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# DESTABILIZING EFFECTS OF BANK OVERLEVERAGING ON REAL ACTIVITY—AN ANALYSIS BASED ON A THRESHOLD MCS-GVAR

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We investigate the consequences of overleveraging and the potential for destabilizing effects arising from financial- and real-sector interactions. In a theoretical framework, we model overleveraging and demonstrate how a highly leveraged banking system can lead to unstable dynamics and downward spirals. Inspired by models developed by Brunnermeier, Sannikov and Stein, we empirically measure the deviation-from-optimal-leverage for a sample of large EU banks. This measure of overleveraging is used to condition the joint dynamics of credit flows and macroeconomic activity in a large-scale regime change model: a Threshold Mixed-Cross-Section Global Vector Autoregressive (T-MCS-GVAR). The regime-switching component of the model is meant to make the relationship between credit and real activity dependent on the extent to which the banking system is overleveraged. We find significant nonlinearities as a function of overleverage. The farther the observed leverage in the banking system from optimal leverage, the more detrimental is the effect of a deleveraging shock on credit supply and economic activity.

**Keywords:** Macro-Financial Linkages, Leverage, Credit Supply

## 1. INTRODUCTION

The banking sector has, in particular since the outbreak of the global financial crisis, gained in prominence for what concerns the public perception and political as well as academic interest in macro-financial linkages, i.e., its role in causing and amplifying economic recessions around the world. Numerous studies confirm the understanding that the US financial crisis of the years 2007–09 was caused by excessive leveraging of the US banking sector, its exposure to the US real estate sector, and the highly nonlinear amplification effects that were materializing once the banking sector became vulnerable and unstable after the arrival of adverse shocks. The regulatory proposals of Basel III after the years 2009–10 were concentrated on the excessive leveraging of the banking sector, pointing to the fact that overleveraging renders the banking and financial sector fragile.

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Credit cycles are a common feature of financial systems and tend to positively correlate with the business cycle, reflecting fluctuations in borrowers' demand for financing.[1] Cycles in credit developments and thereby implicitly in financial sector leverage are exacerbated by the inherent pro-cyclical behavior of financial institutions.[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)].

There are many studies addressing the mechanisms of how excessive leveraging and fragility of the banking sector can lead to adverse macroeconomic feedback effects. Brunnermeier and Sannikov (2014), in a stylized manner, focus on financial experts representing financial institutions that are highly leveraged. In their view, it is a shock to asset prices that creates a vicious cycle through the balance sheets of the banks, contagion effects, and macro-feedback loops. In Mittnik and Semmler (2013), the vulnerability of banks and the downward instability is seen to be caused by the limited liability of decision makers in banks, improper incentive systems, and a lack of constraints imposed on financial institutions that allow for unrestricted growth of capital assets (through borrowing). In Stein (2012), the destabilizing mechanism also results from a linkage of asset prices and borrowing. When the interlinkages of asset prices and borrowing allow the bank to enjoy capital gains beside the normal returns, they start to become overleveraged. This is when actual leveraging turns out to exceed optimal leveraging, a rapid deterioration of the balance sheets of banks can occur, and thereby triggering amplifying effects downward.[3]

Although most recent research points to the excessive leveraging of the banking sector as an essential driving force for macroeconomic instability, the question that arises is how overleveraging can actually be measured. We introduce our own measure of overleveraging, following in spirit Brunnermeier and Sannikov (2014) and Stein (2012), i.e., defining it as a situation whereby a borrower's debt capacity is being exceeded. As to the empirical estimates of the measurement of excessive debt for the EU countries, we follow the method developed in Schleer et al. (2014), employing an extended data set. Details of the measurements can be found in Schleer et al. (2014) and in Gross et al. (2016b).

In a large-scale regime switching global vector autoregressive (GVAR), we then evaluate the overleveraging hypothesis for a regime of high and low leveraging of the banking sector and assess whether regimes of overleveraging of the banking sector are accompanied by more severe credit and output contractions than periods of underleveraging. A useful entry point to the GVAR literature is a recent survey paper by Chudik and Pesaran (2014), and the contributions by Pesaran et al. (2004), Pesaran and Smith (2006), and Dees et al. (2007).

Our model uses the Mixed-Cross Section (MSC) variant of the GVAR that was first developed by Gross and Kok (2013) and applied to banks' balance sheets in Gross et al. (2016a). It allows combining different cross-section types,

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e.g., countries with banks or banking systems, central banks, etc. The model that we present here extends the MCS-GVAR by yet another feature—a regime conditionality, which in our application is upon the degree of overleveraging of a banking system. The global solution of the model becomes *regime constellation dependent*.[4]

The Mixed-Cross-Section feature of the model is not only useful for individual bank model applications, but also for banking system models as the one presented in this paper. The MCS structure implies that weights are allowed to be *equation*-specific, not only variable-specific. A useful example to highlight this point is to consider a consolidated loan growth variable. With the MCS feature, economic activity variables on the right-hand side of the loan growth equations are weighed based on banks' exposure profiles, as they should, and not be based on trade [as in the traditional GVAR literature; as e.g., in Eickmeier and Ng (2011)].[5] 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 macroeconomic developments in other countries is instead its own exposure to the other country.

In Section 2, we present our dynamic model of optimal leveraging and explain how we quantify overleveraging. Section 3 is devoted to the threshold MCS-GVAR model, in which the overleveraging metric serves as the regime conditioning variable. Section 4 concludes.

## 2. A THEORETICAL MODEL

Brunnermeier and Sannikov (2014) and Stein (2012) when studying overleveraging start with a continuous time model. We follow their approach but employ a discrete time dynamics version of it. In contrast to Mittnik and Semmler (2013), who also work with nonlinear finance-macro links, we, in line with the previous literature, develop here a stochastic model. For the solution of the model, we use a novel method, referred to as Nonlinear Model Predictive Control (NMPC), as presented in Gruene et al. (2015). Commonly adopted dynamic policy models, such as DSGE models, tend to smooth out potentially destabilizing feedback mechanisms by assuming infinite-horizon decisions. Here, we propose a framework with a finite horizon that allows for vulnerabilities of financial institutions and destabilizing macro-financial feedback loops to occur. It provides solutions that, when specifying a very long horizon, approach the usual infinite-horizon solutions. From this dynamic model, empirical measures on overleveraging can be derived.

### 2.1. Leveraging and Banks as Risk Drivers

To introduce leveraging and net worth dynamics for financial institutions in a finite horizon decision model, we start with a low-dimensional stochastic model specification. The essential features of the model we employ can be found in

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Brunnermeier and Sannikov (2014, Section 2) and also in Stein (2012).[6] Both specifications are stochastic, but they do not explicitly model macroeconomic feedback loops.

Payout and leveraging are decision variables and the main state variable is net worth, namely $x_{1t}$, in equation (3). In order to solve such a stochastic model through NMPC, one needs to add a stochastic shock sequence, see equation (4), representing another state variable. In Brunnermeier and Sannikov (2014), capital returns are—due to capital gains—stochastic, as is the interest rate. Brunnermeier and Sannikov (2014) start with a model where only the capital return is stochastic and they add a stochastic interest rate later by referring to time-varying borrowing cost, reflecting the cost of screening and monitoring. Stein (2012) adds something important to this type of model by providing a static solution for the model in terms of a mean variance approach that allows us to measure excess leveraging.

Although Brunnermeier and Sannikov (2014) specify their model in continuous time, we here adopt a discrete-time framework with a discounted instantaneous payout, $c_t$, and a leveraging, $\alpha_t$, as decision variables.[7] The model is stated in equations (1)–(4), where preferences are given by (1), the dynamics of the aggregate capital stock, $k_t$, by (2),[8] net worth, $x_{1t}$, by (3), and the stochastic shock process, $x_{2t}$, by (4). Adopting a discrete-time framework and decision horizon of $N$ periods, our model is given by

$$V = \max_{c_t, \alpha_t} E_t \sum_{t=0}^{N} \beta^t U(c_t x_{1t}), \tag{1}$$

s.t.

$$k_{t+1} = k_t + h(g_t - \delta)k_t \tag{2}$$

$$x_{1,t+1} = x_{1t} + hx_{1t}[\alpha_t(y + \nu_1 lnx_{2t} + r) + (1-\alpha_t)(i - \nu_2 lnx_{2t}) - \varphi(x_{1t}) - c_t] \tag{3}$$

$$x_{2,t+1} = \exp(\rho \ln x_{2t} + z_k). \tag{4}$$

In the above model (1)–(4), $c$ and $\alpha$ are the two decision variables,[9] with the payout $c = C/x_1$, and $\alpha = 1 + f$, with $f = d/x_1$ the leverage ratio, measured as liability over net worth, $d$, is debt, $y$, the capital gains, driven by a stochastic shock, $\nu_1 lnx_{2t}$. Furthermore, $r$, is the return on capital, $i$, the interest rate paid on debt, also driven by a stochastic shock, $\nu_2 lngx_{2t}$,[10] $\varphi(x_{1t})$ is a convex adjustment cost, $h$, the time step size, $\rho$, a persistence parameter, with $\rho = 0.9$, and $z_k$ is an i.i.d. random variable with zero mean and a variance, $\sigma = 0.05$.

We can solve the model variant (1), (3), and (4) through a stochastic version of NMPC, see Gruene et al. (2015). Figure 1 presents the path of the payout, $c_t$ and leveraging $\alpha_t = 1 + f_t$. As can be seen, the stochastic capital gains and interest rates generate volatility of both payout and leveraging. We shall note that we solve here only for optimal leveraging, not actual leveraging, which is an aspect that we will further discuss below. The payout tends to move with leveraging. Since

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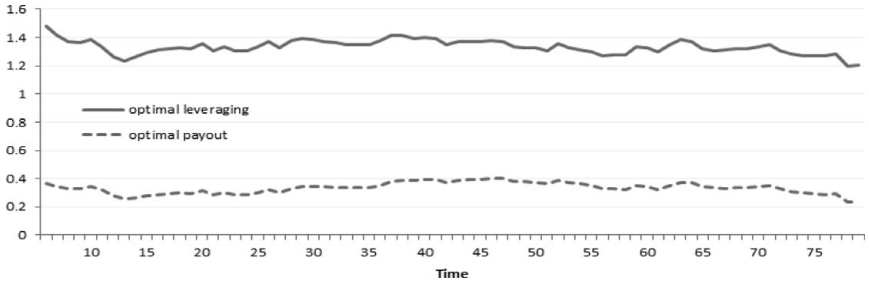



**FIGURE 1.** Path of optimal payout, $c$ and optimal leveraging, $\alpha = (1 + f)$.

$\alpha_t$ is a choice variable, both Brunnermeier and Sannikov (2014) and Stein (2012) assume that debt is redeemed in each period and, without cost, can be obtained on the market without frictions.

In Brunnermeier and Sannikov (2014), there is only an implicit capture of a macro-feedback loop, namely an externality, i.e., endogenous volatility, that is triggered below the steady state which makes the steady state unstable downward and not mean reverting as in Bernanke et al. (1999). In Brunnermeier and Sannikov (2014), feedback loops arise from large shocks below some steady state, triggering fire sales of assets, fall of asset prices and fall in net worth, and generating a downward spiral.[11] Although model (1)–(4) does not yet directly model instability, Figure 1 depicts the volatility of $\alpha_t$, and thus the optimal leveraging $f_t$, and the payouts, $c_t$.[12]

Through our numerical computations, we can also indirectly observe leveraging as defined in BS (2004) as the ratio of assets to net worth: This is determined by the upper line in Figure 1. As Brunnermeier and Sannikov (2014) rightly state, through leveraging, the capital share of banks in total capital—the share of financial experts in their terms—rises with leveraging, even at the stochastic steady state. This is also what creates in Brunnermeier and Sannikov (2014) the source for endogenous risk.

Next we want to allow for regime change for the banks' fundamental variables such as the interest rate paid on bank liabilities. If there is a jump in the interest rate the bank has to pay for its debt, thus a jump in $i - \nu_2 ln x_{2t}$, where the second expression would be negative, the optimal leveraging is likely to move down. Re-running now the stochastic model (1), (3), and (4) with low interest rates of $i = 0.02$, first and then switching to a high interest rate regime of $i = 0.12$ after 73 periods, in both cases with the stochastic shock added, we obtain the results as shown in Figure 2. We can observe how a jump of the interest rate—as the interbank borrowing and lending rate, for example, represented by the TED spread—may impact the optimal leveraging.

We can observe a significant shift downward of the optimal leveraging, due to the interest rate jump, measured by our leverage ratio $1 + f_t$. A similar shift downward can be observed for net worth. As Figure 2 shows, through the upward

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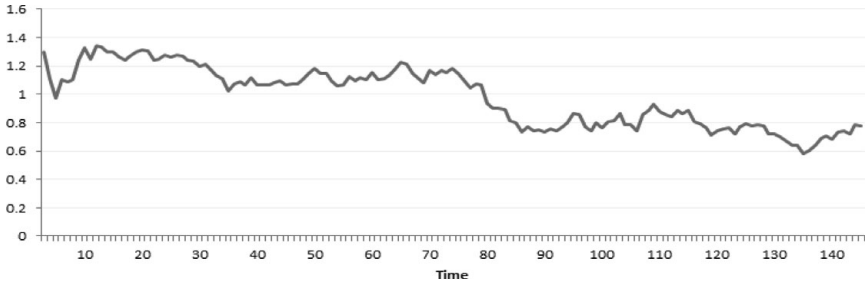



**FIGURE 2.** Regime change in interest rates, and shift in optimal leveraging $1 + f_t$: line up to period 73, leveraging for interest rate = 0.02; line from period 73, leveraging for interest rate 0.12.

jump in the interest rate around period 73, the sustainable leveraging has clearly declined. Given some actual leveraging, the rise in the interest rate, fall in capital gains, and fall in the sustainable (optimal) debt, the excess leveraging has then been increased.

These observable effects of a persistently higher interest rates might lead to the question of why the banks do not rationally expect this and adjust their actual leveraging appropriately. Since we work here with a model of finite time horizon, and there prevails some expectation at some shorter time horizon by banks, we implicitly assume that there is some shortsightedness that allows the emergence of overleveraging and vulnerability of balance sheets of banks that in fact makes our model more realistic compared to infinite time horizon models.[13]

Similar results can also be derived from our static mean variance model of the next section. Thus, when interest rates jump, this change is likely to add to the vulnerability of banks—since banks tend to become even more overleveraged because the sustainable leverage has declined.[14]

## 2.2. Measuring Overleveraging

We now briefly describe a static measure for optimal debt and the calculation of both optimal and actual debt, and thus overleveraging. Subsequently, we can use our measure of overleveraging for inferring over- and underleveraging regimes.[15]

One can show how the optimal debt ratio can directly be derived in the simplified case of logarithmic utility using the model (1), (3), and (4).[16] The state variable is a stochastic differential equation in net worth as defined in equation (3):

$$dX(t) = X(t)[(1 + f(t))(dP(t)/P(t) + \beta(t)dt) - i(t)f(t) - cdt], \quad \textbf{(5)}$$

where $X(t)$ is the net worth[17], $f(t) \equiv L(t)/X(t)$ debt over net worth; thus, leverage, $dP(t)/P(t)$ denotes stochastic capital gains or losses, and $i(t)$ the interest rate, also stochastic. Again assets over net worth are defined as $(1 + f(t))$, $\beta(t)$ is the trend in bank capital returns, and $C(t)/X(t) \equiv c(t)$ is consumption over net worth. In the derivation, $c$ is taken as given.

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The optimal debt ratio $f^*$ maximizes the difference between the mean $M(f(t))$ and risk $R(f(t))$ that represents a mean-variance formulation. So we have

$$f^* = \text{argmax}[M(f(t)) - R(f(t))] = \left[(a(t) + \beta(t) - i) - \left(\sigma_p^2 - \rho\sigma_i\sigma_b\right)\right]/\sigma^2, \tag{6}$$

where $\sigma$ is a risk element given by $\sigma^2 = \sigma_i^2 + \sigma_r^2 - 2\rho\sigma_i\sigma_r$, and $\sigma_i^2$ is the variance of the interest rate, $\sigma_r^2$ is the variance of capital gains, and $\rho$ defines the correlation of $i$ and $r$. In this model variant, Stein (2012) assumes that the asset price grows at a trend rate $r$ and there is a deviation from the trend, $y$, see equation (7):[18]

$$dP(t)/P(t) = (r + \alpha(0 - y))dt + \sigma_r dw_p. \tag{7}$$

Moreover, $\beta(t)$, the return on capital, is considered as being deterministic. The optimal debt or leverage ratio $f^*(t)$ is then defined as follows:

$$f^*(t) = \left[(r - i) + \beta - \alpha y(t) - \frac{1}{2}\sigma_r^2 + \rho\sigma_i\sigma_r\right] \Big/ \sigma^2, \tag{8}$$

where $i$ is the credit cost of banks, $\beta$ the trend return on capital, and $y(t)$ is the deviation of capital gains from its trend. Then, follows the variance term with the parameters as indicated above.

Given those measures, one can employ actual data to derive the optimal debt ratio, in our case for a sample of EU banks. We rely on data obtained from Thomson Reuters Datastream. Details of the computation of the components of $f^*(t)$ can be found in Schleer et al. (2014) and Gross et al. (2016b). The optimal debt ratio is normalized by calculating the difference between the optimal debt ratio and the mean over the period and dividing it by the standard deviation, see Schleer et al. (2014).

The actual debt ratio is calculated as long-term debt over total assets. Again, the actual debt ratio is normalized to match its unit to the one of the optimal debt ratio and then the optimal debt is subtracted from it to obtain the overleveraging metric. What still needs to be done, however, is to integrate the overleveraging of banks, as the financial sector risk drivers, into a macro-econometric model, to assess the macro-financial regime-dependent feedback mechanisms that arise when overleveraging is used as a regime-defining variable in the macromodel.

## 3. THE THRESHOLD MCS-GVAR MODEL

### 3.1. Model Structure

Our MCS-GVAR model comprises two cross sections: $i = 1, \ldots, N$ EU countries and a cross section of banking systems $j = 1, \ldots, M$. The endogenous variables from the two cross-sections are collected in the vectors $\boldsymbol{x}_{it}$ and $\boldsymbol{y}_{jt}$. For a given cross-section item, the two vectors are of size $k_i^x \times 1$ and $k_j^y \times 1$.[19] The model has

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the following form:

$$\begin{aligned}\boldsymbol{x}_{it} &= \boldsymbol{a}_{ir} + \sum_{p_1=1}^{P_1} \boldsymbol{\Phi}_{i,p_1,r}\boldsymbol{x}_{i,t-p_1} + \sum_{p_2=0}^{P_2} \boldsymbol{\Lambda}_{i,0,p_2,r}\boldsymbol{x}^{*,C-C}_{i,t-p_2} \\ &\quad + \sum_{p_3=0}^{P_3} \boldsymbol{\Lambda}_{i,1,p_3,r}\boldsymbol{y}^{*,C-B}_{i,t-p_3} + \boldsymbol{\epsilon}_{it} \\ \boldsymbol{y}_{jt} &= \boldsymbol{b}_{jr} + \sum_{q_1=1}^{Q_1} \boldsymbol{\Pi}_{j,q_1,r}\boldsymbol{y}_{j,t-q_1} + \sum_{q_2=0}^{Q_2} \boldsymbol{\Xi}_{j,0,q_2,r}\boldsymbol{x}^{*,B-C}_{j,t-q_2} \\ &\quad + \sum_{q_3=0}^{Q_3} \boldsymbol{\Xi}_{j,1,q_3,r}\boldsymbol{y}^{*,B-B}_{j,t-q_3} + \boldsymbol{\omega}_{jt} \end{aligned} \tag{9}$$

The intercept terms $\boldsymbol{a}_{ir}$ and $\boldsymbol{b}_{jr}$ are of size $k_i^x \times 1$ and $k_j^y \times 1$. The two equation blocks contain a set of autoregressive terms—$(\boldsymbol{\Phi}_{i,1,r}, \ldots, \boldsymbol{\Phi}_{i,P_1,r})$ and $(\boldsymbol{\Pi}_{j,1,r}, \ldots, \boldsymbol{\Pi}_{j,Q_1,r})$—which are of size $k_i^x \times k_i^x$ and $k_j^y \times k_j^y$, respectively. The within- and across-cross-section dependence is introduced via the "star" variable vectors. The corresponding coefficient matrices in the first equation block for $\boldsymbol{x}_{it}$—$(\boldsymbol{\Lambda}_{i,0,0,r}, \ldots, \boldsymbol{\Lambda}_{i,0,P_2,r})$ and $(\boldsymbol{\Lambda}_{i,1,0,r}, \ldots, \boldsymbol{\Lambda}_{i,1,P_3,r})$—are of size $k_i^x \times k_i^{*x}$ and $k_i^x \times k_i^{*y}$. The corresponding coefficient matrices in the second equation block for $\boldsymbol{y}_{jt}$—$(\boldsymbol{\Xi}_{j,0,0,r}, \ldots, \boldsymbol{\Xi}_{j,0,Q_2,r})$ and $(\boldsymbol{\Xi}_{j,1,0,r}, \ldots, \boldsymbol{\Xi}_{j,1,Q_3,r})$—are of size $k_j^y \times k_j^{*x}$ and $k_j^y \times k_j^{*y}$.

All coefficient matrices are assigned a subscript $r$ to indicate their regime dependence. Also the cross section-specific shock vectors—$\boldsymbol{\epsilon}_{it}$ and $\boldsymbol{\omega}_{jt}$—which are of size $k_i^x \times 1$ and $k_j^y \times 1$—have regime-dependent covariance matrices $\boldsymbol{\Sigma}_{ii}^x$ and $\boldsymbol{\Sigma}_{jj}^y$, along with zero means. A global matrix $\boldsymbol{\Sigma}$ captures the covariance structure of the combined set of residuals from the two equation blocks under an assumed *regime constellation* (more on that below). The regimes are defined as a function of the banking system-specific overleveraging indicator that was presented in the previous section. It is a discrete, for the time being exogenous, switching scheme, defining the two regimes for a given banking system and corresponding country as Regime 1 when overleveraging is negative (reflecting underleveraging), and as being in Regime 2 when the overleveraging indicator is larger than zero.

There are six variables involved in the model, three in the country cross section and three in the bank cross section. The country cross-section vector includes nominal GDP, a GDP deflator, and long-term interest rates. GDP and the GDP deflator are modeled in quarter-on-quarter (QoQ) differences of natural log levels. Long-term interest rates are modeled in QoQ differences. The three endogenous variables for the banking systems include nominal credit stocks, nominal loan interest rates, and a capital ratio.[20] Nominal credit volumes are sourced from the ECB's Balance Sheet Statistics, which capture domestic lending as well as direct

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cross-border lending to households and non-financial corporations. The capital ratio is defined as equity capital over total assets. Nominal credit is modeled in QoQ differences of natural log levels. Loan interest rates and the capital ratio are modeled in QoQ differences.

The variable vectors that are assigned an asterisk in equation (9) need to be generated by means of a set of weights that link the items within and across the cross sections. We outline the weight settings briefly in the following and refer to Gross et al. (2016a, 2016b) for details.

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 are sourced from the IMF trade statistics. It has an annual frequency that is interpolated to quarterly by means of a quadratic match sum conversion method.

Banking systems–Countries ($\boldsymbol{W}^{B-C}$): The weights are calibrated based on BSI domestic and cross-border credit exposures.

Countries–Banking systems ($\boldsymbol{W}^{C-B}$): Can be seen as the mirror of the weights for linking countries to banking systems ($\boldsymbol{W}^{B-C}$), i.e., $\boldsymbol{W}^{C-B}$ will be the transpose of the bank-country matrix for every quarter over the sample period.

Banking systems–Banking systems ($\boldsymbol{W}^{B-B}$): We employ domestic and cross-border credit exposures to financial corporations as a basis for calibrating these weights.[21]

Two of the four weight matrices are square matrices that have zero entries on their diagonals at every point in time, namely the $\boldsymbol{W}^{C-C}$ and $\boldsymbol{W}^{B-B}$ matrix. 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 banking system weight on the country to which it belongs 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" banking system will, in general, be the highest. The model setup is flexible in the sense that countries can be included in the model for which there are no corresponding banking systems. Vice versa, banking systems could be included in the model for which the corresponding country would not be included. An asymmetry is in fact present in our model application as 28 EU economies are covered in the country cross section, while having only 14 banking systems (for which the overleveraging indicator is available from the computations as outlined in Section 2.2.).

The model is estimated based on data covering the 1995Q1–2014Q4 period (80 observations). All weight matrices are time varying over the whole sample period. The model has $3 \times 28 + 3 \times 14 = 126$ equations that are all individually estimated by means of an Iteratively Reweighted Least Squares method. The method is more robust to outliers than Ordinary LS and helps stabilize the dynamics of the global model. Each equation is estimated twice, conditional on the banking system and corresponding country being either in Regime 1 or 2.

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### 3.2. Empirical Results

Our empirical assessment based on the T-MCS-GVAR model relies on sign-restricted impulse responses.[22] We introduce three different shock types, the first two of which involve sign constraints. All three shock types—to which we refer as Type 1, Type 2, and Type 3—start from the same positive capital ratio shock of a banking system-specific amount $\Delta$.

*Contractionary deleveraging* (Type 1): Banks are assumed to move to the higher capital ratio by shrinking their balance sheet, with equity capital by assumption being constant and debt shrinking along with assets.

*Expansionary deleveraging* (Type 2): Banks are assumed to raise equity capital and invest the additional funds, while holding debt constant by assumption.[23,24]

*Unconstrained deleveraging* (Type 3): Banks are not constrained as to how they move to a higher capital ratio. They may partly shrink their balance sheet size or raise equity, to also replace debt if they wish.[25]

The Type 1 and 2 shock sizes are calibrated based on the formulas in equations (10) and (11), with $E_0$, $A_0$, and $\Delta$ denoting capital, total assets, and the capital ratio shock, respectively:

$$\text{shock}^{\text{Type1}} = \ln\left(\frac{E_0}{\frac{E_0}{A_0}+\Delta}\right) - \ln\left(A_0\right) \tag{10}$$

$$\text{shock}^{\text{Type2}} = \ln\left(A_0 - E_0\left(\frac{\left(\Delta+\frac{E_0}{A_0}\right)\left(A_0-E_0\right)}{E_0\left(\Delta+\frac{E_0}{A_0}-1\right)}+1\right)\right) - \ln\left(A_0\right). \tag{11}$$

The respective first terms in the two equations reflect total assets after the capital ratio shock $\Delta$ is applied. The shock amounts equal the log difference between total assets post- and preshock. The log percentage shock computed based on capital and total assets is assumed to apply to the loan stock of a country.

The capital ratio shock under the Type 1 simulation is combined with the sign restriction imposed on banking system loan volumes and loan interest rates that are assumed to be negative and positive, respectively, for only the first period in which the shock arrives. This combination of sign constraints makes the impulse an identified negative loan supply shock. Under the Type 2 simulation, the same capital ratio shock is combined with the opposite of the Type 1 restrictions, i.e., a positive and negative constraints on the $T = 1$ responses for loan volumes and rates. It is, therefore, an identified positive supply shock.[26,27]

The Type 3 simulation—without the imposition of any sign constraints—is meant to reveal how banking systems went about the deleveraging process on average historically. Under none of the three simulation types are there any constraints imposed on GDP, the GDP deflator, and long-term interest rates.

Along with the three different simulation types, we distinguish between two regime constellations. A first is to set all countries and banking systems simultaneously to Regime 1, i.e., for all to jointly rest in the underleveraging

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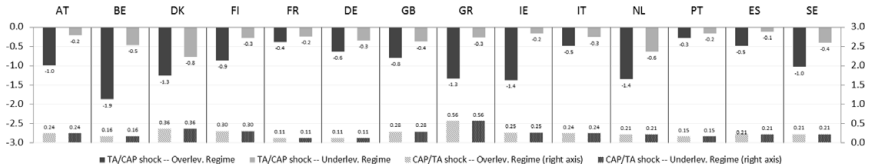



**FIGURE 3.** Capital ratio and implied leverage shocks under over- and underleveraging regimes. Residual-based 1-standard deviation shocks for capital ratios.

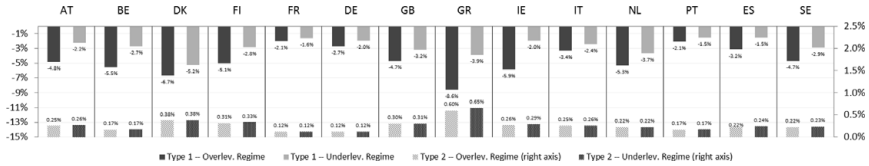



**FIGURE 4.** Capital ratio shock-implied loan supply shocks under Type 1 and 2 simulations.

regime. The second constellation is to assume them all simultaneously being in Regime 2, the overleveraging regime.[28] The shock sizes are calibrated based on the full-sample residuals (1-standard deviation based), i.e., are on purpose not made regime conditional to thereby be able to judge the difference of responses due to Type 1/2/3 and due to the different regime dynamics. The starting point capital ratios to which the shocks are attached are regime conditional, however, by first identifying the two points in time when the capital ratio of a banking system came closest to the average capital ratio under the overleveraging and underleveraging regime, respectively, for each banking system.

Figure 3 shows the capital and implied leverage ratio (assets over equity capital) shocks under the two regimes for all banking systems. The capital ratio shocks are the same under the two regimes. The implied shocks to the leverage multiples are, however, different that reflects the effect of levered balance sheets. During low leverage (high capital ratio) periods, the same percentage point shock to capital ratios has less of an effect on leverage, very mechanically so.

Figure 4 shows the capital ratio shock-implied impulses for loan volumes under the Type 1 and Type 2 simulations. The absolute shock sizes under the Type 1 scenario are larger than the corresponding absolute shock sizes under Type 2. Again, this is the mechanical effect resulting from the nature of levered balance sheets; recalling that the underlying capital ratio shock for Type 1 and 2 is the same for any one banking system. Second, there is a pronounced difference between implied loan volume shocks for Type 1 when differentiating between the initial overleveraging versus underleveraging regime. Under the overleveraging (too low capital ratio) regime, the implied shock sizes are more sizable than under initial underleveraging.

We present the model responses for real GDP of five example simulations in Figure 5—applying positive capital ratio shocks to the banking systems of

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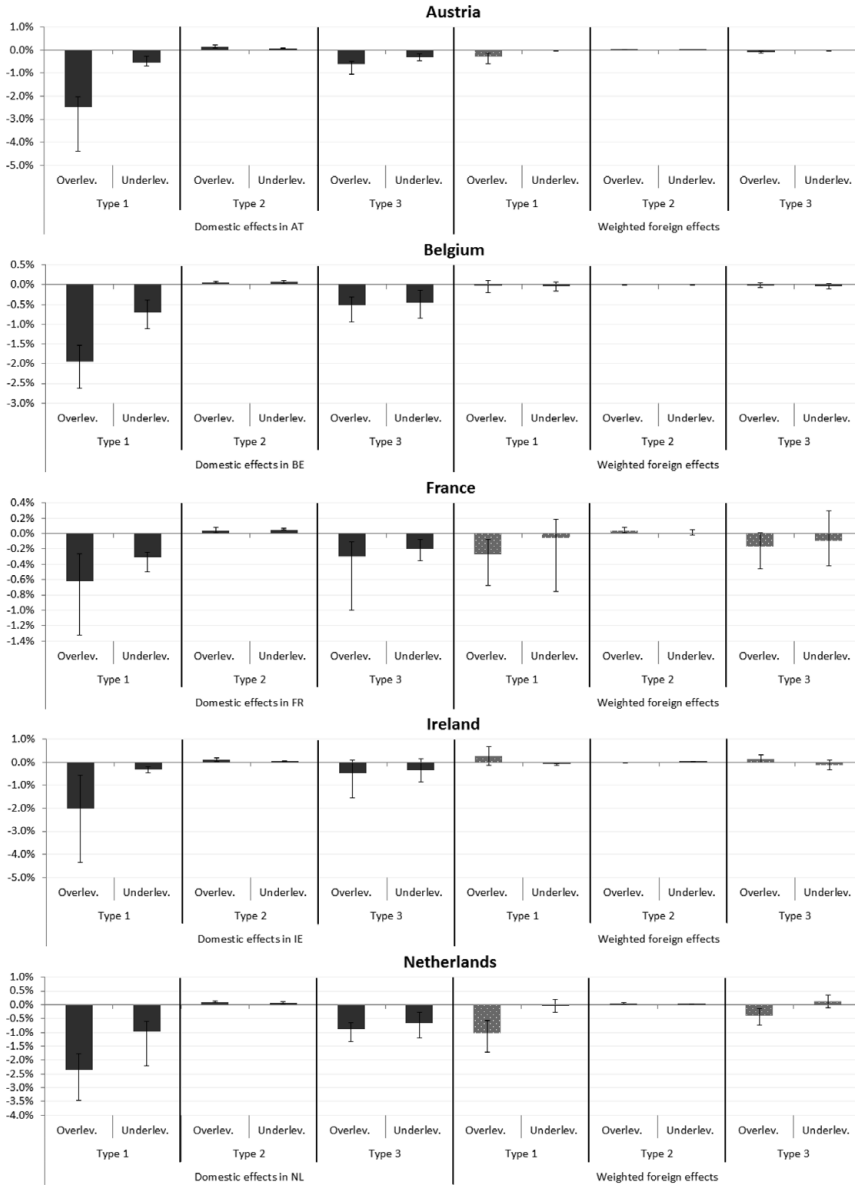



**FIGURE 5.** Shock to banking system capital ratios—Real GDP responses.

Austria, Belgium, France, Ireland, and the Netherlands. The time dimension (12 quarters) is compressed by showing only cumulative long run effects. Along with the domestic responses, the cross-border responses are compressed by computing weighted aggregate responses after having obtained the full cross-country response

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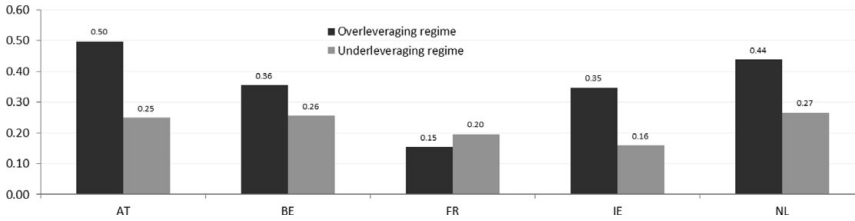



**FIGURE 6.** Real GDP to nominal credit long run impact ratios.

profiles from the simulation, using the cross-border loan exposures for defining the weights.[29] The responses of real GDP are obtained by subtracting the responses of the GDP deflator from those of nominal GDP responses. The error bounds around the cumulative responses in Figure 5 mark the 80th and 20th percentiles of the response distributions, reflecting parameter uncertainty as well as the draws from the sign restriction procedure.

For Austria, the initial capital ratio shock (+0.24pp) that implied a loan supply shock under the Type 1 simulation equaling −4.8pp and −2.2pp under the over- and underleveraging regime, would result in a GDP drop relative to cumulative long-run baseline growth of about −2.5pp and −0.5pp under the two regimes. Looking at the Type 1 domestic effects, the clear asymmetry that was visible for the underlying loan supply shocks feeds, as expected, through to the GDP responses. Under the Type 2 simulation, the effects are slightly positive, reflecting the underlying positive supply shock. The responses of GDP or the deflator were not constrained, i.e., the fact that real GDP responses are negative and positive, respectively, under Type 1 and 2 is driven by the stable relation between credit and GDP. The Type 2 effects for real GDP are less sizable in absolute terms compared to the Type 1 effects, being reflective again of the asymmetric shock sizes that were implied for loan supply. The Type 3 responses fall between the Type 1 and 2 estimates, equalling −0.6pp and −0.3pp under the two regime constellations. For the case of the Austrian banking system shock, the weighted cross-border real GDP effects appear to be relatively limited, with the maximum effect at −0.3pp under the overleveraging regime for all banking systems coupled with the assumed Type 1, i.e., full asset-side deleveraging, reaction of the Austrian banking system. The remaining cases, with shocks applied to Belgium, France, Ireland, and the Netherlands, suggest the same response pattern concerning Type 1 versus 2 versus 3, and the over- versus underleveraging regime constellation.

Figure 6 shows the real GDP to regime-conditional nominal credit long-run impact ratios for the five example shock scenarios. They are the same for the Type 1 and 2 simulation (as the two are operating with identical shocks and just opposite sign restrictions).

The GDP to credit impact ratios suggest that with the exception of only France, the ratio is higher under the over- than under the underleveraging regime. This suggests that there is a markedly stronger relation between credit and GDP under the overleveraging regime, which is an effect that is independent of, i.e., to be seen

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in addition to, the aforementioned mechanical effect of levered balance sheets that imply different loan shock sizes for the same capital ratio shock.

Clearly, a large scale empirical model of the kind presented here calls for the conduct of robustness checks. In the interest of not multiplying the outputs too significantly, we refer the reader to Gross et al. (2016a/b) where the results from numerous robustness checks are presented. Additional model diagnostics are presented therein, e.g., residual cross-correlation statistics to examine and confirm that the GVAR structure manages well to capture local and global effects for the model residuals to turn out to not significantly correlate neither through time nor the cross sections.[30]

## 4. CONCLUSIONS

Much recent research point to the excessive leveraging of the banking sector as being the essential driving force for macroeconomic instability. We show here, based on a model by Brunnermeier and Sannikov (2014) and Stein (2012) how to measure overleveraging and build it into a large-scale macro model. We pursue this from an empirical perspective by making use of a study by Schleer et al. (2014) for a sample of European countries with an aggregate of 40 banks' individual measures of overleveraging for 14 banking systems. We use such an overleveraging variable as a transition variable in a large-scale regime change model, specifically a Threshold Mixed-Cross-Section GVAR for 28 countries and 14 banking systems of the EU.

A first conclusion is that one reason for why macroeconomic responses to bank capital shocks are likely significantly stronger under an overleveraging regime is that the same percentage point capital ratio shock translates into a much stronger asset side reaction (which is particularly visible under a full asset-side deleveraging scenario) than under an initial low-leverage (i.e., high capital ratio) regime. This effect is very much mechanic, though quite essential.

Second, our observation is that GDP to credit long-run response ratios are higher under a bank overleveraging regime. It is an effect that arises in addition to the shock amplification effect (previous point), whereby credit and GDP tend to co-move more strongly, hence rendering economic activity more susceptible to changes in bank credit supply under the overleveraging regime.

Third, cross-border spillover effects appear to be more pronounced when capital ratio shocks hit the banking system during a period of overleveraging. This finding reflects the fact that bank credit supply does not only exert its state-dependent effect on the domestic economy but implies cross-border effects through the cross-border supply of credit.

### *NOTES*

1. See Borio et al. (2001) and Brunnermeier et al. (2009).

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

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3. There are currently also many DSGE models, pointing to the possible destabilizing role of financial intermediaries, see Christiano and Ikeda (2013), and Gerali et al. (2010). From a different perspective, see Goodhart et al. (2012).

4. It is not the first application that combines a GVAR with a regime-switching mechanism; Binder and Gross (2013) combined a Markov-switching, i.e., continuous, regime switching with the GVAR.

5. 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 the MCS structure with banking system—country weights is superior to the traditional GVAR with variable-specific weights. The test results are available upon request from the authors.

6. For further details of the model and the derivation of the measures, see Schleer et al. (2014) and Gross et al. (2016b).

7. Note that Brunnermeier and Sannikov (2014) use $x_t$ as a notation for their decision variable leveraging and assume that $x_t > 1$.

8. In the solution procedure used here, we neglect (2). In Brunnermeier and Sannikov (2014), it represents the aggregate capital (with $g$ the growth rate and $\delta$ the resource use for managing the assets) of financial specialists and households. A larger fraction of it will be held by financial specialists, since they can borrow. Those details can be neglected here. Aggregate capital is more specifically considered in Brunnermeier and Sannikov (2014).

9. Note that in our model version here, we neglect the dynamics of (2). In Brunnermeier and Sannikov (2014), it represents the aggregate capital of financial specialists and households (with $g$ being the growth rate of capital, another decision variable, and $\delta$ the resource use for managing the assets). A larger fraction of the assets will be held by financial specialists since they have a lower discount rate, and with $\alpha_t > 0$ they can borrow. Those details can be neglected here. The dynamics of aggregate capital is more specifically considered in Brunnermeier and Sannikov (2014).

10. Stein (2012) posits that the interest rate shocks are highly negatively correlated with capital gains' shocks, we have thus a negative sign in (3) for the effect of the shocks on interest rates. We here also assume that the interest rate shocks have a smaller variance than the capital gains' shocks.

11. In Stein (2012), the vulnerabilities and possibly an adverse feedback loop are triggered by overleveraging, capital losses and rising borrowing cost.

12. Excess leveraging in Stein (2012) is driven by actual leverage over and above the optimal leverage, caused by a sequence of persistent shocks to increase capital gains and lowering interest rates, both giving rise to excess leveraging. In this sense, he explores only the vulnerability of the overleveraged sector, but does not model particular, possibly amplifying feedback loops, as Mittnik and Semmler (2013) do. However, Stein's (2012) model can distinguish between optimal debt, actual debt and excess debt. For empirical measures of those, see Schleer et al. (2014).

13. We want to thank a referee who has made this important point.

14. For details of how those appear also in the overleveraging measure, see Schleer et al. (2014), and the discussion in Gross et al. (2016b).

15. For details of the derivation and the documentation of the database, we want to refer the reader Gross et al. (2016b) and Schleer et al. (2014).

16. For a complete description of the derivation, see Stein (2012, Chap. 4.9), Schleer et al. (2014), and Gross et al. (2016b).

17. Since we have here only one state variable, we are using $X(t)$ now as net worth.

18. For more details, see Schleer et al. (2014) and Gross et al. (2016b).

19. For details that we omit, see Gross and Kok (2013) and Gross et al. (2016a,b).

20. We do not yet capture the foreign operations of banks via subsidiaries and branches (as we use the ECB's BSI statistics, i.e., a locational concept of monetary financial institutions). We have 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,

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our 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.

21. Despite the fact that our measure of loan volumes in the core of the model captures only credit to the private sector, we use a banking system exposure measure to generate the weights that link the banking systems. The rationale is that a shock propagation channel for loan volumes and prices toward the private sector can nonetheless be a function of the size of interbank exposure. Various robustness checks with different weighting schemes, in particular, in this respect confirm that our simulation results are robust.

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

23. This scenario also reflects a more gradual build-up of capital by retaining earnings.

24. We shall note that the Type 2 scenario does not literally reflect the creation of new loans up to the full potential that some new equity capital would imply. For that reason, the positive Type 2 impulse likely underestimates the upside potential of the additional credit supply as a result of higher capitalization levels. For that reason, less emphasis should be given to the Type 2 scenario, and more to the Type 1 and 3 scenario simulations.

25. An additional, fourth simulation type could in principle be one under which banks are assumed to raise capital to replace debt, while holding total assets constant by assumption. This scenario is one that can be called a *static deleveraging*, which we do not see as very relevant, as too hypothetical and not implying structural changes, for what concerns the empirical assessment that we wish to conduct.

26. The identification scheme ignores the fact that while banks having raised equity should be in a position to supply more credit, hence pushing lending rates down, the additional equity 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 to reinstall a desired ROE target. By only imposing the sign restriction in the first period, we do want to allow for such rent seeking behavior in subsequent periods. It should also be noted that the Type 2 behavior of banks does not only reflect equity raising but as well a gradual rise in capital by retaining earnings.

27. Although we do aim to emphasize with the Type 2 reaction of banks that raising equity to achieve higher capital ratios can be useful to avoid an asset side deleveraging and implied contraction of economic activity, we abstract from whether and to what extent this would be possible, in particular, during recession periods in general, or banking crises episodes specifically, when raising capital from the market from all banks simultaneously might prove difficult.

28. Many more regime constellations would be conceivable, with subsets of countries and banking systems being either in the over- or underleveraging regime. We do not present them all and focus instead on the two polar constellations. Prior to the outbreak of the financial crisis period (2007), all countries comprised by our sample rested in the overleveraging regime (except Finland); thus, the all-in-overleveraging regime comes close to an observed regime constellation.

29. GDP-based weights would be an alternative. It is a matter of preference. The exposure-based weights mean that the results reflect the response of countries that are relevant for the banking system that is shocked in terms of their exposure.

30. Average pair-wise cross-section correlation estimates for the residuals confirm that the model manages well to capture the within and across cross-section dependencies that is an indirect test and confirmation for the weak exogeneity assumption to hold. The residual correlation estimates fall into a narrow $-3/+3\%$ interval. We also conducted a robustness check regarding the lag structure of the model, adding a second lag beyond the contemporaneous inclusion and first lag of the foreign variable vectors in the model. The impulse responses presented here changed by only a small margin, by a factor ranging narrowly between 0.9 and 1.1.

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# ANNEX: GLOBAL SOLUTION OF THE MCS-GVAR MODEL

The system presented in the set of equation (9) contains time-contemporaneous relationships and hence is not yet ready for being used for forecasting or simulation purposes. The global model has, therefore, to be solved, meaning that the equations for all countries and banking systems need to be stacked and then reformatted in a way to contain only lagged relationships. The global solution of the model can be derived in four steps.

Step 1: Generate A-matrices. We start by stacking the within-cross-section vectors along with the cross-cross-section weighted variable vectors in (here) two vectors $\boldsymbol{m}_{it}^{x}$ and $\boldsymbol{m}_{jt}^{y}$. In this first step, the fact that the model has a threshold structure does not have any implication yet

$$\begin{aligned}\boldsymbol{m}_{it}^{x} &= \begin{pmatrix} \boldsymbol{x}_{it\prime} & \boldsymbol{x}_{it}^{*,C-C\prime} & \boldsymbol{y}_{it}^{*,C-B\prime} \end{pmatrix}' \\ \boldsymbol{m}_{jt}^{y} &= \begin{pmatrix} \boldsymbol{y}_{jt\prime} & \boldsymbol{x}_{jt}^{*,B-C\prime} & \boldsymbol{y}_{jt}^{*,B-B\prime} \end{pmatrix}'. \end{aligned} \tag{12}$$

We can rewrite the equation system with these $\boldsymbol{m}$ vectors as follows:

$$\begin{aligned}\underbrace{\begin{pmatrix} \mathbf{I}_{k_i^x} & -\Lambda_{i,0,0} & -\Lambda_{i,1,0} \end{pmatrix}}_{\equiv \boldsymbol{A}_{i0}^{x}} \boldsymbol{m}_{it}^{x} &= \boldsymbol{a}_i + \underbrace{\begin{pmatrix} \Phi_{i1} & \Lambda_{i,1,1} \end{pmatrix}}_{\equiv \boldsymbol{A}_{i1}^{x}} \boldsymbol{m}_{i,t-1}^{x} + \cdots + \boldsymbol{\epsilon}_{it} \\ \underbrace{\begin{pmatrix} \mathbf{I}_{g_j^y} & -\Xi_{j,0,0} & -\Xi_{j,1,0} \end{pmatrix}}_{\equiv \boldsymbol{A}_{j0}^{y}} \boldsymbol{m}_{jt}^{y} &= \boldsymbol{b}_j + \underbrace{\begin{pmatrix} \Pi_{j1} & \Xi_{j,1,1} \end{pmatrix}}_{\equiv \boldsymbol{A}_{j1}^{y}} \boldsymbol{m}_{j,t-1}^{y} + \cdots + \boldsymbol{\omega}_{jt}. \end{aligned} \tag{13}$$

At this point, in equation (13), a choice has to be made for the regime-dependent coefficient matrices. In order to not overload the notation, we do not introduce any additional scripting but note that a regime choice has to be made here. For each country or banking system, either Regime 1 or Regime 2 conditional parameters shall be set. Overall, for across countries and banking systems, it is, therefore, a *regime constellation* that should be defined. Each regime constellation implies different global model dynamics.

Step 2: Generate L-matrices (link matrices). With a global, stacked variable vector $\boldsymbol{s}_t = \left(\boldsymbol{x}_{1t}', \ldots, \boldsymbol{x}_{Nt}', \boldsymbol{y}_{1t}', \ldots, \boldsymbol{y}_{Mt}'\right)$ at hand, we can link the cross-section-specific variable vectors $\boldsymbol{m}_{it}^{x}$ and $\boldsymbol{m}_{jt}^{y}$ to $\boldsymbol{s}_t$. The link matrices $\boldsymbol{L}_i^{x}$ and $\boldsymbol{L}_j^{y}$ are used to map the local cross

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section variables into the global vector, which involve the weights from the weight matrices $\boldsymbol{W}$:

$$\begin{aligned} \boldsymbol{m}_{it}^{x} = \boldsymbol{L}_{i}^{x}\boldsymbol{s}_{t} \quad &\rightarrow \quad \boldsymbol{A}_{i0}^{x}\boldsymbol{L}_{i}^{x}\boldsymbol{s}_{t} = \boldsymbol{a}_{i} + \boldsymbol{A}_{i1}^{x}\boldsymbol{L}_{i}^{x}\boldsymbol{s}_{t-1} + \cdots + \boldsymbol{\epsilon}_{it} \\ \boldsymbol{m}_{jt}^{y} = \boldsymbol{L}_{j}^{y}\boldsymbol{s}_{t} \quad &\rightarrow \quad \boldsymbol{A}_{j0}^{y}\boldsymbol{L}_{j}^{y}\boldsymbol{s}_{t} = \boldsymbol{b}_{j} + \boldsymbol{A}_{j1}^{y}\boldsymbol{L}_{j}^{y}\boldsymbol{s}_{t-1} + \cdots + \boldsymbol{\omega}_{jt}. \end{aligned} \tag{14}$$

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

$$\begin{aligned} \boldsymbol{G}_{0}^{x} &= \begin{pmatrix} \boldsymbol{A}_{10}^{x}\boldsymbol{L}_{1}^{x} \\ \cdots \\ \boldsymbol{A}_{N0}^{x}\boldsymbol{L}_{N}^{x} \end{pmatrix}, \boldsymbol{G}_{1}^{x} = \begin{pmatrix} \boldsymbol{A}_{11}^{x}\boldsymbol{L}_{1}^{x} \\ \cdots \\ \boldsymbol{A}_{N1}^{x}\boldsymbol{L}_{N}^{x} \end{pmatrix}, \ldots, \boldsymbol{a} = \begin{pmatrix} \boldsymbol{a}_{1} \\ \cdots \\ \boldsymbol{a}_{N} \end{pmatrix} \\ \boldsymbol{G}_{0}^{y} &= \begin{pmatrix} \boldsymbol{A}_{10}^{y}\boldsymbol{L}_{1}^{y} \\ \cdots \\ \boldsymbol{A}_{M0}^{y}\boldsymbol{L}_{M}^{y} \end{pmatrix}, \boldsymbol{G}_{1}^{y} = \begin{pmatrix} \boldsymbol{A}_{11}^{y}\boldsymbol{L}_{1}^{y} \\ \cdots \\ \boldsymbol{A}_{M1}^{y}\boldsymbol{L}_{M}^{y} \end{pmatrix}, \ldots, \boldsymbol{b} = \begin{pmatrix} \boldsymbol{b}_{1} \\ \cdots \\ \boldsymbol{b}_{M} \end{pmatrix}. \end{aligned} \tag{15}$$

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

$$\boldsymbol{G}_{0} = \begin{pmatrix} \boldsymbol{G}_{0}^{x} \\ \boldsymbol{G}_{0}^{y} \end{pmatrix}, \boldsymbol{G}_{1} = \begin{pmatrix} \boldsymbol{G}_{1}^{x} \\ \boldsymbol{G}_{1}^{y} \end{pmatrix}, \ldots, \boldsymbol{d} = \begin{pmatrix} \boldsymbol{a} \\ \boldsymbol{b} \end{pmatrix}. \tag{16}$$

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

$$\boldsymbol{s}_{t} = \underbrace{\mathbf{G}_{0}^{-1}\mathbf{d}}_{\equiv \mathbf{H}_{0}} + \underbrace{\mathbf{G}_{0}^{-1}\mathbf{G}_{1}}_{\equiv \mathbf{H}_{1}}\mathbf{s}_{t-1} + \cdots + \boldsymbol{G}_{0}^{-1}\boldsymbol{\varphi}_{t}. \tag{17}$$

It is useful to recall at this point that the coefficient matrices $H$ are the result of the above-mentioned assumption about a *regime constellation* across countries and banking systems. Moreover, since the weights are time varying, a choice has to be made as to the reference point in time of which the weights are taken to solve the regime-constellation-dependent global model. The shock simulations that are presented in this paper take the end-sample (2014Q2) weight sets as a basis for deriving the global solution.

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