periods over which the sign restrictions are applied (1 period for our Type 1 and 2 simulations). The simulation results based on sign restrictions for more than one period differ to some extent in terms of their strength, as they in general imply a wider corridor for the responses of the macro variables resulting from the Type 1 and 2 simulations, but they do not differ in qualitative terms nor with regard to their implied cross-country relative strength of the scenario responses.[40] It is clear that imposing a constraint on one variable for more periods strengthens the responses of related variables. Though there is no practical guidance in our view (and to the best of our knowledge from the literature) about an 'optimal' setting for this parameter. It remains a matter of how strong prior beliefs about underlying theories are. One additional option can be (for future work) to assess how persistent deleveraging episodes are (were historically) to thereby further inform the sign restriction settings.

4 Conclusions

The objective of the paper was to present a first prototype of a large-scale semi-structural model that is developed for the purpose of assessing the impact of changes in bank leverage and credit supply on real economic activity in the EU countries. The model is based on a GVAR structure that is augmented to feature the presence of multiple cross-sections — countries, banks and central banks in

[40] We do not present these additional results (they are available on request) as they would consume significant additional space while not adding much value.

our application. The MCS-GVAR comprises 28 EU economies along with a sample of 42 significant listed European banking groups. An alternative model variant based on aggregate banking system data was developed in parallel to the individual bank version, covering all 28 EU banking systems. Variables at bank/banking-system level — loan volumes, loan interest and deposit rates, leverage ratios and banks' probability of default — are combined with real and nominal activity measures at the country level.

Three types of scenario simulations are conducted with the model: two polar cases under which banks are assumed to approach a higher capital ratio either by full asset side deleveraging or by raising equity capital and investing that, i.e. generating slightly positive loan growth in the latter case. A third, unconstrained simulation is meant to reveal how banks were going about the deleveraging process historically. The results suggest that economic activity can drop materially under the first polar scenario. Some mild upside potential for growth can be measured under the capital raising scenario. The unconstrained capital ratio shocks tend to produce mixed, though on average somewhat negative, responses of real activity across countries.

The simulation results suggest, moreover, that cross-border and cross-bank/banking-system effects are sizable in many cases. Cross-border spillover effects arise due to one or a combination of two features: that banks are active across borders, and that countries trade with one another. For an assessment of the possible effects of capital-based macroprudential policy instruments, a model as the MCS-GVAR is useful as it allows gauging the cross-border implications, under the assumption that banks would adjust their lending behaviour to all markets to which they are exposed. More nuanced simulations can be conducted where, by assumption or by additional risk-return considerations, loan business in some countries would react more or less than in others.

The mixed-cross-section feature of the GVAR is not only useful for an application involving individual banks. Also when operating with aggregate banking systems the MCS structure is relevant and should be superior to the traditional GVAR with variable-specific weights, the reason being that the MCS-GVAR allows weights to be *equation*-specific, not only variable-specific. For example, for the loan growth equations in the system this means that economic activity variables can be weighed based on loan exposure profiles, as they should, and not be based on trade, as the traditional GVAR (even with a variable-specific weighting scheme) would do.

The MCS-GVAR model in its current form already contains variables and channels that allow for conducting further simulation exercises. For instance, the fact that the central bank cross-section is embedded in the model in an endogenous manner can be exploited further; monetary policy shocks can be simulated and their responses across banks and economies be assessed. Moreover, the framework is being combined with the ECB's stress test framework, for the combined tool-kit to help assess the costs and benefits of macroprudential policy measures. We also aim to further augment the identification approach to disentangle bank credit demand and supply, for instance by augmenting the model by some non-bank credit volumes and/or prices that can serve as substitutes for bank credit (considering e.g. corporate bond volumes or prices, or other non-bank aggregates). Non-bank aggregates can be constrained such that they substitute bank supply, i.e. in the case of a negative (Type 1) bank supply shock for example by constraining non-bank credit volumes to expand and their prices to fall.

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Annex A: Weight matrices for the MCS-GVAR

The variable vectors that are assigned an asterisk in equation (1) need to be generated by means of a set of weights that link the items within and across the cross-sections. Table B provides an overview of how the weights are parameterized for the individual bank and the banking system version of the model.

All weight matrices are time-varying over the 1999Q1-2014Q4 sample period. Unit weights related to the central bank cross-section are constant over time (for countries that joined the euro area in between 1999Q1 and 2014Q4, the unit weight switches to 1 only at the point when a country joined).

Countries — Countries ($\boldsymbol{W}^{C-C}$): A measure of *bilateral trade* (sum of nominal imports and exports between any two countries) is used to calibrate the cross-country weights. The weight of a country to itself is zero at any point in time. The trade data is sourced from the IMF trade statistics.

Banks — Countries ($\boldsymbol{W}^{B-C}$): For those variables at bank-level that are allowed to be a function of variables in the country cross-section, the corresponding weights are based on the banks' *credit exposure profile*. For the subset of SSM banks in the sample, the exposures are sourced from the databases that were published as part of the ECB's 2014 Comprehensive Assessment (CA). The database contains the information as to the sizes of the SSM banks' top-10 exposures. The residual, the consolidated loan stock less the sum of the top-10 exposures (which is rather small in general) is distributed in equal shares to the remaining countries. The exposure of a bank to countries that are not included in the model will be excluded from the weighting.[41] Important to note is that the CA-based exposure profiles allow the derivation of weights for one point in time, that is 2013Q4. The historical evolution of the weights is inferred by backcasting the country-specific weights at bank-level by means of historical MFI aggregate loan growth series for domestic and country-specific foreign activity. Like the backcasting for the pre-2013Q4 period, the weight evolution for the year 2014 is inferred using the same link to MFI loan growth aggregates. For the banking-system version of the model, BSI loan exposure statistics, including domestic and country-specific cross-border loan exposures to the private sector (household and non-financial corporates) are used as a basis for calibrating the weights.

Countries — Banks ($\boldsymbol{W}^{C-B}$): Can be seen as the mirror (transpose) of the weights for linking countries to banks ($\boldsymbol{W}^{B-C}$). Likewise for the banking system version of the model, the weights are the

[41] For the remaining non-SSM banks in the sample, a unit weight is assigned to the banks' home country. This assumption shall be fine as banks that were not part of the CA sample are relatively less significant, i.e. shall have less significant cross-border exposure.

Table B: Weight matrix parameterization

From...	To...	Weight matrices	
		Banking system-based model	Individual bank-based model
Countries -	- Countries	Bilateral trade (sum of nominal inports and exports)	
	- Banks	Transpose of Banking system (banks) - Countries matrices	
	- Central Banks	Unit weights for countries to their respective central bank; e.g. for EA countries set unit weight to ECB	
Banks -	- Countries	BSI domestic and cross-border exposure data	Stress test exposure data for SSM banks; unit weights on domestic economies for non-SSM banks
	- Banks	BSI cross-banking system exposure to financial institutions	Bank-size-based; across whole bank sample for SSM banks; across domestic banks for non-SSM banks
	- Central Banks	Unit weights for banking systems to respective central bank; e.g. for EA systems unit weight on ECB	Unit weights for banks to respective central bank; e.g. for EA banks unit weight on ECB
Central banks -	- Countries	HICP official weights for the Taylor rule, for both GDP and inflation	
	- Banks	*not needed given the current model structure*	
	- Central Banks	*not needed given the current model structure*	

transpose of the banking system - country weights at every point in time.

Banks — Banks ($\boldsymbol{W}^{B-B}$): Ideally, one would use bilateral cross-bank exposure data to calibrate the bank-bank weights. Such information is not in general publicly available. The alternative that is used is the following: for banks on the SSM list, which are deemed large and many of which are engaged in cross-border business, a size (total assets)-based weighting on the interbank market vis-a-vis all banks in Europe is assumed. For the banks that are not on the SSM list, we assume that they are less significant and hence less likely to engage in cross-border interbank borrowing and lending. Thus we assume total asset-based weights only for the banks in the same country and zero weights for banks from abroad. For the banking system version of the model, BSI domestic and cross-border loan volumes are again employed, in this case referring to only the exposures among financial institutions.

Central banks — Countries ($\boldsymbol{W}^{CB-C}$): Official HICP weights, i.e. size-of-the-economy-based weights are employed for the euro area policy rate equation. For the other currency areas, unit weights are imposed on the central banks' corresponding economies.

Two of the weight matrices are square matrices that have zero entries on their diagonals at every single point in time, namely the $\boldsymbol{W}^{C-C}$ and $\boldsymbol{W}^{B-B}$ matrix (if the cross central bank link was allowed then also $\boldsymbol{W}^{CB-CB}$ would have zeros on the diagonal). The other matrices, cross-linking the cross-sections are not square unless the number of items in two sections would be equal. Moreover, their diagonals do not need to equal zero; in fact, the weights in the cells on and near the diagonal should usually be the highest. A bank's weight on the country in which it is domiciled is generally the highest as banks provide the highest portion of credit to their home country. Likewise, the weight for a country on its 'own' banks will in general be the highest.

The model set-up is flexible in the sense that countries can be included in the model for which there are no there-domiciled banks (or the corresponding banking system is missing in the model). Vice versa, banks (or banking systems) could be included in the model for which the corresponding host country would not be included. The same possibly asymmetric setting holds for central banks. One asymmetry is in fact present in the individual bank version of our model as 28 EU economies are covered in the country cross-section, while the banks are domiciled in a subset of only 14 countries.

Table 1: Individual bank sample coverage

#	ID	Bank name	Leverage ratio (TA/E)				Leverage ratio shock	Corresponding capital ratio shock [pp]	Implied Type 1 loan supply shock [%]	Implied Type 2 loan supply shock [%]	Availability model variables				
			Historical average	Historical min	Historical max	2014Q4					Nominal loan volumes	I-income / I-bearing assets	I-expense / I-generating liabilities	Leverage	Banks' prob. of default
1	ATERST	Erste Group Bank AG	19.3	12.4	30.1	14.6	-1.2	0.6	-8.6	0.7	64	61	64	64	64
2	ATOBS	Oberbank AG	15.3	11.6	22.0	11.6	-0.9	0.7	-8.3	0.8	52	46	52	52	64
3	ATVBH	Oesterreichische Volksbanken AG	29.5	17.0	95.3	23.4	-4.6	1.0	-21.7	1.1	31	31	27	31	64
4	BEKBC	KBC Groep NV/ KBC Groupe SA	18.9	14.8	30.7	14.8	-1.9	1.0	-13.4	1.0	47	42	39	47	64
5	CYBOCG	Bank of Cyprus Group	17.9	7.7	92.6	7.7	-1.3	2.7	-18.8	3.1	35	35	30	35	-
6	CYHB	Hellenic Bank Public Company Limited	16.6	12.5	19.8	12.7	-1.1	0.7	-8.9	0.8	29	51	28	51	-
7	DEAAB	Aareal Bank AG	20.5	17.5	28.3	18.2	-0.4	0.1	-2.1	0.1	27	27	27	27	47
8	DECOMM	Commerzbank AG	33.9	20.4	54.1	20.7	-0.9	0.2	-4.6	0.2	61	61	61	61	64
9	DEDEBK	Deutsche Bank AG	37.9	22.7	69.0	23.3	-1.2	0.2	-5.4	0.2	52	52	51	52	64
10	DKDANSKE	Danske Bank A/S	29.1	21.0	36.8	22.6	-0.8	0.2	-3.6	0.2	28	61	35	61	64
11	DKJYSK	Jyske Bank A/S (Group)	18.3	14.4	22.1	19.7	-0.6	0.2	-3.1	0.2	28	29	29	29	64
12	DKSYDB	Sydbank A/S	16.8	13.5	22.3	13.5	-0.6	0.3	-4.6	0.4	28	29	29	29	64
13	ESBBVA	Banco Bilbao Vizcaya Argentaria SA	16.4	11.5	25.7	12.2	-0.5	0.4	-4.5	0.4	64	64	27	64	64
14	ESBSAB	Banco de Sabadell SA	14.5	8.5	20.8	14.6	-1.6	0.8	-11.4	0.9	55	55	55	55	35
15	ESPOPU	Banco Popular Espanol SA	14.2	11.0	16.3	12.7	-0.5	0.3	-4.3	0.4	64	64	64	64	64
16	ESSAN	Banco Santander SA	15.1	6.5	19.0	14.1	-1.4	0.8	-10.8	0.9	64	64	43	64	64
17	ESBKT	Bankinter SA	21.4	14.8	29.1	15.7	-1.0	0.4	-6.6	0.5	64	64	64	64	64
18	FIAKTAV	Aktia Bank Plc	20.9	15.5	32.8	15.5	-1.7	0.8	-11.5	0.8	18	43	-	43	-
19	FIALBAV	Alandsbanken Abp-Bank of Aland Plc	20.0	14.8	22.7	21.9	-1.3	0.3	-6.1	0.3	64	64	18	64	64
20	GRALPH	Alpha Bank AE	17.2	7.6	77.9	9.5	-1.2	1.5	-13.5	1.7	32	55	55	55	64
21	GRTATT	Attica Bank SA-Bank of Attica SA	15.1	8.4	60.6	11.1	-0.9	0.8	-8.3	0.9	51	51	51	51	64
22	GREURO	Eurobank Ergasias SA	22.6	8.7	152.7	12.0	-2.4	2.1	-22.8	2.4	33	55	-	55	64
23	HUOTP	OTP Bank Plc	8.9	6.6	13.1	8.7	-0.5	0.7	-5.9	0.8	51	51	51	51	64
24	ITCARI	Banca Carige SpA	11.6	7.9	25.8	21.1	-1.7	0.4	-8.6	0.4	61	61	61	61	64
25	ITMPS	Banca Monte dei Paschi di Siena SpA	20.5	12.9	34.6	30.6	-3.0	0.4	-10.2	0.4	25	64	-	64	59
26	ITBPER	Banca popolare dell'Emilia Romagna	14.0	11.0	17.0	11.0	-0.6	0.5	-5.3	0.5	55	55	55	55	64
27	ITBPM	Banca Popolare di Milano SCaRL	13.6	10.6	17.4	10.6	-0.9	0.9	-9.1	1.0	38	38	37	38	64
28	ITBAPO	Banco Popolare	12.5	10.9	14.9	15.2	-0.7	0.3	-5.0	0.4	29	30	-	30	64
29	ITCRVA	Credito Valtellinese Soc Coop	12.6	9.2	17.6	14.2	-1.0	0.5	-7.4	0.6	22	38	26	38	64
30	ITISP	Intesa Sanpaolo	15.6	7.4	24.6	14.3	-2.1	1.2	-16.1	1.3	60	60	22	60	64
31	ITMDB	Mediobanca SpA	8.5	5.1	13.3	8.7	-1.3	1.0	-8.6	1.2	24	57	37	57	64
32	ITUCG	UniCredit SpA	16.6	13.3	20.7	16.0	-1.2	0.5	-7.9	0.5	61	61	-	61	64
33	ITUBI	Unione di Banche Italiane Scpa-UBI Banca	11.6	9.3	14.8	11.8	-0.8	0.6	-7.2	0.7	43	43	41	43	46
34	LTSAB1L	Siauliu Bankas	10.2	6.8	17.5	15.2	-0.8	0.4	-5.5	0.4	39	39	39	39	-
35	PLPKO	Powszechna Kasa Oszczednosci Bank Polski - PKO	9.4	7.3	13.5	9.0	-0.6	0.8	-6.7	0.9	45	45	45	45	40
36	PTBPI	Banco BPI SA	21.8	14.0	52.2	16.7	-1.5	0.6	-9.3	0.6	24	64	27	64	-
37	PTBCP	Banco Comercial Português, SA-Millennium bcp	18.1	11.7	31.5	15.3	-1.0	0.5	-6.8	0.5	26	64	64	64	-
38	PTBES	Banco Espirito Santo SA	14.3	-8.1	19.6	19.6	-0.5	0.1	-2.8	0.2	61	61	61	61	-
39	SENDA	Nordea Bank AB (publ)	22.7	17.5	27.3	22.4	-1.2	0.2	-5.4	0.3	64	64	64	64	64
40	SESEBA	Skandinaviska Enskilda Banken AB	26.3	17.1	34.0	19.6	-1.1	0.3	-5.8	0.3	36	64	27	64	64
41	SESHBA	Svenska Handelsbanken	25.2	21.4	29.7	22.2	-1.3	0.3	-6.1	0.3	64	64	25	64	64
42	SESWEDA	Swedbank AB	22.5	16.6	29.3	18.1	-1.2	0.4	-6.8	0.4	64	64	64	64	64

Note: The leverage ratio statistics are based on the 1999Q1-2014Q4 period. The leverage ratio shock sizes reflect 1 standard deviation of the MCS-GVAR model residuals. The implied Type 1 and 2 loan supply shocks are expressed as log percentage. Under the column 'availability of model variables', the number of time series observations since 1999Q1 is reported.

Table 2: Banking system / country sample coverage

#	ID	Country	Leverage ratio (TA/E)				Leverage ratio shock	Corresponding capital ratio shock [pp]	Implied Type 1 loan supply shock [%]	Implied Type 2 loan supply shock [%]	Availability model variables									
			Historical average	Historical min	Historical max	2014Q4					Nominal GDP	GDP deflator	House prices	Long-term interest rates	Nominal loan volumes	Loan interest rates	Deposit rates	Leverage	Banks' prob. of default	Policy rate
1	AT	Austria	14.8	9.0	21.4	9.3	-0.5	0.7	-6.0	0.8	64	64	64	64	64	48	64	64	64	64
2	BE	Belgium	22.9	16.9	35.4	17.4	-0.9	0.3	-5.2	0.3	64	64	64	64	64	48	60	64	64	64
3	BG	Bulgaria	8.8	7.8	14.3	11.3	-0.2	0.2	-1.9	0.2	64	64	64	49	43	32	32	43	-	60
4	CY	Cyprus	9.5	4.2	15.2	4.2	-0.7	4.0	-17.3	5.3	64	64	51	55	36	28	37	36	-	64
5	CZ	Czech Republic	9.4	8.3	11.0	8.4	-0.2	0.3	-2.4	0.3	64	64	-	58	51	44	44	51	-	64
6	DE	Germany	21.6	16.6	25.1	16.7	-0.4	0.2	-2.7	0.2	64	64	47	64	64	48	64	64	64	64
7	DK	Denmark	16.4	12.9	21.3	15.2	-1.0	0.5	-6.7	0.5	64	64	64	64	47	-	48	57	64	64
8	EE	Estonia	8.4	7.1	11.0	7.2	-0.3	0.5	-3.6	0.6	64	64	45	64	27	40	28	27	-	64
9	ES	Spain	12.1	7.2	16.0	7.7	-0.3	0.7	-4.9	0.8	64	64	64	64	64	48	64	64	64	64
10	FI	Finland	16.0	9.6	27.2	20.3	-0.7	0.2	-3.4	0.2	64	64	64	64	64	48	64	64	64	64
11	FR	France	16.5	14.5	19.1	15.7	-0.3	0.1	-2.2	0.2	64	64	64	64	64	48	64	64	64	64
12	GB	United Kingdom	13.2	10.8	17.8	11.5	-0.5	0.5	-4.9	0.5	64	64	64	64	63	44	44	63	64	64
13	GR	Greece	11.7	5.4	22.5	5.5	-1.1	4.5	-22.5	5.6	64	63	64	64	64	48	64	64	64	64
14	HR	Croatia	5.4	5.1	5.8	5.1	-	-	-	-	59	59	-	27	-	-	-	64	-	55
15	HU	Hungary	10.1	6.4	14.2	8.5	-0.6	1.3	-8.8	1.6	64	64	-	62	47	40	40	47	-	64
16	IE	Ireland	16.6	7.8	24.3	9.7	-0.7	1.0	-8.2	1.1	64	64	20	64	64	48	63	64	64	64
17	IT	Italy	12.9	9.5	15.5	9.5	-0.3	0.4	-3.5	0.4	64	64	64	64	64	48	64	64	64	64
18	LT	Lithuania	7.4	7.0	8.0	7.5	-0.3	0.6	-4.3	0.7	64	64	64	55	43	41	-	43	-	64
19	LU	Luxembourg	23.7	15.5	49.8	15.9	-0.5	0.2	-3.2	0.2	64	64	64	64	64	48	64	64	64	64
20	LV	Latvia	11.0	9.7	13.1	9.9	-	-	-	-	64	64	59	55	-	44	-	-	-	64
21	MT	Malta	8.2	4.8	13.1	10.8	-0.6	0.7	-6.6	0.8	59	59	59	64	39	31	31	39	-	64
22	NL	Netherlands	21.9	18.4	27.0	20.3	-1.1	0.3	-5.6	0.3	64	64	64	64	64	48	64	64	64	64
23	PL	Poland	7.4	6.3	9.5	7.1	-0.2	0.5	-3.3	0.6	64	64	-	61	43	40	40	43	64	64
24	PT	Portugal	11.7	7.6	13.9	7.9	-0.2	0.3	-2.5	0.3	64	64	64	64	64	48	64	64	-	64
25	RO	Romania	7.5	4.9	10.0	5.4	-0.2	0.6	-3.2	0.8	64	-	-	38	-	32	32	40	-	64
26	SE	Sweden	17.2	13.6	22.9	17.1	-0.7	0.3	-4.5	0.3	64	64	64	64	52	38	38	52	64	64
27	SI	Slovenia	11.8	9.6	16.9	10.2	-0.8	0.7	-7.2	0.8	64	64	39	51	43	48	39	43	-	64
28	SK	Slovakia	8.9	6.9	12.0	7.0	-0.2	0.3	-2.4	0.4	64	64	39	55	35	28	28	35	-	64

Note: The leverage ratio statistics are based on the 1999Q1-2014Q4 period. The leverage ratio shock sizes reflect 1 standard deviation of the MCS-GVAR model residuals. The implied Type 1 and 2 loan supply shocks are expressed as log percentage. Under the column 'availability of model variables', the number of time series observations since 1999Q1 is reported.

Table 3: Robustness — Multiples of cumulative responses relative to 'base' model

			YEN	YED	HP	LTN	L	I	D	PD	STN	Average
Model variant 1	domestic	Q=0.05	0.92	0.82	0.97	0.81	1.00	0.87	0.92	0.96	0.91	0.91
		Q=0.25	1.00	0.93	0.99	1.03	1.01	0.94	0.99	1.00	1.00	0.99
		Q=0.50	1.03	0.99	1.02	1.07	1.02	1.00	1.01	1.02	1.02	1.02
		Q=0.75	1.07	1.12	1.05	1.09	1.04	1.09	1.07	1.04	1.04	1.07
		Q=0.95	1.14	1.29	1.09	1.24	1.09	1.26	1.30	1.15	1.10	1.18
	foreign	Q=0.05	0.85	0.74	0.87	0.89	0.89	0.88	0.80	0.90	0.89	0.86
		Q=0.25	0.98	0.88	0.99	1.06	1.00	0.99	0.98	1.00	1.01	0.99
		Q=0.50	1.09	1.00	1.09	1.13	1.07	1.07	1.09	1.06	1.09	1.08
		Q=0.75	1.21	1.18	1.18	1.18	1.16	1.15	1.19	1.12	1.19	1.17
		Q=0.95	1.41	1.48	1.40	1.38	1.41	1.32	1.38	1.30	1.42	1.39
Model variant 2	domestic	Q=0.05	0.97	0.90	0.98	0.96	0.97	0.83	0.88	0.94	0.94	0.93
		Q=0.25	1.00	1.00	0.99	1.00	0.99	1.01	0.95	0.98	0.98	0.99
		Q=0.50	1.01	1.03	1.00	1.01	1.01	1.04	1.00	1.01	1.00	1.01
		Q=0.75	1.03	1.07	1.02	1.03	1.02	1.10	1.04	1.03	1.03	1.04
		Q=0.95	1.07	1.22	1.05	1.25	1.07	1.22	1.09	1.07	1.04	1.12
	foreign	Q=0.05	0.86	0.85	0.90	0.96	0.84	0.83	0.75	0.89	0.92	0.87
		Q=0.25	0.99	1.00	0.99	1.00	0.99	0.99	0.95	0.99	1.00	0.99
		Q=0.50	1.03	1.03	1.03	1.04	1.03	1.04	1.02	1.02	1.03	1.03
		Q=0.75	1.10	1.10	1.09	1.08	1.09	1.13	1.08	1.08	1.09	1.09
		Q=0.95	1.38	1.42	1.34	1.35	1.39	1.42	1.35	1.31	1.38	1.37
Model variant 3	domestic	Q=0.05	0.96	0.93	0.96	0.94	0.97	0.85	0.82	0.95	0.98	0.93
		Q=0.25	0.98	0.96	0.99	0.98	0.99	0.93	0.92	0.98	0.99	0.97
		Q=0.50	1.00	1.00	1.00	1.01	1.00	0.99	0.97	0.99	0.99	0.99
		Q=0.75	1.01	1.01	1.01	1.04	1.01	1.05	1.07	1.01	1.00	1.02
		Q=0.95	1.05	1.06	1.02	1.15	1.03	1.17	1.19	1.04	1.03	1.08
	foreign	Q=0.05	0.88	0.88	0.87	0.89	0.86	0.83	0.77	0.86	0.89	0.86
		Q=0.25	0.96	0.95	0.94	0.96	0.94	0.93	0.90	0.93	0.97	0.94
		Q=0.50	1.00	0.99	0.99	0.99	0.99	0.98	0.98	0.98	1.01	0.99
		Q=0.75	1.06	1.05	1.06	1.04	1.07	1.05	1.09	1.02	1.07	1.06
		Q=0.95	1.28	1.25	1.24	1.27	1.27	1.32	1.40	1.20	1.29	1.28

Note: The table reports the multiples of the cumulative responses to Type 1/2/3 shocks that were applied to all banking systems in the banking system version of the model. The multiples are computed relative to the 'base' model results as presented in the core of the paper. The multiples are computed for only those cumulative responses that were significant at least at a 20% level in the 'base' model. The multiples reported in the loan volume growth (L) column are based on the Type 3 shock simulation results only, as under the Type 1 and 2 simulation, the paths of credit growth are predetermined (see text for details).

Table 4: Pair-wise cross-correlations — Banking system version of the model

			Data										Residuals									
			CS1				CS2					CS3	CS1				CS2					CS3
			YEN	YED	HP	LTN	L	LEV	I	D	PD	STN	YEN	YED	HP	LTN	L	LEV	I	D	PD	STN
All countries and banking systems	CS1	YEN	0.50	0.13	0.27	0.03	0.24	0.05	0.41	0.44	-0.12	0.30	0.02	0.01	0.01	0.00	0.01	-0.01	0.00	0.01	-0.02	0.00
		YED		0.10	0.09	0.02	0.13	0.08	0.12	0.10	0.03	0.07		0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.04	-0.01
		HP			0.19	0.04	0.17	0.06	0.19	0.21	-0.06	0.14			0.05	0.01	-0.01	-0.01	0.00	-0.01	-0.01	-0.03
		LTN				0.32	0.03	0.02	0.03	0.04	0.00	0.09				-0.01	0.00	0.01	0.01	-0.01	0.00	-0.01
	CS2	L					0.26	0.13	0.22	0.21	0.03	0.19					0.06	0.01	-0.01	0.01	0.01	0.02
		LEV						0.13	0.10	0.05	0.06	0.10						0.05	0.00	-0.01	0.02	0.02
		I							0.49	0.44	-0.06	0.35							0.03	-0.01	0.00	0.02
		D								0.46	-0.10	0.33								0.09	0.01	0.00
		PD									0.14	-0.02									0.05	-0.02
	CS3	STN										0.21										0.08
DE vs all	CS1	YEN	0.55	0.06	0.24	0.03	0.13	-0.03	0.48	0.51	-0.21	0.33	0.03	-0.04	-0.01	0.03	-0.03	-0.01	0.01	-0.10	-0.11	0.01
		YED	-0.04	-0.07	-0.08	-0.04	-0.19	-0.12	-0.06	-0.08	-0.10	-0.10	0.02	0.01	0.04	0.00	-0.05	0.01	0.01	0.03	-0.05	-0.05
		HP	-0.02	-0.01	-0.03	-0.04	-0.03	0.10	0.04	0.04	0.00	0.00	0.03	-0.01	0.04	0.02	-0.02	0.07	0.00	0.02	-0.04	-0.04
		LTN	0.16	-0.01	0.11	0.44	0.00	-0.10	0.06	0.13	-0.13	0.11	0.00	0.01	0.05	-0.04	-0.07	-0.11	0.06	0.04	-0.08	-0.02
	CS2	L	0.31	0.10	0.10	0.01	0.28	0.19	0.47	0.42	0.07	0.36	-0.02	0.00	-0.10	-0.03	0.10	0.05	-0.03	0.06	0.13	0.09
		LEV	0.10	0.11	0.04	-0.01	0.12	0.20	0.08	0.06	0.10	0.11	-0.01	0.01	-0.04	-0.01	-0.03	0.11	-0.04	0.01	0.09	0.04
		I	0.59	0.15	0.28	0.07	0.27	0.08	0.66	0.62	-0.13	0.45	-0.01	0.06	0.06	-0.02	-0.01	-0.03	0.05	0.02	0.16	0.09
		D	0.61	0.14	0.29	0.08	0.30	0.10	0.63	0.65	-0.14	0.46	-0.01	-0.01	0.03	0.03	0.02	0.02	-0.02	0.10	-0.08	-0.07
		PD	-0.42	0.00	-0.21	0.04	-0.03	0.07	-0.27	-0.34	0.33	-0.12	-0.01	0.04	0.06	0.01	-0.01	0.06	0.03	-0.05	0.14	-0.03
FR vs all	CS1	YEN	0.62	0.17	0.35	0.08	0.27	0.07	0.48	0.53	-0.15	0.37	0.01	0.01	-0.03	0.01	-0.05	-0.01	-0.05	-0.02	-0.04	-0.02
		YED	0.42	0.24	0.28	-0.06	0.37	0.22	0.41	0.36	0.05	0.17	0.03	-0.01	-0.05	-0.01	-0.01	0.02	0.03	0.11	0.06	-0.03
		HP	0.52	0.11	0.37	-0.02	0.26	0.07	0.35	0.40	-0.11	0.26	-0.02	-0.02	0.10	-0.03	0.05	0.01	-0.05	-0.08	0.13	-0.03
		LTN	0.12	0.02	0.10	0.51	0.01	-0.04	0.09	0.14	-0.09	0.12	-0.01	-0.01	0.01	-0.01	-0.07	-0.08	0.06	0.04	-0.09	-0.05
	CS2	L	0.50	0.23	0.32	0.18	0.43	0.18	0.48	0.49	0.02	0.39	0.01	0.00	-0.04	0.00	0.16	0.04	-0.08	0.03	0.13	0.11
		LEV	0.10	0.13	0.12	-0.05	0.24	0.21	0.08	-0.02	0.06	0.07	-0.01	0.03	-0.04	0.02	0.06	0.10	-0.04	-0.02	0.03	-0.06
		I	0.52	0.17	0.22	0.01	0.29	0.14	0.65	0.57	-0.07	0.43	0.05	0.03	0.07	0.02	-0.02	0.01	0.06	0.04	0.00	0.04
		D	0.44	0.12	0.19	0.06	0.24	0.11	0.61	0.56	-0.04	0.40	-0.03	0.01	0.04	0.00	-0.04	-0.04	0.02	-0.04	0.05	-0.03
		PD	-0.28	0.04	-0.15	0.04	0.00	0.12	-0.15	-0.23	0.29	-0.05	-0.01	0.06	-0.06	-0.02	-0.03	0.03	-0.01	0.03	0.12	-0.02
IT vs all	CS1	YEN	0.53	0.13	0.35	0.12	0.24	0.09	0.42	0.43	-0.14	0.32	0.00	-0.01	0.06	0.00	-0.02	0.03	-0.06	-0.02	0.09	0.08
		YED	-0.07	0.09	0.06	0.16	0.06	0.13	-0.05	-0.09	0.09	0.01	-0.04	-0.03	0.03	-0.02	0.01	0.06	-0.02	-0.04	0.12	0.13
		HP	0.33	0.16	0.31	0.17	0.35	0.13	0.18	0.21	0.00	0.21	-0.02	-0.03	0.14	0.04	0.00	0.02	0.00	-0.03	0.00	0.00
		LTN	0.06	0.03	0.05	0.39	0.04	0.10	0.12	0.13	0.04	0.14	-0.03	0.03	-0.08	-0.03	-0.04	0.08	-0.01	-0.02	0.15	0.06
	CS2	L	0.45	0.19	0.28	0.09	0.34	0.17	0.36	0.34	-0.02	0.32	0.03	-0.01	-0.07	0.01	0.05	0.05	0.01	-0.03	-0.09	0.03
		LEV	-0.09	0.05	-0.06	-0.10	0.01	0.09	-0.04	-0.08	0.14	-0.08	0.02	0.03	0.04	0.00	-0.06	0.05	0.00	0.08	0.12	-0.09
		I	0.50	0.14	0.20	0.06	0.23	0.15	0.63	0.59	-0.07	0.46	-0.01	-0.02	-0.01	0.04	-0.04	0.04	0.04	0.01	-0.08	0.08
		D	0.60	0.17	0.27	0.03	0.29	0.12	0.67	0.65	-0.09	0.47	0.02	0.04	-0.06	-0.07	0.02	-0.04	-0.04	0.09	0.06	0.00
		PD	-0.29	0.03	-0.16	0.03	0.01	0.09	-0.14	-0.19	0.30	-0.04	-0.04	0.05	-0.04	-0.02	0.04	0.08	0.03	-0.01	0.13	0.09
ES vs all	CS1	YEN	0.54	0.22	0.42	0.09	0.41	0.19	0.41	0.43	-0.10	0.32	0.07	0.01	0.01	-0.05	0.04	0.00	-0.07	0.07	-0.09	0.00
		YED	0.38	0.21	0.34	0.06	0.42	0.17	0.26	0.27	-0.02	0.11	0.03	0.05	-0.02	-0.05	0.06	-0.01	-0.05	0.08	-0.05	-0.03
		HP	0.37	0.10	0.34	0.09	0.28	0.12	0.15	0.19	-0.09	0.16	-0.03	-0.02	0.13	0.02	-0.01	0.05	0.07	-0.06	0.09	0.04
		LTN	0.10	0.02	0.07	0.38	0.07	0.04	0.03	0.13	0.00	0.11	-0.01	-0.01	-0.05	-0.06	0.04	0.05	-0.06	0.15	0.08	-0.02
	CS2	L	0.37	0.21	0.35	0.13	0.41	0.19	0.21	0.18	0.02	0.20	0.02	0.02	-0.04	0.03	0.10	0.03	0.00	0.02	0.09	-0.02
		LEV	0.40	0.17	0.28	0.25	0.31	0.08	0.29	0.33	-0.04	0.29	0.04	0.02	-0.03	-0.01	0.04	0.00	0.01	0.03	-0.02	0.08
		I	0.56	0.16	0.23	0.06	0.26	0.13	0.65	0.62	-0.11	0.45	0.01	0.05	-0.04	0.00	-0.06	-0.01	0.02	0.09	-0.10	-0.04
		D	0.59	0.16	0.27	0.04	0.27	0.07	0.60	0.61	-0.07	0.43	0.00	0.03	-0.02	-0.01	-0.07	-0.04	0.00	0.11	0.03	-0.03
		PD	-0.21	0.02	-0.10	0.11	0.06	0.08	-0.14	-0.12	0.26	-0.02	-0.08	-0.02	-0.02	0.00	0.01	0.00	-0.01	0.03	0.11	0.01
NL vs all	CS1	YEN	0.59	0.22	0.34	0.06	0.38	0.17	0.52	0.52	-0.08	0.36	0.04	-0.01	0.03	0.05	0.02	0.05	0.05	-0.01	-0.04	-0.03
		YED	0.15	0.13	0.10	-0.08	0.19	0.17	0.25	0.18	0.04	0.01	-0.01	0.04	-0.04	0.02	0.00	0.00	0.10	-0.02	-0.05	-0.06
		HP	0.33	0.18	0.29	0.04	0.37	0.18	0.27	0.25	-0.01	0.25	0.01	-0.04	0.05	0.03	0.02	0.00	0.05	-0.08	-0.05	-0.04
		LTN	0.13	0.02	0.10	0.47	0.03	-0.05	0.07	0.11	-0.10	0.10	0.04	0.00	0.03	-0.03	0.09	-0.06	-0.02	0.03	-0.13	-0.07
	CS2	L	0.51	0.15	0.23	0.05	0.23	0.01	0.39	0.45	-0.11	0.29	0.02	0.02	-0.02	-0.03	0.12	-0.03	-0.03	-0.02	-0.01	0.05
		LEV	-0.30	-0.02	-0.06	-0.02	-0.11	0.10	-0.24	-0.33	0.12	-0.18	0.01	0.03	0.03	0.01	0.00	0.04	0.02	-0.04	0.07	-0.08
		I	0.58	0.14	0.26	0.04	0.25	0.08	0.65	0.61	-0.12	0.44	0.03	0.01	0.01	-0.01	-0.10	-0.09	0.09	0.06	0.05	-0.02
		D	0.61	0.15	0.28	0.07	0.28	0.06	0.63	0.64	-0.14	0.44	0.00	0.01	0.08	0.01	0.02	-0.04	0.01	0.14	-0.03	-0.04
		PD	-0.24	0.06	-0.11	-0.03	0.02	0.13	-0.12	-0.21	0.24	-0.02	0.01	0.05	-0.08	0.00	0.04	0.02	0.00	-0.03	0.17	0.04
Central banks vs all	CS3 STN	ECB	0.55	0.09	0.28	0.14	0.23	0.01	0.51	0.61	-0.19	0.39	-0.01	-0.03	-0.01	-0.04	0.03	-0.04	0.01	0.00	-0.12	0.10
		BG	0.39	0.20	0.21	0.10	0.38	0.24	0.51	0.40	0.04	0.28	-0.02	0.01	-0.01	-0.01	0.01	0.09	0.08	-0.01	0.08	0.07
		CZ	0.48	0.10	0.23	0.10	0.28	0.13	0.53	0.49	-0.03	0.27	0.01	0.00	-0.01	0.01	0.02	0.02	0.00	0.02	0.05	0.10
		DK	0.59	0.15	0.30	0.10	0.32	0.12	0.65	0.62	-0.11	0.30	0.02	0.00	0.05	0.00	0.04	-0.06	0.03	0.07	-0.10	0.15
		HR	-0.12	0.00	-0.03	0.04	0.03	0.11	-0.05	-0.12	0.10	0.00	-0.04	-0.03	-0.05	0.02	0.02	0.05	0.01	-0.10	0.07	0.10
		HU	-0.02	0.06	-0.01	0.11	0.11	0.17	0.12	0.01	0.14	0.09	0.05	0.01	-0.07	0.00	0.06	0.07	0.05	0.02	0.09	0.12
		LT	0.07	0.05	0.02	0.04	0.14	0.18	0.24	0.05	0.07	0.07	-0.01	0.03	0.00	0.03	0.01	0.05	0.08	-0.04	0.05	0.00
		PL	0.37	0.01	0.13	0.13	0.18	0.07	0.42	0.44	0.00	0.22	-0.01	-0.01	-0.08	0.00	0.03	0.06	0.01	-0.01	0.15	0.08
		RO	-0.02	0.04	-0.04	-0.05	0.10	0.12	0.10	0.08	0.16	0.03	-0.01	0.01	-0.10	0.00	0.03	0.04	0.00	0.07	0.15	0.01
		SE	0.48	0.07	0.21	0.19	0.18	-0.03	0.46	0.57	-0.17	0.34	-0.01	-0.07	-0.03	-0.04	0.01	-0.04	-0.01	-0.02	-0.14	0.05
		GB	0.46	0.04	0.24	0.12	0.15	-0.01	0.37	0.51	-0.20	0.27	0.00	-0.06	-0.01	-0.04	0.01	-0.02	-0.02	0.02	-0.14	0.08
			YEN	YED	HP	LTN	L	LEV	I	D	PD	STN	YEN	YED	HP	LTN	L	LEV	I	D	PD	STN
			CS1				CS2					CS3	CS1				CS2					CS3
			Data										Residuals									

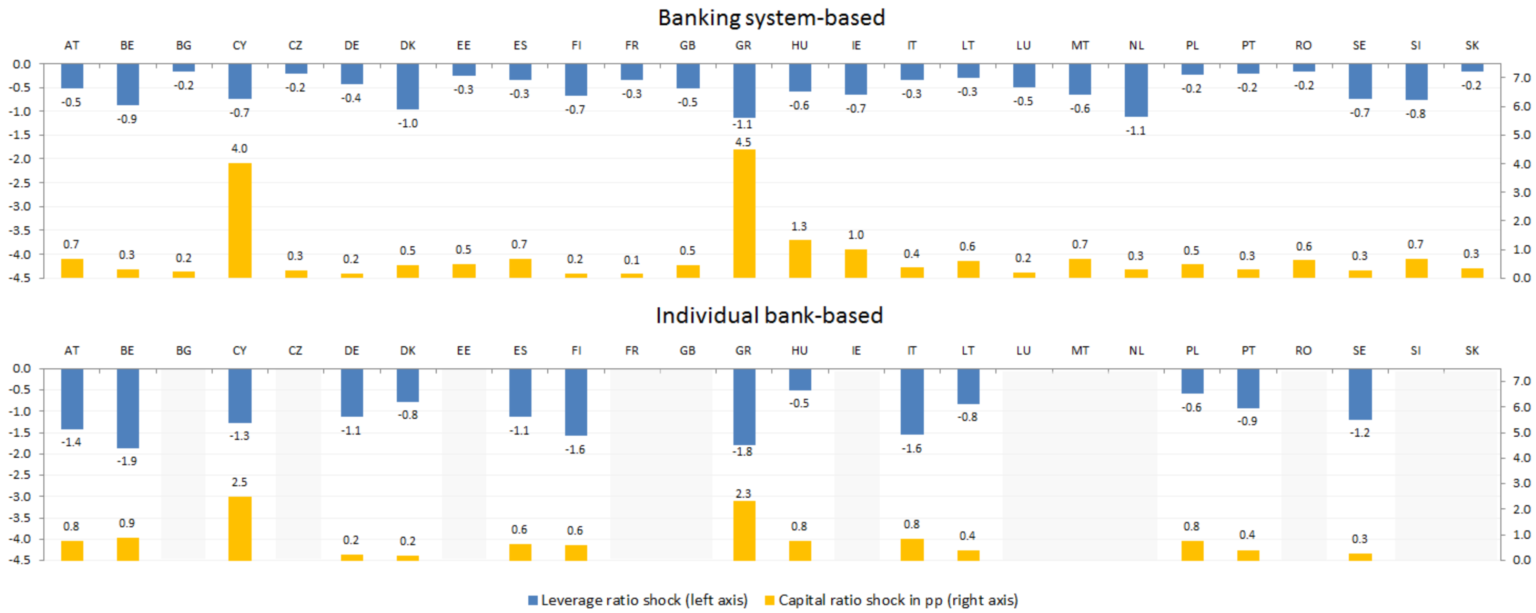
Note: The table shows the average cross-correlations of the data and the model residuals for the model overall (first block at the top), from the perspective of selected countries (the largest five euro area countries), as well as from the perspective of all central banks (ECB plus 10 non-EA EU central banks' short term policy rates) in the model.

Table 5: Pair-wise cross-correlations — Individual bank version of the model

			Data										Residuals									
			CS1				CS2					CS3	CS1				CS2					CS3
			YEN	YED	HP	LTN	L	LEV	I	D	PD	STN	YEN	YED	HP	LTN	L	LEV	I	D	PD	STN
All countries and banking systems	CS1	YEN	0.51	0.08	0.27	0.08	0.08	-0.04	0.09	0.14	-0.22	0.34	0.00	0.02	0.00	-0.01	-0.01	-0.01	0.00	0.00	-0.01	0.02
		YED		0.06	0.03	0.05	0.03	0.03	0.03	0.04	-0.02	0.08		0.00	0.01	-0.02	-0.01	0.01	0.00	0.01	0.01	0.03
		HP			0.19	0.05	0.05	-0.01	0.06	0.07	-0.14	0.16			0.04	0.03	0.00	0.00	0.01	-0.01	-0.01	-0.01
		LTN				0.38	0.07	0.00	-0.02	-0.02	0.02	0.15				-0.03	-0.01	0.00	0.01	-0.03	0.01	-0.07
	CS2	L					0.15	0.00	0.01	0.04	-0.01	0.10					0.04	-0.01	-0.01	0.01	0.02	0.04
		LEV						0.08	0.03	0.05	0.01	0.01						0.06	0.01	-0.01	0.02	0.01
		I							0.07	0.10	-0.08	0.10							0.01	-0.03	-0.02	0.00
		D								0.15	-0.05	0.18								0.03	0.06	0.01
		PD									0.41	-0.15									0.08	-0.08
	CS3	STN										0.35										0.08
DE vs all	CS1	YEN	0.64	0.04	0.37	0.10	0.08	-0.06	0.13	0.19	-0.29	0.45	-0.02	-0.01	0.00	0.03	-0.05	0.01	0.03	-0.01	0.06	0.04
		YED	0.04	0.07	-0.03	0.04	-0.03	-0.07	0.05	-0.02	-0.06	-0.05	0.01	-0.04	0.02	0.05	-0.02	-0.06	0.01	-0.07	-0.07	-0.11
		HP	0.01	0.07	0.10	0.04	0.05	0.09	0.07	0.06	-0.05	0.00	-0.01	0.01	-0.05	0.03	0.02	0.03	-0.01	-0.04	0.04	-0.01
		LTN	0.24	-0.01	0.20	0.46	0.04	-0.04	0.14	0.16	-0.08	0.14	0.10	0.05	0.09	0.01	0.03	-0.10	0.14	0.10	0.01	0.02
	CS2	L	-0.04	0.06	0.01	0.06	0.09	0.03	-0.03	-0.04	-0.04	0.06	0.02	0.04	-0.02	-0.02	0.05	0.00	0.00	0.00	-0.03	0.11
		LEV	0.04	0.02	0.05	-0.16	0.02	0.07	0.10	0.15	-0.09	0.05	-0.04	-0.01	0.04	0.04	-0.03	0.03	-0.02	0.01	-0.01	-0.04
		I	0.16	0.06	0.11	0.02	0.00	0.05	0.10	0.11	-0.21	0.11	0.01	0.00	-0.01	0.01	-0.03	0.04	0.06	-0.07	-0.10	-0.02
		D	0.21	0.06	0.08	0.09	0.10	-0.01	0.05	0.11	-0.14	0.19	-0.03	-0.03	-0.05	-0.01	0.05	-0.05	-0.08	0.03	0.02	0.06
		PD	-0.29	-0.03	-0.18	0.04	0.02	-0.02	-0.11	-0.12	0.44	-0.21	-0.01	0.02	-0.02	0.00	0.05	0.00	-0.05	0.05	0.10	-0.09
IT vs all	CS1	YEN	0.50	0.10	0.29	0.12	0.08	0.01	0.12	0.17	-0.29	0.33	-0.01	0.04	0.04	-0.03	-0.03	0.08	0.02	0.01	-0.03	0.09
		YED	-0.10	0.07	-0.04	0.17	0.01	0.07	0.02	-0.02	0.09	-0.01	-0.01	0.00	0.03	-0.03	-0.04	0.07	0.02	0.01	0.00	0.13
		HP	0.22	0.13	0.23	0.13	0.08	0.01	0.10	0.07	-0.10	0.18	0.01	0.00	0.03	0.04	0.02	0.00	0.04	-0.09	-0.08	-0.03
		LTN	0.06	0.08	0.15	0.40	0.12	0.12	0.14	0.14	0.04	0.17	0.05	0.05	-0.06	0.01	-0.01	0.12	0.03	0.04	0.12	0.09
	CS2	L	0.06	0.02	0.03	0.07	0.14	-0.01	0.01	0.05	0.04	0.05	0.00	-0.03	0.00	0.02	0.04	-0.03	-0.02	0.02	0.05	-0.02
		LEV	-0.08	0.00	-0.04	0.02	-0.03	0.09	0.00	0.02	0.06	-0.01	-0.01	0.00	-0.01	-0.03	-0.03	0.08	0.01	0.00	0.04	0.01
		I	0.06	0.03	0.05	-0.02	0.01	0.03	0.06	0.06	-0.06	0.08	0.01	0.01	0.00	0.01	-0.01	0.01	0.02	-0.02	-0.01	0.02
		D	0.21	0.07	0.13	-0.01	0.04	0.04	0.12	0.20	-0.17	0.22	0.03	0.04	0.02	-0.01	-0.02	0.00	0.01	0.01	0.03	0.01
		PD	-0.25	-0.03	-0.17	0.06	-0.03	0.03	-0.09	-0.04	0.46	-0.17	-0.01	0.02	-0.02	0.02	0.00	0.03	-0.02	0.06	0.12	-0.11
ES vs all	CS1	YEN	0.55	0.13	0.28	0.09	0.10	0.03	0.08	0.17	-0.30	0.32	0.11	0.06	0.02	-0.09	-0.02	0.02	0.00	0.01	-0.01	0.05
		YED	0.24	0.09	0.09	0.00	0.08	0.04	0.00	0.07	-0.12	0.16	0.02	0.11	0.00	-0.08	-0.01	0.01	-0.02	0.02	0.02	0.00
		HP	0.27	0.00	0.21	0.17	0.08	0.01	0.07	0.02	-0.21	0.12	-0.02	-0.01	0.11	0.07	0.00	0.02	0.04	-0.03	-0.06	0.00
		LTN	0.18	0.08	0.11	0.44	0.14	0.03	-0.02	0.00	0.10	0.22	-0.01	0.00	0.02	-0.08	0.03	-0.01	-0.02	0.03	0.05	-0.01
	CS2	L	0.11	0.03	0.09	0.06	0.17	0.02	0.03	0.06	-0.02	0.10	0.00	-0.01	0.00	-0.05	0.07	-0.02	-0.03	0.03	0.09	0.06
		LEV	-0.03	0.05	0.01	-0.07	0.01	0.07	0.06	0.07	0.03	0.02	-0.01	0.02	-0.01	0.00	-0.01	0.03	0.00	0.02	0.07	0.00
		I	0.19	0.07	0.14	-0.03	0.06	0.04	0.10	0.17	-0.13	0.18	0.00	0.00	0.06	0.03	0.00	0.03	-0.01	-0.03	-0.01	-0.02
		D	0.34	0.11	0.18	0.03	0.06	0.10	0.16	0.30	-0.13	0.37	0.02	-0.01	-0.02	-0.07	0.04	-0.01	-0.05	0.10	0.09	0.05
		PD	-0.07	-0.01	-0.09	-0.01	0.01	0.00	-0.04	0.01	0.38	-0.08	0.00	-0.02	-0.03	0.01	0.03	0.00	-0.02	0.07	0.08	-0.08
Central banks vs all	CS3 STN	ECB	0.53	0.11	0.30	0.18	0.14	0.00	0.08	0.18	-0.31	0.55	0.03	0.03	0.01	-0.09	0.06	-0.04	0.01	0.00	-0.17	0.16
		BG	0.43	0.23	0.26	0.17	0.47	0.32	0.53	0.47	0.10	0.28	-0.01	0.06	0.04	0.01	0.07	0.18	0.12	0.00	0.15	0.09
		CZ	0.54	0.17	0.29	0.18	0.29	0.14	0.58	0.55	0.07	0.36	0.03	0.02	0.02	0.03	0.03	0.06	0.10	0.11	0.07	0.15
		DK	0.63	0.17	0.38	0.18	0.35	0.21	0.73	0.69	-0.10	0.39	0.10	0.08	0.05	0.02	0.07	-0.05	0.13	0.12	-0.01	0.12
		HR	-0.03	0.08	0.01	0.07	0.10	0.15	0.03	-0.11	0.11	0.07	0.02	0.01	0.00	0.09	0.09	0.13	0.05	-0.04	0.14	0.12
		HU	-0.02	0.09	0.01	0.19	0.20	0.24	0.16	0.06	0.21	0.09	0.14	0.10	-0.06	0.09	0.09	0.13	0.06	0.05	0.11	0.09
		LT	-0.06	0.03	-0.11	0.02	0.00	0.03	0.14	0.17	0.02	-0.07	-0.06	0.01	-0.08	-0.04	0.00	0.04	-0.01	0.01	0.05	-0.07
		PL	0.34	0.07	0.15	0.19	0.11	0.05	0.11	0.21	-0.10	0.27	0.07	0.03	0.01	-0.06	0.04	0.04	0.00	0.02	-0.06	0.14
		RO	-0.01	0.05	0.05	-0.04	0.16	0.15	0.11	0.16	0.17	0.04	0.00	0.04	-0.01	0.04	0.08	0.04	0.06	0.11	0.18	0.08
		SE	0.54	0.11	0.29	0.23	0.14	-0.01	0.05	0.15	-0.21	0.51	0.05	0.03	0.02	-0.09	0.07	-0.01	0.01	0.01	-0.12	0.13
		GB	0.51	0.07	0.27	0.21	0.16	0.04	0.39	0.54	-0.20	0.32	0.09	0.00	0.04	0.01	0.03	0.06	0.01	0.08	-0.07	0.10
			YEN	YED	HP	LTN	L	LEV	I	D	PD	STN	YEN	YED	HP	LTN	L	LEV	I	D	PD	STN
			CS1				CS2					CS3	CS1				CS2					CS3
			Data										Residuals									

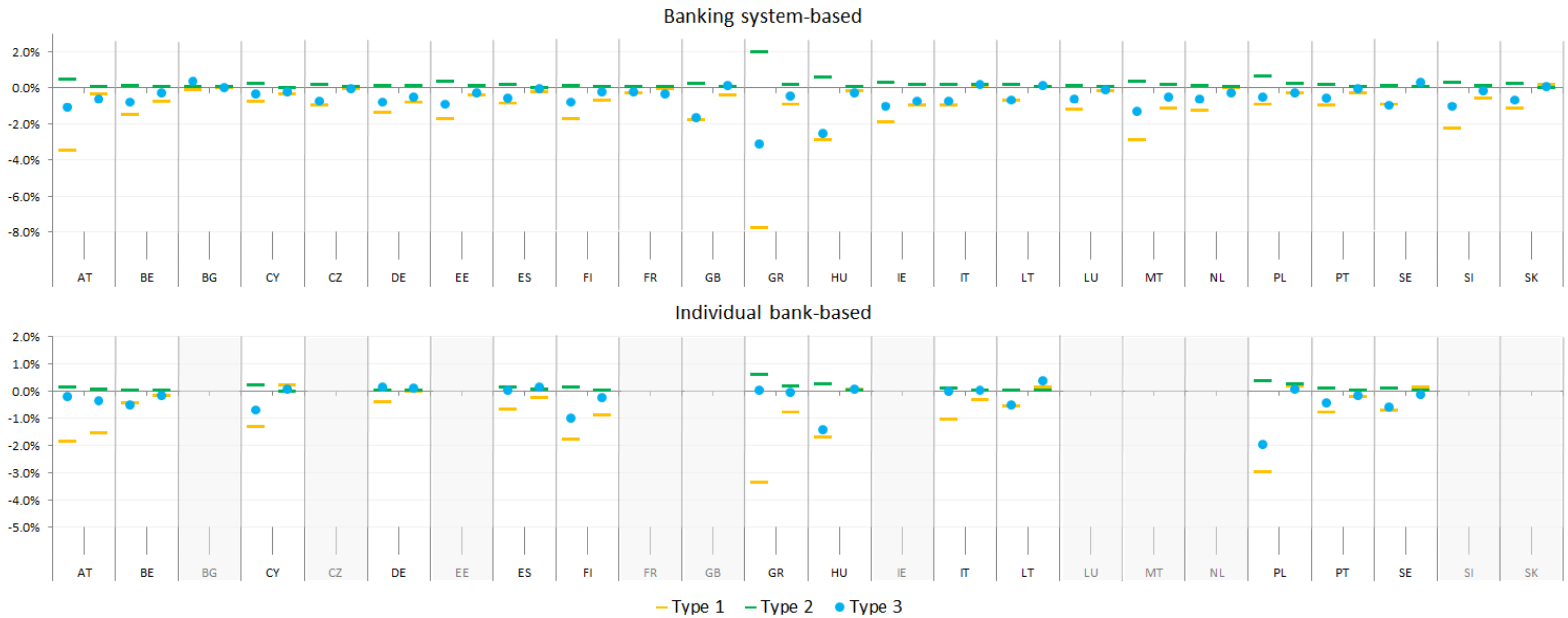
Note: The table shows the average cross-correlations of the data and the model residuals for the model overall (first block at the top), from the perspective of selected countries (excluding FR and NL as there were no banks from these countries included in the individual bank version of the model), as well as from the perspective of all central banks (ECB plus 10 non-EA EU central banks' short term policy rates) in the model.

Figure 1: Leverage (capital) ratio shocks



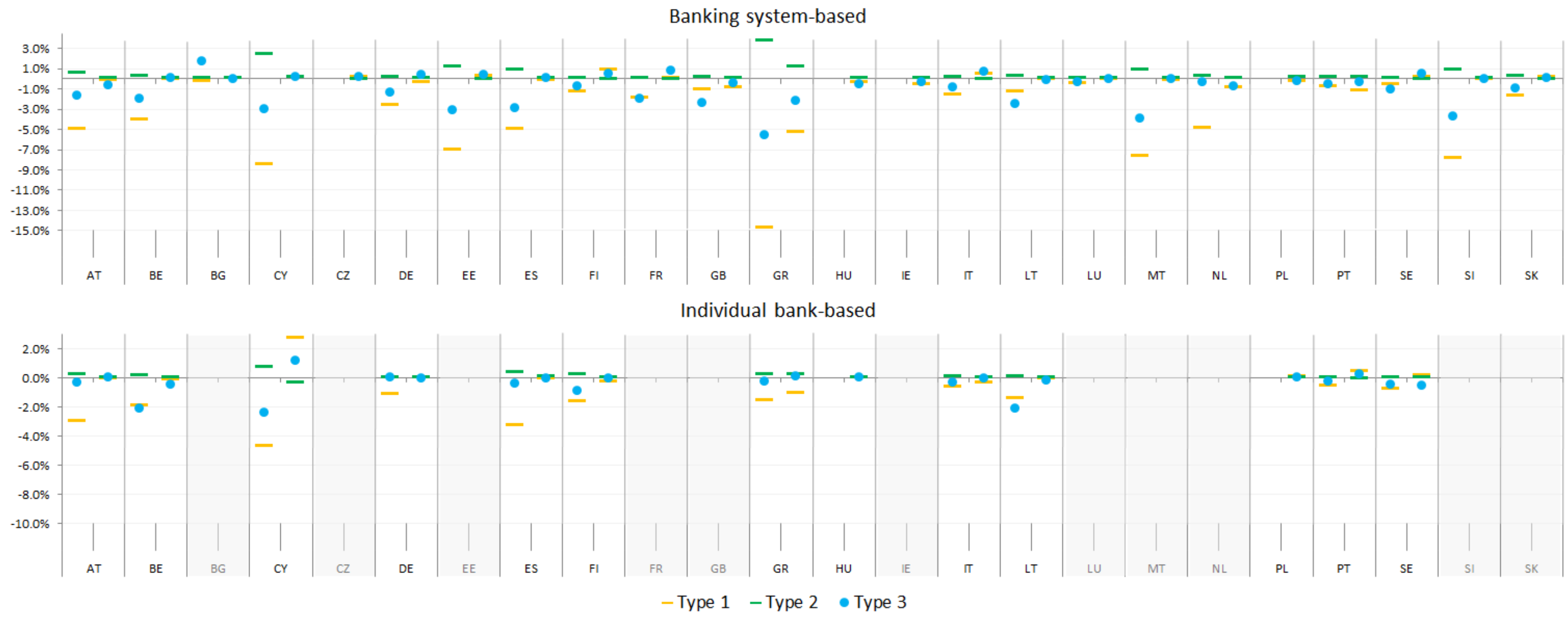
Note: The leverage ratio is defined as total assets (TA) over equity (E), the capital ratio as the inverse (E/TA). The shocks for the individual bank-based model are here displayed as weighted aggregates per banking system of the underlying individual bank shocks.

Figure 2: Real GDP — Capital ratio shock responses



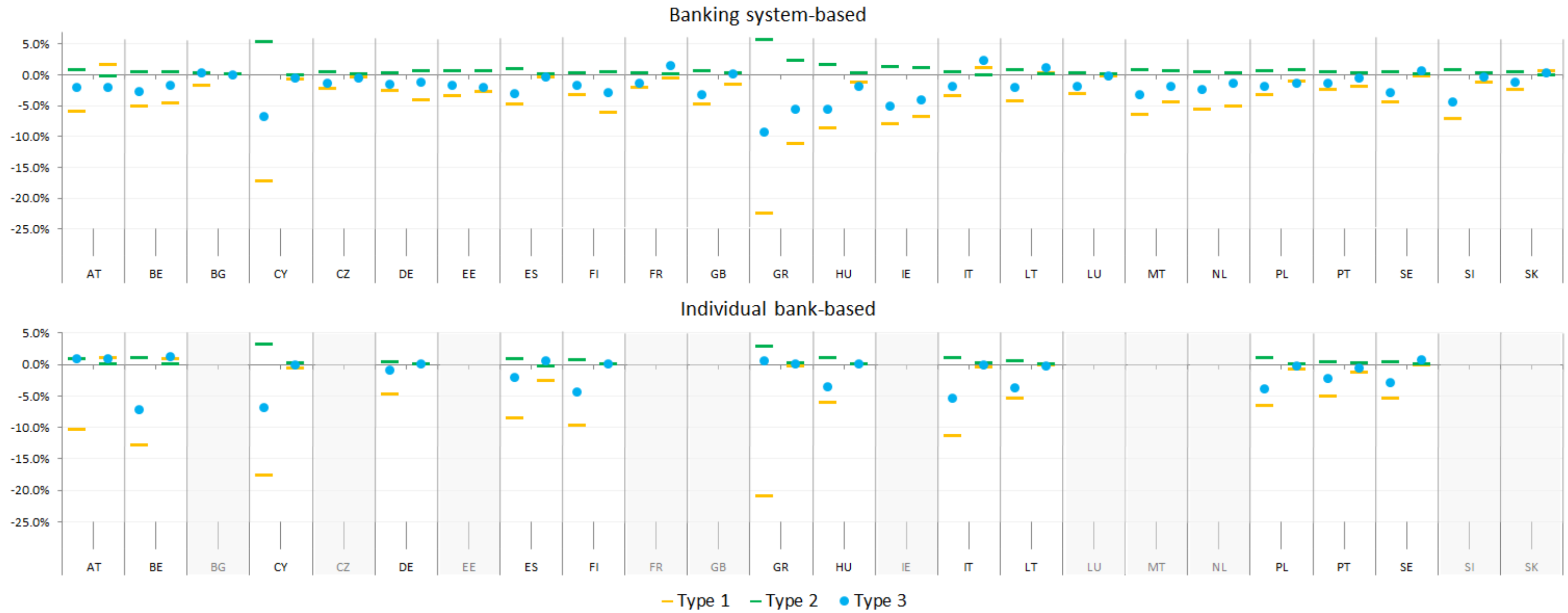
Note: The responses are expressed as long-run log percentage point deviations from baseline growth. All three shock types (Type 1/2/3) start from the same capital ratio shock per banking system. Type 1: achieve higher capital ratio by full asset side deleveraging. Type 2: achieve higher capital ratio by raising equity and expanding credit. Type 3: unconstrained capital ratio shock. Type 1 and 2 shocks are identified as negative/positive credit supply shocks by imposing sign constraints on the loan interest rate responses in period 1.

Figure 3: House prices — Capital ratio shock responses



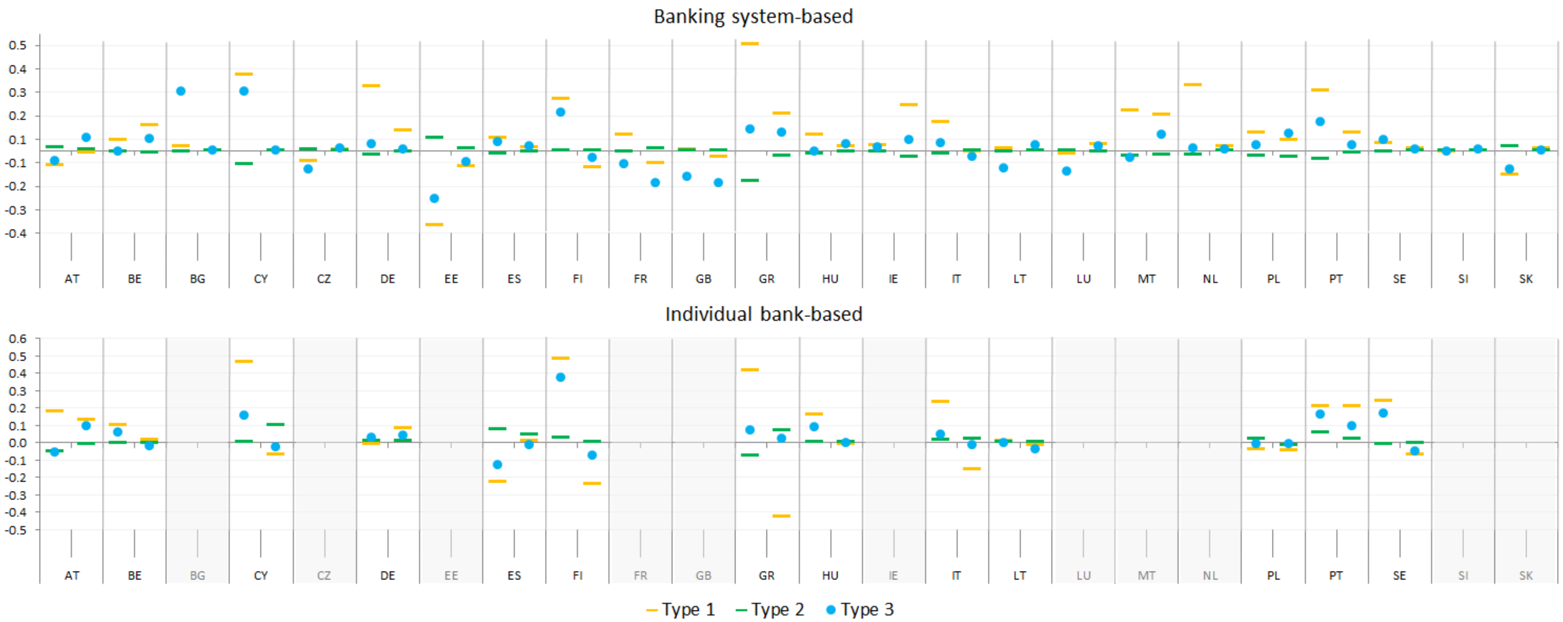
Note: The responses are expressed as long-run log percentage point deviations from baseline growth. All three shock types (Type 1/2/3) start from the same capital ratio shock per banking system. Type 1: achieve higher capital ratio by full asset side deleveraging. Type 2: achieve higher capital ratio by raising equity and expanding credit. Type 3: unconstrained capital ratio shock. Type 1 and 2 shocks are identified as negative/positive credit supply shocks by imposing sign constraints on the loan interest rate responses in period 1.

Figure 4: Nominal loan growth — Capital ratio shock responses



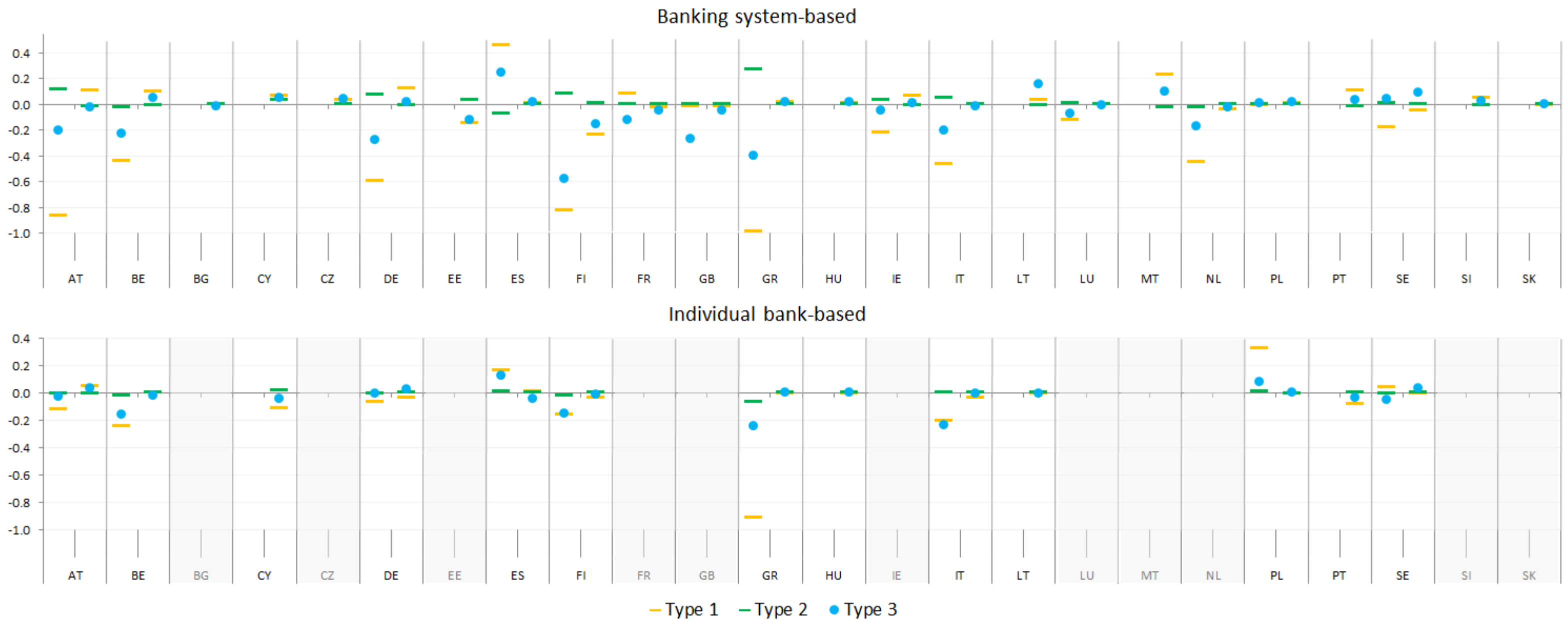
Note: The responses are expressed as long-run log percentage point deviations from baseline growth. Under Type 1 and 2, the deviations are to be interpreted as shocks, not responses (specific to loan growth). All three shock types (Type 1/2/3) start from the same capital ratio shock per banking system. Type 1: achieve higher capital ratio by full asset side deleveraging. Type 2: achieve higher capital ratio by raising equity and expanding credit. Type 3: unconstrained capital ratio shock. Type 1 and 2 shocks are identified as negative/positive credit supply shocks by imposing sign constraints on the loan interest rate responses in period 1.

Figure 5: Nominal loan interest rates — Capital ratio shock responses



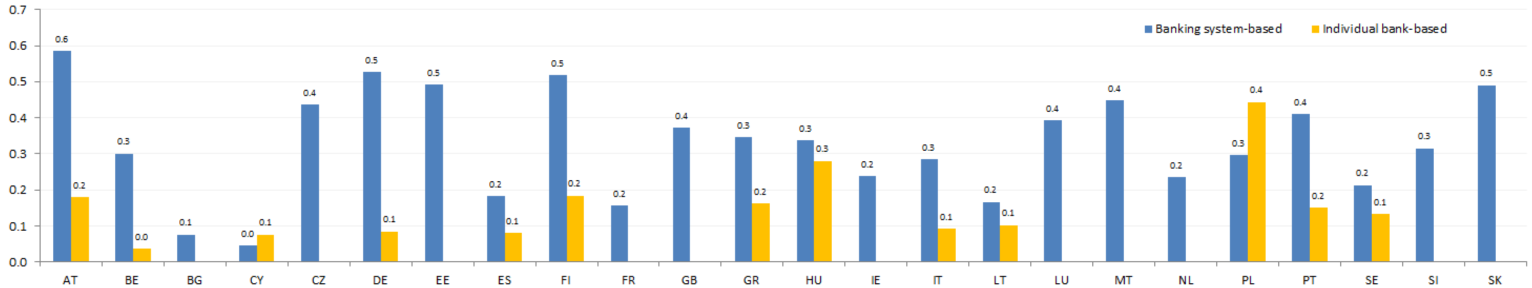
Note: The responses are expressed as long-run absolute deviations from baseline levels. All three shock types (Type 1/2/3) start from the same capital ratio shock per banking system. Type 1: achieve higher capital ratio by full asset side deleveraging. Type 2: achieve higher capital ratio by raising equity and expanding credit. Type 3: unconstrained capital ratio shock. Type 1 and 2 shocks are identified as negative/positive credit supply shocks by imposing sign constraints on the loan interest rate responses in period 1.

Figure 6: Probability of default — Capital ratio shock responses



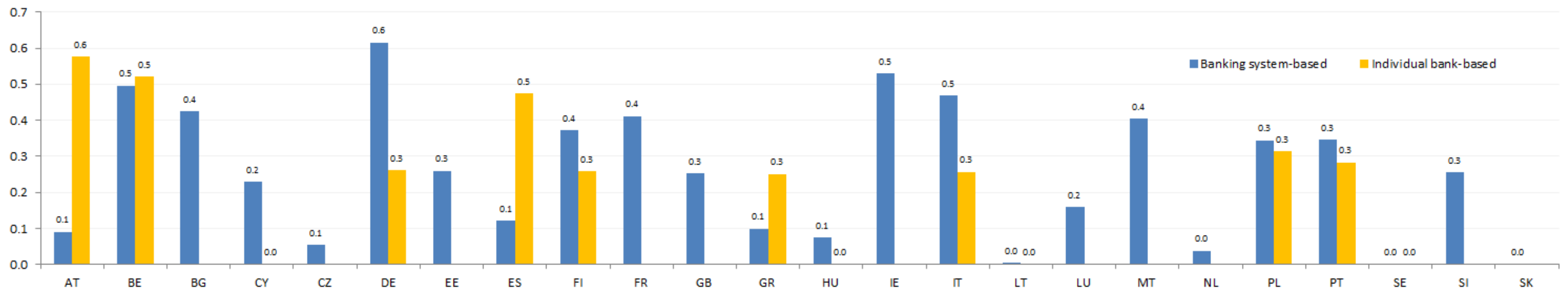
Note: The responses are expressed as long-run absolute deviations from baseline levels. All three shock types (Type 1/2/3) start from the same capital ratio shock per banking system. Type 1: achieve higher capital ratio by full asset side deleveraging. Type 2: achieve higher capital ratio by raising equity and expanding credit. Type 3: unconstrained capital ratio shock. Type 1 and 2 shocks are identified as negative/positive credit supply shocks by imposing sign constraints on the loan interest rate responses in period 1.

Figure 7: Real GDP to nominal loan growth multipliers



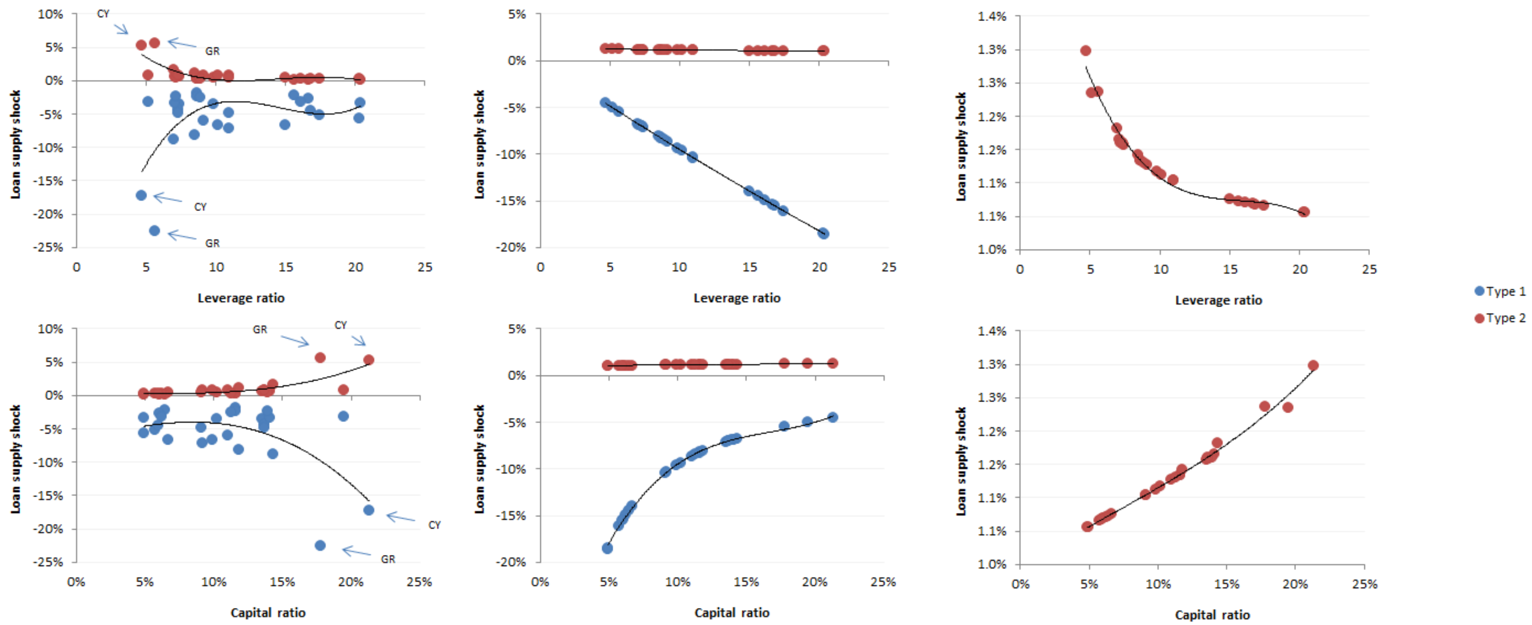
Note: The reported multipliers are defined as the ratio of long-run real GDP responses relative to consolidated banking system nominal loan growth shocks. The underlying shocks to capital/leverage ratios are reported in Figure 1.

Figure 8: Cross-border to domestic response ratios (based on real GDP responses)



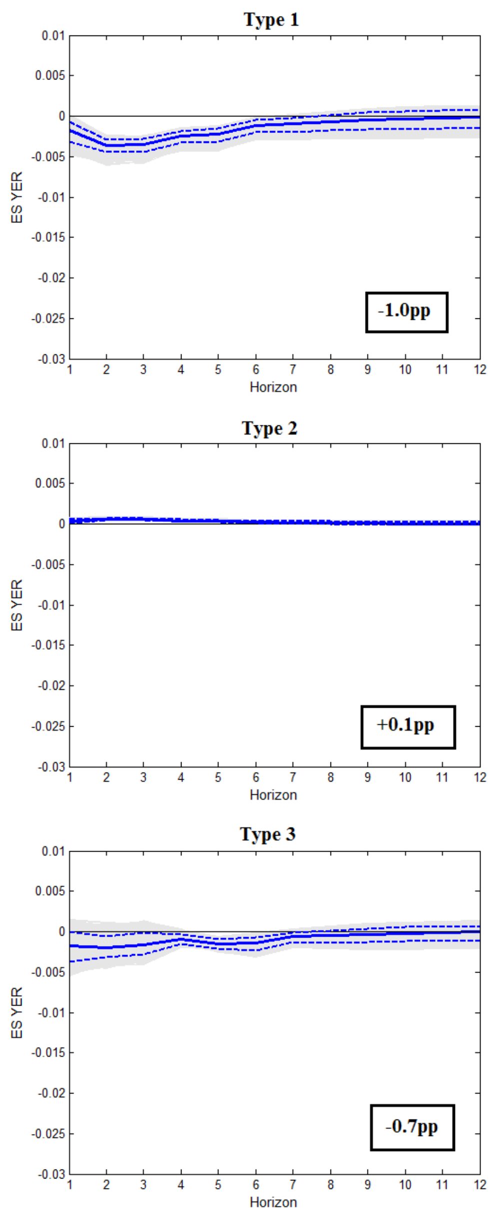
Note: The ratio presented here is defined as weighted foreign long-run real GDP responses relative to domestic long-run real GDP responses. The corresponding shocks to consolidated nominal loan growth under the Type 1/2 simulation are reported in Figure 4. The ratios are the same for the Type 1 and 2 simulation, i.e. are reported only once.

Figure 9: Initial leverage ratios (capital ratios) versus implied loan supply shocks



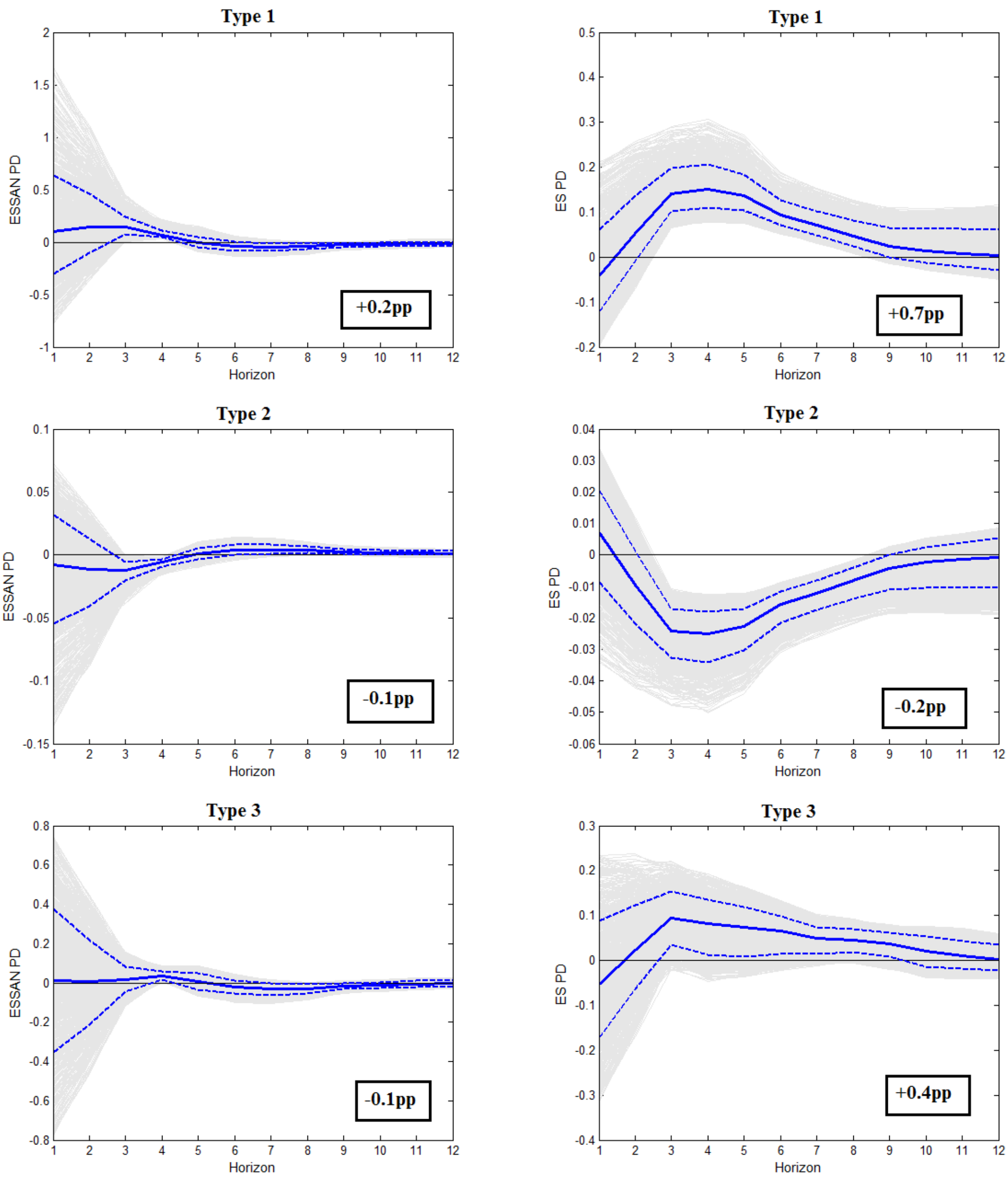
Note: The two scatter plots on the left show the loan supply shocks under Type 1 and 2 as used for the shock simulations for which the results are presented in the main section of the paper. The two scatters in the middle and right column show the loan supply shocks that are implied by +1pp shocks to capital ratios instead of residual-based shocks. The scatters in the right column repeat the Type 2 relation that is also shown in the middle column. The reason for showing them twice, along with the Type 1 relation in the middle in addition, is to highlight the different scales of the Type 1 and 2 relation, which is much more pronounced for the Type 2 relation of initial leverage and implied loan supply shocks.

Figure 10: Responses of real GDP in Spain to 1pp capital ratio shock to Santander (left column) or Spanish banking system (right column)



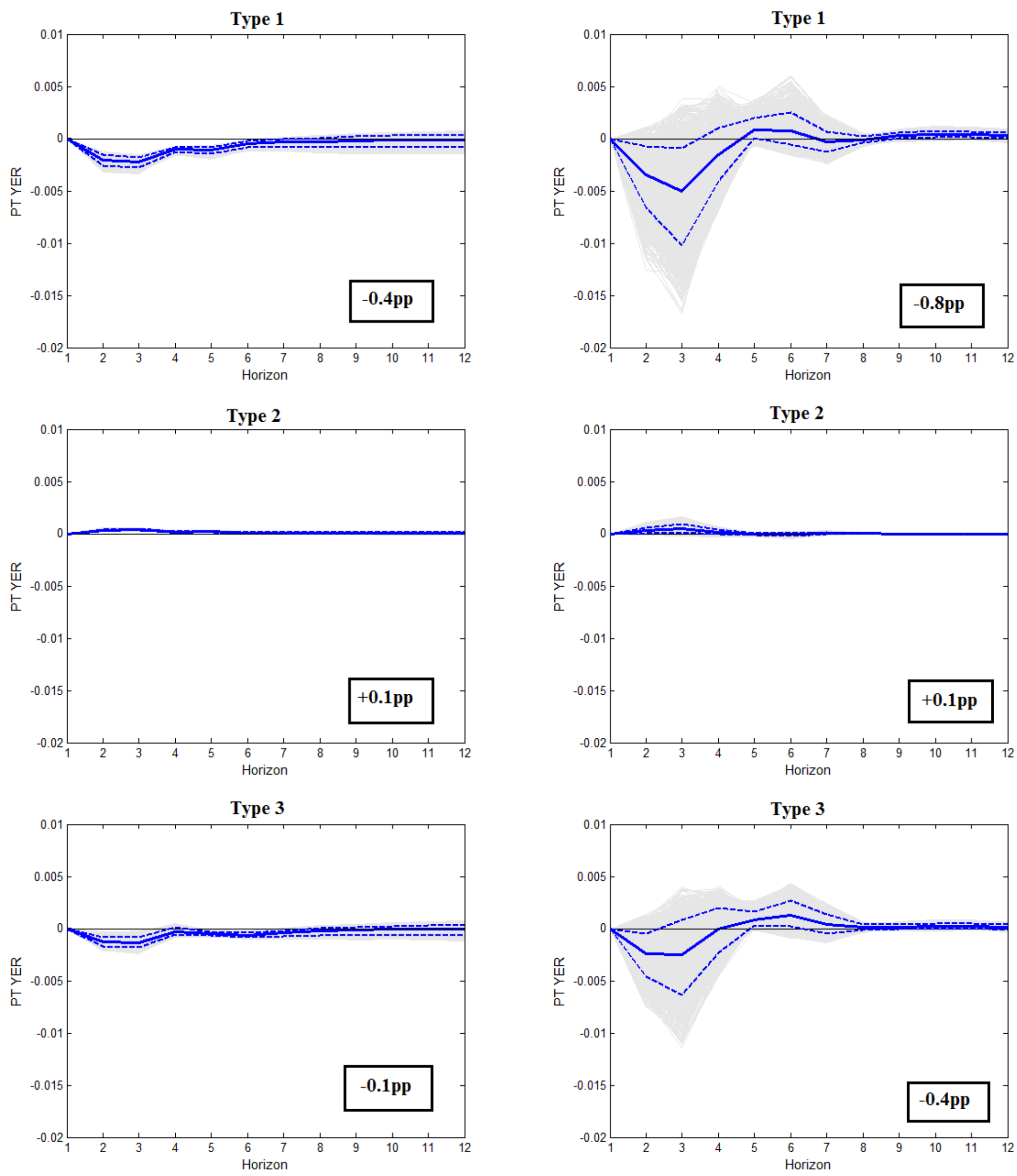
Note: The error bounds mark the 25th and 75th percentile of the response distribution, reflecting the draws from the sign restriction methodology as well as parameter uncertainty. 3-year cumulative responses are displayed in the square boxes in the lower right corner of the charts.

Figure 11: Responses of bank PDs to 1pp capital ratio shock to Santander (left column for Santander) or Spanish banking system (right column for Spanish banking system)



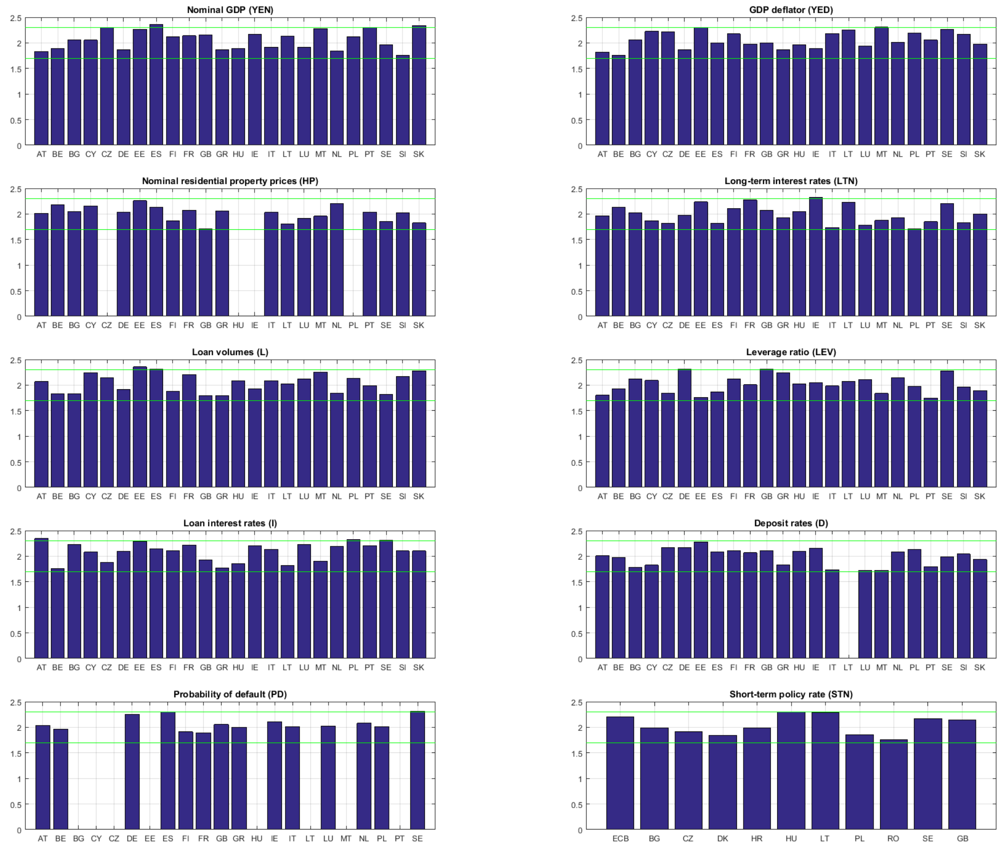
Note: The error bounds mark the 25th and 75th percentile of the response distribution, reflecting the draws from the sign restriction methodology as well as parameter uncertainty. 3-year cumulative responses are displayed in the square boxes in the lower right corner of the charts.

Figure 12: Responses of real GDP in Portugal to 1pp capital ratio shock to Santander (left column) or Spanish banking system (right column)



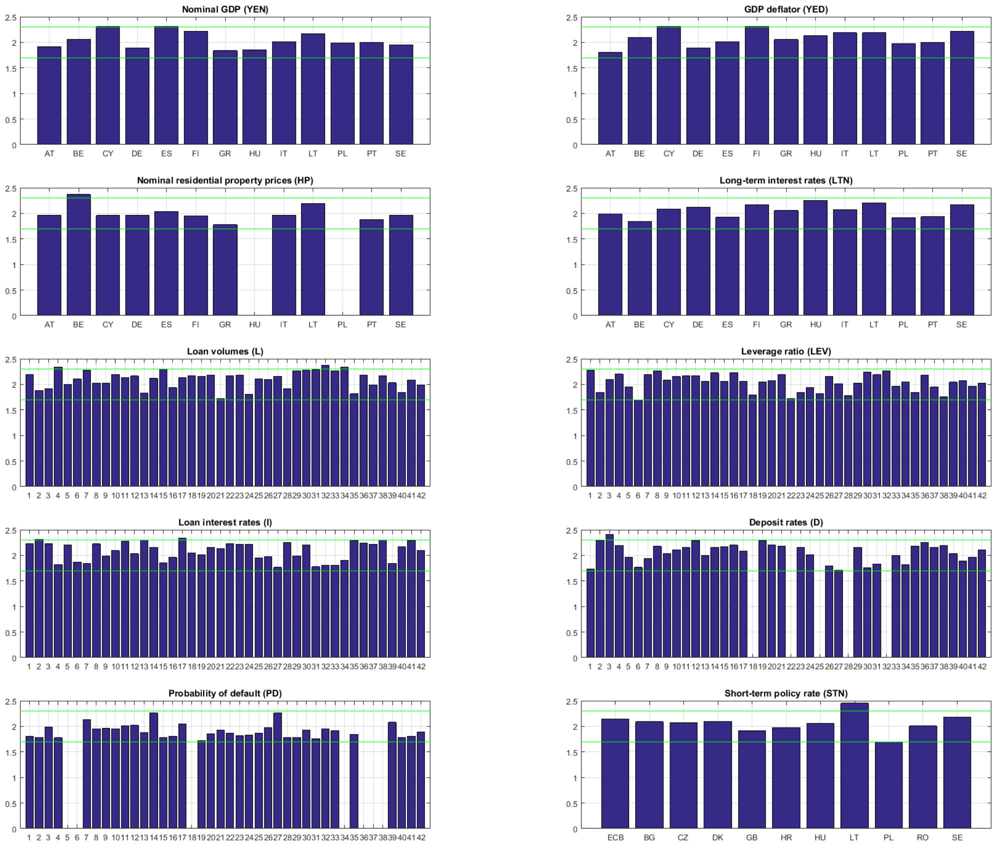
Note: The error bounds mark the 25th and 75th percentile of the response distribution, reflecting the draws from the sign restriction methodology as well as parameter uncertainty. 3-year cumulative responses are displayed in the square boxes in the lower right corner of the charts.

Figure 13: Durbin Watson statistics — Banking system version of the model



Note: The figure collects the Durbin Watson (DW) statistics across model equations from the banking system version of the MCS-GVAR. DW statistics in an approximate range between 1.7-2.3 are deemed to signal sufficiently minor remaining serial correlation in the model residuals.

Figure 14: Durbin Watson statistics — Individual bank version of the model



Note: The figure collects the Durbin Watson (DW) statistics across model equations from the individual bank version of the MCS-GVAR. The order of banks (1-42) for the variables in the bank cross-section (loan volumes, leverage, loan interest rates, deposit rates and probabilities of default) corresponds to the banks as listed in Table 1. DW statistics in an approximate range between 1.7-2.3 are deemed to signal sufficiently minor remaining serial correlation in the model residuals.

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