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Systemic Risk Modelling System (SRMS): a macroprudential stress testing model

Laurynas Naruševičius*

(Financial Stability Department, Bank of Lithuania)

Ieva Mikaliūnaitė-Jouvanceau*

(Financial Stability Department, Bank of Lithuania)

* Contacts: Laurynas Naruševičius (e-mail: lnarusevicius@lb.lt), Ieva Mikaliūnaitė-Jouvanceau (email: imikaliunaite@lb.lt). We thank Skirmantė Matkėnaitė and Jaunius Karmelavičius for their helpful suggestions. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Bank of Lithuania or the Eurosystem.

Gedimino pr. 6, LT-01103 Vilnius

www.lb.lt

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ABSTRACT

This paper introduces the Systemic Risk Modelling System (SRMS), a new macroprudential stress testing model for the Lithuanian banking sector. The SRMS addresses the limitations of traditional static models by incorporating dynamic balance sheet assumptions and capturing second-round effects, providing a more comprehensive assessment of systemic risks. The model's applications extend beyond stress testing, including macroprudential policy stance assessment, capital-at-risk analysis, and macroprudential policy impact evaluation. The SRMS model enhances the understanding of systemic risks within the Lithuanian banking sector and offers a potential benchmark for other national central banks seeking to strengthen their financial stability frameworks.

Keywords: macroprudential stress testing, macroprudential policy, feedback loop, secondround

effects.

JEL: E37, E58, G21, G28

1 Introduction

Macroprudential bank stress testing has become an essential tool for regulators to assess the resilience of banks under adverse economic conditions. Pioneering stress testing models, typically based on static balance sheet assumptions, have significant limitations in capturing dynamic interactions within the financial system. These limitations can result in the underestimation of systemic risks. To address these shortcomings, central banks and regulatory institutions are developing innovative approaches that incorporate dynamic balance sheet adjustments and second-round effects.

This paper introduces the Systemic Risk Modelling System (SRMS), a macroprudential stress testing model tailored for the Lithuanian banking system. The SRMS model builds on the foundational work of Butkus and Naruševičius (2015) by integrating dynamic balance sheet adjustments and feedback loops between the banking sector and the real economy, providing a more comprehensive assessment of systemic risks.

The SRMS is a semi-structural model comprising two principal components: the macro block and the bank-level block. The macro block is designed to simulate the dynamics of the Lithuanian economy and to design stress-testing scenarios using a narrative scenario generation algorithm. In the bank-level block, the dynamics of individual banks' balance sheets and profit and loss accounts are modelled, to assess the relationships between macroeconomic variables and bank-specific outcomes. The bank-level behaviours in loan issuance and pricing are then aggregated at the macro level, enabling the evaluation of their impact on the macroeconomy through a dynamic feedback loop.

The model introduces two key innovations. First, the dynamic balance sheet assumption allows banks to adjust their assets and loan pricing in response to changing macroeconomic conditions. Second, the feedback loop examines how shocks transmitted from the macroeconomic environment to banks feed back into the economy, potentially amplifying the initial shocks and creating a more pronounced economic downturn. This enables the SRMS to capture not only the immediate impacts of adverse economic scenarios on banks but also subsequent feedback loops between the banking sector and the real economy.

The development of the SRMS aligns with a broader trend in the literature towards more sophisticated stress testing models (Krznar and Matheson, 2017; Andersen et al., 2019; Morell et al., 2022). Drawing inspiration from the European Central Bank's Banking Euro Area Stress Test (BEAST) model (Budnik et al., 2023), known for its advanced methodology including second-round effects, the SRMS ensures alignment with best practices in macroprudential stress testing.

Beyond traditional stress testing applications, the SRMS serves as a versatile tool for evaluating a macroprudential policy stance, assessing capital-at-risk, and understanding the broader impacts of macroprudential policies. Its design ensures relevance for both supervisory and policy-making purposes.

The remainder of this paper details the SRMS model's structure and applications. Section 2 provides a general overview of the model and its components. Section 3 delves into the macroeconomic block and approach to scenario design. Section 4 focuses on the banking block and the econometric models used for bank-level dynamics and discusses the financial accounts, including bank-level balance sheets and profit-loss accounts. Section 5 explains the feedback loop and its integration into the SRMS model. Section 6 presents several applications of the SRMS model. Finally, Section 7 offers concluding remarks.

2 Model overview

The SRMS model uses a semi-structural approach, integrating both data-driven and structural components. The model links macroeconomic and bank-level data, providing a comprehensive framework to analyse the Lithuanian banking sector's developments and reactions to macroeconomic shocks (see Figure 1).

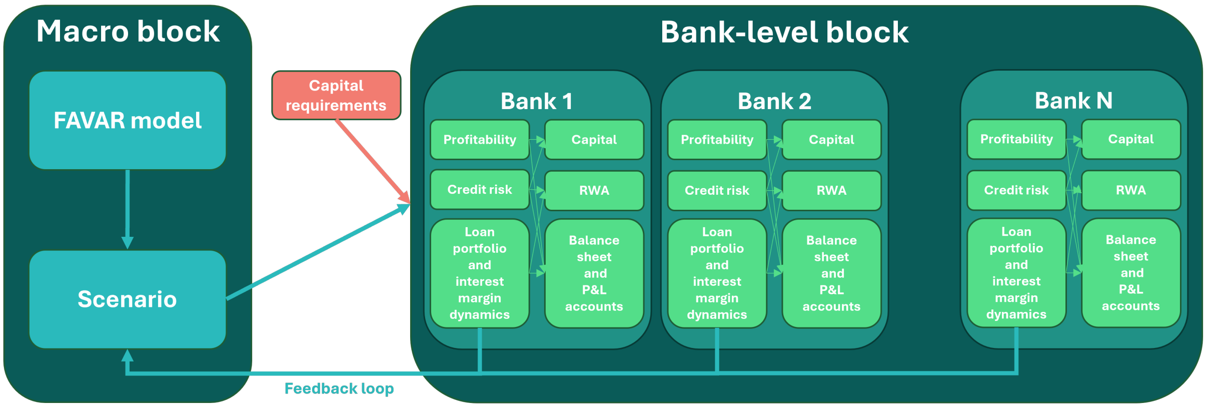

Figure 1: Schematic illustration of the SRMS model

The macro block captures the dynamics of the Lithuanian economy, estimated using the structural factor-augmented autoregressive model (FAVAR). This model represents the Lithuanian economy through key macroeconomic variables such as GDP, inflation, and house prices. The FAVAR model is employed to construct macroeconomic scenarios (Section 3).

The banking block incorporates data from the 11 largest banks operating in Lithuania, which collectively cover approximately 82% of total banking assets. A portion of the model's equations maps the transmission of scenarios into bank behavioural responses. Banks adjust their loan portfolios and margins in response to changes in general economic conditions, considering their financial situations (Section 4.1.1 and 4.1.2). These responses are estimated using bank-level data. Theoretical foundations underpin all empirical specifications of the behavioural equations, ensuring the model's robust long-term properties. Another set of equations links the dynamics of macroeconomic variables with developments in a bank's credit risk and profitability parameters (Sections 4.3 and 4.2). The third set of equations (accounting identities) aggregates modelling results into simplified balance sheets and profit and loss accounts for each bank, assessing changes in capital and risk-weighted assets (Section 4.5).

The model incorporates a second-round effect, i.e. the feedback loop between the banking sector and the real economy. Given the normal economic environment, banks adjust their loan portfolios and margins in response to aggregate credit demand. However, in adverse conditions, banks focus on restoring depleted capital levels by deleveraging and increasing margins. Actions by individual banks to repair their capital levels can lead to a negative credit supply shock, disrupting the macroeconomy (Section 5).

3 Macro block

3.1 Macroeconomic model

The SRMS model uses a factor-augmented vector autoregressive (FAVAR) model to analyze the Lithuanian economy. FAVAR models, introduced by Bernanke et al. (2005) and further explored by Boivin et al. (2009), address the inherent interdependence of economic variables by incorporating latent factors that capture a significant amount of additional information. This approach complements the standard VAR framework by allowing for a more parsimonious representation of complex dynamics while maintaining internally consistent co-movements between the core variables of interest.

Endogenous variables in a FAVAR include a set of observable variables F_t^y and a set of latent factors F_t^x:

$$\begin{bmatrix} F_t^y \\ F_t^x \end{bmatrix} = \phi(L) \begin{bmatrix} F_{t-1}^y \\ F_{t-1}^x \end{bmatrix} + \varepsilon_t \tag{1}$$

where $\phi(L)$ is a lag polynomial of order p and vector $\varepsilon \sim \mathcal{N}(0, \Sigma)$ includes the reduced form innovations. The macro-econometric model incorporates six observable variables, namely $F_t^y \in$ {real GDP, HICP, Unemployment rate, House price index, Credit, Interest rate on new loans} (see Table 1). These variables capture the primary developments in the economic environment and serve as key drivers of banks' profitability and the quality of their loan portfolios.

Table 1: Observed macroeconomic variables in the FAVAR

Variable name	Transformation	Definition
GDP	log difference	Real GDP (level, constant prices)
HICP	log difference	Harmonized index of consumer prices (quarterly average)
URX	level	Unemployment rate (percent)
IHX	log difference	Residential property price index (new and existing dwellings)
CRE	log difference	Loans held by other MFIs (outstanding amount at the end of the period)
IRN	level	Interest rate on new loans granted by other MFIs

The model is estimated in two steps. First, based on observed variables F_t^y and X_t the unobserved factors are estimated. Second, we replace F_t^x in the equation (1) with the estimated unobserved factors. We then estimate the reduced form VAR(p) model using Bayesian methods, applying the Gibbs sampler with Normal-Wishart priors. The number of lags, p (in our case $p = 1$), is determined based on a set of standard lag selection criteria, such as the Akaike

Information Criterion (AIC) and the Bayesian Information Criterion (BIC).

The latent factors in F_t^x are computed based on a set of macroeconomic series contained in X_t, which includes a set of N observable variables different from those in F_t^y. In our case, using the principal component analysis, we extract two factors that are used in the model. The identification of F_t^x ensures that latent factors are orthogonal to the observed variables in F_t^y:

$$X_t = \Lambda^y F_t^y + \Lambda^x F_t^x + u_t \tag{2}$$

where Λ^y and Λ^x are matrices of factor loadings, which measure the sensitivity of the individual variables in X_t to each common factor (observed and unobserved), and u_t is a vector of idiosyncratic disturbances assumed to be normally distributed with mean zero and diagonal covariance matrix. In our empirical application, X_t consists of additional macroeconomic variables (such as private consumption, export, gross value added, etc.; see Table 13 in the Appendix). The strength of the FAVAR model lies in its ability to track the propagation of structural shocks into those additional macroeconomic variables. This broader set of variables can be used in other equations within the banking block.

3.1.1 Shock identification

The reduced-form FAVAR estimates allow the identification of a structural FAVAR. Imposing zero and sign restrictions motivated by the existing literature on impulse response functions (IRFs) and applying the algorithm proposed by Arias et al. (2018), six structural shocks, which are important in the stress testing, were estimated, as outlined in Table 2. The two remaining structural shocks and unobserved factors are left unrestricted.

Table 2: Structural shocks

	Credit supply	Credit demand	House prices	Unemp rate	Aggregate demand	Aggregate supply
Real GDP	+	+		0	+	+
HICP	0	0	0		+	-
Unemployment rate	0		0	-		
House price index			+			
Credit	+	+				
Interest rate on new loans	-	+	0		+	

The identification of a credit supply shock relies on the assumption that (on impact) the innovation in credit supply results in inverse movements of lending rates and credit volumes (Hristov et al., 2012; Barnett and Thomas, 2014; Budnik et al., 2023). Conversely, an exogenous increase in credit demand is expected to affect both the bank lending rate and aggregate loan volumes in the same direction.

A positive house price shock is characterised by an increase in the house price index without a contemporaneous effect on inflation, unemployment rate and interest rate. An unemployment rate shock is described by applying a negative effect on the unemployment rate and zero restriction on gross domestic product (GDP).

A standard set of constraints is applied to distinguish between aggregate demand and aggregate supply shocks (Hristov et al., 2012; Budnik et al., 2023). Positive shocks to aggregate demand simultaneously increase both inflation and GDP. This economic growth also usually leads to an increase in interest rates. In contrast, shocks to aggregate supply lead to a different scenario. Here, inflation and GDP move in opposite directions.

3.2 Scenario design

Macroeconomic scenario design represents the initial phase of the top-down stress testing procedure. Stress tests typically encompass a baseline scenario, reflecting the most likely economic developments, and one or more adverse macroeconomic scenarios representing severe yet plausible economic downturns.

The baseline scenario is generated by producing forecasts conditional on the most recent official forecasts published by the Lietuvos Bankas. Specifically, we employ the macroeconomic Factor-Augmented Vector Autoregression (FAVAR) model, described in Section 3.1, imposing constraints on the trajectory of certain variables to align them with these forecasts. In our application, the constrained variables typically include real gross domestic product (GDP), inflation, and unemployment.[1] This approach enables us to simulate a scenario representing the most probable outcome, while simultaneously observing the responses of other variables in the macroeconomic model that are consistent with the specified economic forecasts.

The adverse scenario is generated using an algorithm that draws inspiration from the narrative scenario generation methodology proposed by Budnik et al. (2023). Our algorithm ensures the generation of scenarios that adhere to specific economic narratives, highlighting the risks and vulnerabilities identified by policymakers while maintaining statistical plausibility by preserving historical correlations and ensuring statistical consistency. The process comprises two principal stages:

1. **Generation of plausible economic scenarios:** Initially, a set of economic scenarios that are statistically and economically plausible is generated.

2. **Selection of a tail event to generate a severe scenario**: Subsequently, a tail event is selected from these plausible scenarios to create a severe scenario.

This approach ensures the generation of a *severe but plausible* scenario, balancing narrative-driven risk identification with statistical rigour. The detailed steps of our algorithm are provided below.

3.2.1 Adverse Scenario Generation Algorithm

Step 1. Forecast Generation Using the FAVAR Model. The FAVAR model described in Section 3.1 is employed to produce a set S of possible macroeconomic forecasts: $S = \{s_1, s_2, ..., s_n, ..., s_N\}$, where s_n contains all the variables contained in F_t^y and X_t. The set of forecasts is obtained by estimating the model using the Bayesian method, which results

[1]The simulation may also depend on other information available, for instance, the market expectations on monetary policy rate.

in a posterior predictive distribution yielding $N = 30,000$ predictions. An example is illustrated in Figure 2. The posterior predictive distribution can be generated using unconditional or conditional forecasts, depending on the application. The latter is used to account for the macroeconomic feedback loop. This process is further elaborated in Section 5.

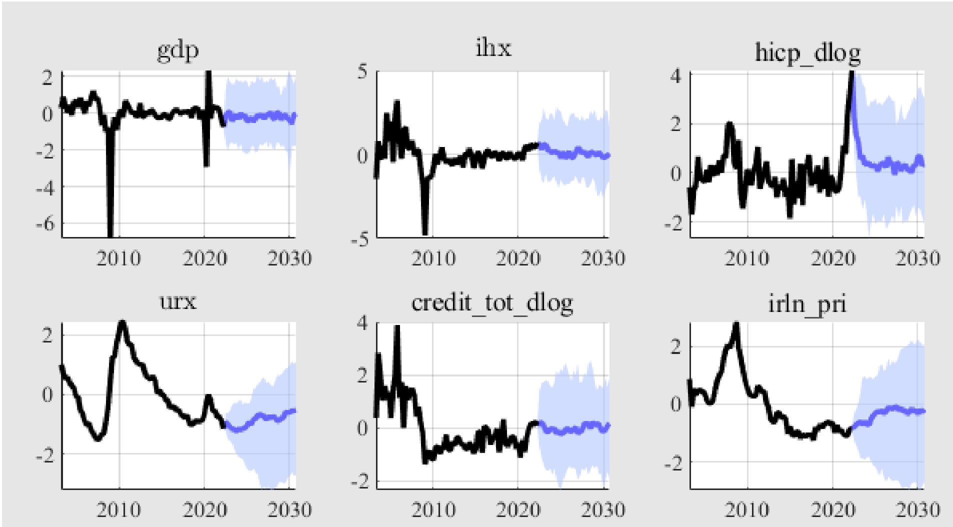

Figure 2: Example of a set S of macroeconomic forecasts

Notes: This figure illustrates an example of $N = 30,000$ predictions from FAVAR model. The figures are only for illustrative purposes. For simplicity, only the projections of variables in F^y are shown.

Step 2. Scenario selection. In the second step, an adverse scenario is constructed from the N predictions by selecting the desired adverse scenario narrative. The narrative is set by selecting the criteria that follow the desired storyline. Then the selection algorithm described below is used to construct the scenario.

a. Selection criteria. The necessary and optional selection criteria are outlined below:

- **Variable selection (y_k).** Select the variables that describe the narrative. To illustrate, if the scenario involves a decline in foreign demand, the export variable could be selected. Alternatively, if the scenario involves imbalances in the housing market leading to a correction in property prices, the house price index might be chosen. Both variables contained in F_t^y or X_t can be selected. The number of variables selected can vary depending on the scenario, but at least one variable must be selected.

- **Percentile selection (p_k).** Select the percentile of the forecast distribution for each variable y_k, indicating the severity of the scenario. Different percentiles might be chosen for each variable.

- **Weights (w_k).** Specify the weights for each variable to indicate the relative importance in the final scenario. It is important to ensure that the sum of the weights for each variable is equal to one: $\sum_{k=1}^{K} w_k = 1$.

- **Horizon (H).** Select the scenario selection horizon. This implies that the selection criteria will be applied solely for a specified period, leaving the rest unrestricted. To illustrate, if the objective is to generate a U-shaped scenario, a longer horizon H may be selected in comparison to a V-shaped scenario. More specifically, the selection criteria will be applied across the horizon $h = 1, ..., H$.
- **Positive growth**. Optionally, specify in which quarter h of the scenario the annual growth in one of the selected variables y_k must be positive.

An example illustrating these criteria is shown in Table 3. Three variables — GDP, export, and house price index — are selected to capture different aspects of the narrative. For each variable, specific percentiles are chosen to reflect the severity of the scenario: the 15th percentile for GDP, the 10th percentile for export, and the 20th percentile for the house price index. The highest weight of 70% assigned to GDP prioritizes it as the most significant variable for the scenario selection. The scenario horizon is set to four quarters, meaning the selection criteria will be applied over one year. Additionally, an optional criterion specifies that GDP must experience positive growth in the first quarter of 2025. This condition indicates that despite the overall severity of the scenario, GDP annual growth should be positive during this particular quarter.

Table 3: Example of selection criteria

Criteria	Example			Type
Variable	GDP	Export	House price index	Necessary
Percentile	0.15	0.10	0.20	Necessary
Weights	0.7	0.2	0.1	Necessary
Horizon		4 quarters		Necessary
Positive growth		$\Delta_{2025Q1} GDP > 0$		Optional

Notes: The table illustrates an example of selection criteria, chosen only for illustrative purposes. The criteria vary depending on the scenario narrative and severity.

b. Criteria-based scenarios ranking. In this step, all scenarios $S = \{s_1, s_2, ..., s_n, ..., s_N\}$ are ranked according to how well they meet the selected criteria, aligning with the desired narrative. This process involves several steps:

1. Let $\Delta Y_{k,h}^{(s_n)}$ denote the cumulative change of $\Delta y_{k,t}^{(s_n)}$ for each scenario $s_n \in S$:

$$\Delta Y_{k,h}^{(s_n)} = \sum_{t=1}^{h} \Delta y_{k,t}^{(s_n)} \quad \text{for each} \quad h \in \{1, \ldots, H\}$$

   where $\Delta y_{k,t}^{(s_n)}$ represents the logarithmic difference of variable y_k at quarter t for scenario s_n. This calculation involves the cumulative sum from the first quarter up to quarter h for each selected variable.

2. For each horizon period $h \in \{1, \ldots, H\}$, find the specified percentile p_k of the forecast distribution. This involves selecting the tail event for each $\Delta Y_{k,h}$ from the distribution of the generated scenario $S = \{s_1, ..., s_n, ..., s_N\}$:

$$P_{k,h} = \text{Percentile}_{p_k}(\{\Delta Y_{k,h}^{(s_n)} \mid s_n \in S\})$$

where Percentile_{p_k} denotes the calculation of the p_k-th percentile related to variable y_k from the set of scenarios S.

3. Quantify how far the scenario's values for each variable deviate from the specified percentiles:

$$D_{k,h}^{(s_n)} = (\Delta Y_{k,h}^{(s_n)} - P_{k,h})^2$$

where $h \in \{1, \ldots, H\}$.

4. Compute the average distances for each scenario $s_n \in S$ over horizon H:

$$D_k^{(s_n)} = \frac{\sum_{h=1}^{H} D_{k,h}^{(s_n)}}{H}$$

5. If a positive growth criterion is selected, only those scenarios that meet this criterion are further retained to align with a specific economic narrative. For instance, the set of scenarios meeting this criterion could be denoted as $S_k^+ = \{s_n \in S \mid \Delta Y_{k,h}^{(s_n)} > 0\}$. For simplicity of notation, we assume this criterion has not been applied in the current context.

6. Rank scenarios based on the calculated average distances $D_k^{(s_n)}$. The ranking indicates how well each scenario meets the selection criteria, with lower distances indicating better adherence:

$$R_k^{(s_n)} = \text{rank}(D_k^{(s_n)})$$

7. The final rank for each scenario is computed as the weighted average over the $R_k^{(s_n)}$:

$$R^{(s_n)} = \sum_k w_k \times R_k^{(s_n)}$$

where w_k represents the weight assigned to variable y_k.

c. Scenario formation. To account for scenario uncertainty, select the M scenarios with the lowest ranks. Let S^{top} denote a set of top-ranked scenarios:

$$S^{\text{top}} = \{s_n \in S \mid R^{(s_n)} \in \text{top } M \text{ ranks}\}$$

Finally, calculate the average value of each variable across the selected top scenarios:

$$s_{k,h}^{\text{final}} = \text{mean}\left(y_{k,h}^{(s_i)} \mid s_i \in S^{\text{top}}\right)$$

An example of scenario formation is illustrated in Figure 3. The figure includes the distribution of all scenarios generated using the FAVAR model, demonstrating the range of possible outcomes (step 1). The selection criteria were applied to three variables: GDP, exports, and house prices, over a scenario horizon of four quarters ($H = 4$). The grey lines represent the top $M = 20$ scenarios selected based on the selection criteria, while the red line represents the final scenario (step 2).

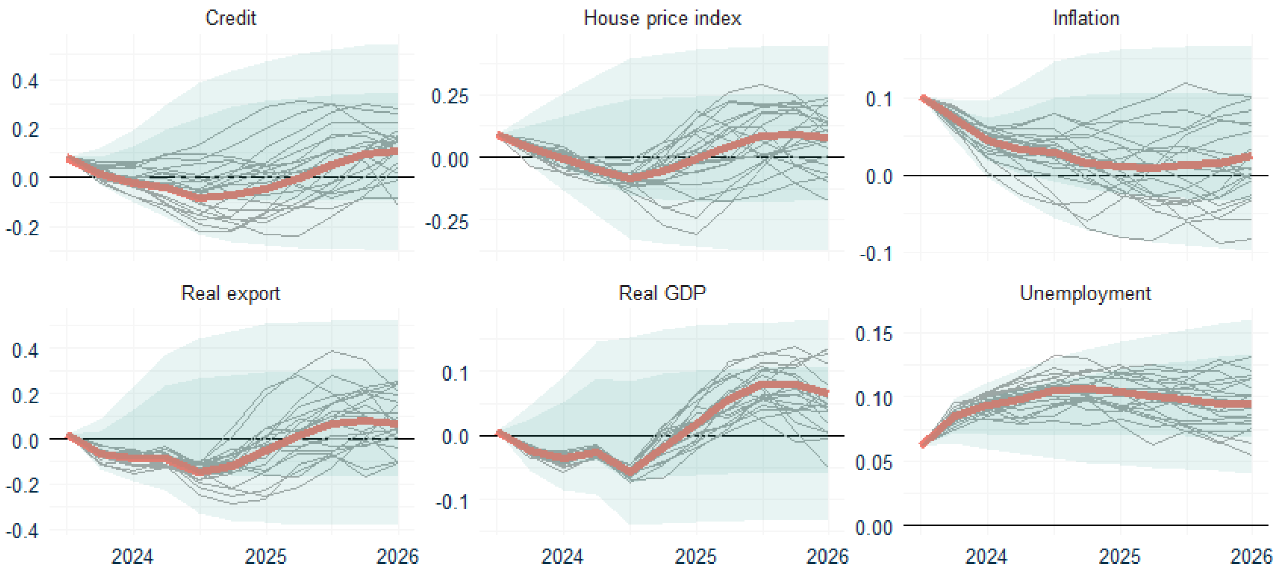

Figure 3: Example of scenario formation

Notes: The criteria used to illustrate the scenario generation in this figure are detailed in Table 3. The last observation of the data used is from Q2 of 2023. The indicated range represents the 80 % and 98 % of projections generated in Step 1. The grey lines display the top $M = 20$ scenarios, while the red line represents the final scenario selected in Step 2.

4 Bank-level block

In the banking block, each bank is described by its balance sheet, profit and loss account, behavioural equations and accounting identities. Behavioural equations describe how the macro-financial scenario is transmitted to bank performance indicators. In the SRMS model, the most attention is given to modelling loan dynamics, interest income and expenses, and credit risk.[2]

Table 4 presents a stylized representation of the bank balance sheet in the model. The Lithuanian banking system may be classified as traditional, where the largest part of assets consists of loans. After COVID, banks have good liquidity positions with cash and cash balances at central banks making up 24.9% of assets. Banks do not engage in trading activities, and financial assets (7.6%) are predominantly held to maturity. Loans and advances are comprised of loans to central banks cb, loans to general governments g, loans to credit institutions and other financial corporations ff, loans to non-financial corporations nfc, loans to households for

[2]All the regressions in the bank-level block are fitted using an unbalanced panel of data from 2004 or 2008 up to the present, depending on data availability.

house purchases hh and loans to households for consumption he. Loans to the non-financial private sector, representing 51.3% of total assets, are the most important part of their business activities.

Concerning liabilities, deposits represent the primary source of financing, accounting for 89.1% of total assets. The remaining components of liabilities are of lesser importance. Finally, equity constitutes 8.4% of total assets.

Table 4: Balance sheet

Variable name	Definition	Share of Total assets
$BA.cash$	Cash, cash balances at central banks and other demand deposits	24.9%
$BA.fina$	Financial assets	7.6%
$BA.Loans$	Loans and advances	66.9%
$Loans^{cb}$	Loans and advances (central banks)	0.2%
$Loans^{g}$	Loans and advances (general governments)	0.6%
$Loans^{ff}$	Loans and advances (credit institutions and other fin. corporations)	14.7%
$Loans^{nfc}$	Loans and advances (non-financial corporations)	21.9%
$Loans^{hh}$	Loans and advances (for house purchase)	23.5%
$Loans^{he}$	Loans and advances (consumer and other credit for households)	5.9%
$BA.other$	Other assets	0.7%
$Assets$	Total assets	100%
$BL.hft$	Financial liabilities held for trading	0.1%
$BL.depo$	Deposits	89.1%
$BL.debt$	Debt securities issued	0.6%
$BL.deriv$	Derivatives – Hedge accounting	0.0%
$BL.flo$	Other financial liabilities	1.2%
$BL.other$	Other liabilities	0.5%
$Liabilities$	Total liabilities	91.6%
$Equity$	Total equity	8.4%

Table 5 shows the main components of a bank's income and expenses, along with their respective proportions in 2023. Net interest income NII is the main source of income, accounting for approximately 82% of total income. The second-largest item is net fee and commission income $NFCI$, which accounts for 14.5% of total income. Since banks are not active in trading activities, net financial assets income $NFAI$ constitutes only 3.6% of total operating income. The remaining items collectively account for a negligible proportion of income.

Table 5: A simplified profit and loss account

	Income			Expenditure	
Variable	Variable name	Share of income	Variable	Variable name	Share of expenditure
NII	Net interest income	82.0%	$OPEX$	Administrative expenses	91.0%
$NFCI$	Net fee and commission income	14.5%	Dep	Depreciation	4.2%
$NFAI$	Net financial assets income	3.6%	$Imprairl$	Impairments on loan portfolio	4.5%
$Oth.income$	Other operating income	0.0%	$Oth.expenses$	Other expenses	0.2%

Administrative expenses $OPEX$, which consist of personnel and other administrative expenses, made up approximately 91% of total operating expenses in 2023. At the same time, impairments on loan portfolio $Impairl$ (credit risk losses), which contributed 4.5% of expenditure, is the second biggest item. However, during the crisis years, impairments on loan portfolio might increase significantly.

4.1 Bank behavioural functions: loan volumes and interest rates

4.1.1 Modelling loan portfolio dynamics

The loan portfolio of banks is influenced by changes in macroeconomic conditions (loan demand factors) and bank-specific characteristics (loan supply factors). A one-system approach is employed to model the dynamics of loan volumes, where loan demand and supply factors are incorporated into a single equation.

The growth rate of the gross carrying amount of loans is modelled using a weighted panel regression, where each private non-financial sector $s \in \{nfc, hh, he\}$ is estimated separately, with bank assets serving as weights:

$$\begin{aligned}\Delta \log(Loansgr^s_{b,t}) = \mu^s_b &+ \sum_{p=1}^{P} \alpha^s_p \Delta \log(Loansgr^s_{b,t-p}) \\ &+ \sum_{k=1}^{K} \beta^s_k B_{k,b,t-1} + \sum_{n=1}^{N} \gamma^s_n M_{n,t-1} \\ &+ \phi^s CGap^{+s}_{t-4} * \mathbb{1}\{\Delta^y GDP_t < 0\} \\ &+ \theta GDPGap^{+}_{t-4} * \mathbb{1}\{\Delta^y GDP_t < 0\} + \varepsilon^s_{b,t}\end{aligned} \tag{3}$$

where μ^s_b represents the bank b specific fixed effect, $\Delta \log(Loansgr^s_{b,t})$ is quarterly change of the gross carrying amount of loans of bank b in sector s, $B_{b,t-1}$ represents bank-level variables (such as margin, capital buffers, provisioning rate, etc.), M_{t-1} - represents macroeconomic variables (such as GDP, HICP, unemployment rate, etc.). $CGap^{+s}_{t-4}$ is positive credit gap of sector s four quarters ago, $GDPGap^{+}_{t-4}$ is a positive GDP gap four quarters ago. $CGap$ and $GDPGap$ are estimated using One-sided HP filter with smoothing parameter $\lambda = 62500$ and $\lambda = 1600$ respectively.

The macroeconomic conditions have a direct and indirect impact on loan dynamics. The direct impact comes from changes in GDP growth, consumer price inflation, or fluctuations in the unemployment rate which affects the demand part of the equations. The indirect effect comes from the supply side, where the macroeconomic situation in Lithuania affects banks' loan portfolio quality, profitability and subsequently capital ratios. Depending on the asset quality, and capital buffers of individual banks, the loan growth adjustments can be very heterogeneous.

The variables considered in each regression are presented in Table 6. There is a high degree of inertia in the growth rates of loans, as evidenced by the positive autoregressive terms. The quality of the loan portfolio expressed in terms of provisioning ratio ($Prov.ratio^s_{b,t-1} = Prov^s_{b,t-1}/Loansgr^s_{b,t-1}$) had a negative impact, while banks' capitalization ($CARBuffer$) had a positive impact on loan growth. The price of loans enters the loan growth equation as two distinct components: the loan margin $margin^s_{b,t-1}$ and the changes in reference rate $\Delta Euribor_{t-1}$[3].

[3]The vast majority of loan contracts use a variable rate, which is directly tied to the Euribor rate.

Both variables have a negative effect on loan dynamics. Depending on the equation, macroeconomic variables—GDP, HICP, House price index (*IHX*)—are included either as annual or quarterly growth rates. *CGap* and *GDPGap* add non-linear reaction of banks to the negative GDP growth rate. If deteriorating macroeconomic conditions follow a period of high credit growth or economic overheating, banks may be more inclined to reduce their loan supply significantly compared to a scenario without such imbalances.

Table 6: Variables in loan growth equations

	Variable	*nfc* equation	*hh* equation	*he* equation
	$\Delta \log(Loansgr^s_{b,t-1})$	+	+	+
	$\Delta \log(Loansgr^s_{b,t-2})$	+		+
$B_{b,t-1}$	$Prov.ratio^s_{b,t-1}$	-	-	-
	$CARBuffer_{b,t-1}$	+	+	+
	$margin^s_{b,t-1}$	-	-	-
M_{t-1}	$\Delta Euribor_{t-1}$	-	-	-
	GDP	+		+
	HICP	+	+	+
	ΔURX_{t-1}	-		-
	IHX		+	
	$CGap^{+s}_{t-4}$	-		-
	$GDPGap^{+}_{t-4}$	-	-	-

Notes: This table shows the variables included in equation 6 for each private non-financial sector s, specifically non-financial corporations (*nfc equation*), households for house purchases (*hh equation*) and loans to households for consumption (*he equation*). The sign of each estimated coefficient is denoted by + (positive) or - (negative).

Other segments of the banks' loan portfolio $s \in \{cb, g, ff\}$ are subject to a constant balance sheet assumption and remain unchanged over time:

$$Loansgr^s_{b,t} = Loansgr^s_{b,t-1} \tag{4}$$

4.1.2 Modelling loan margin dynamics

The dynamics of interest rate margin on new loans are modelled using a weighted panel regression, with each private non-financial sector $s \in \{nfc, hh, he\}$ examined independently. We assume a full pass-through of interbank interest rates into lending rates.[4] The margin on new loans, denoted as $margin^s_{b,t}$, is defined as the difference between the loan interest rate $ir^s_{b,t}$ and the zero-floored reference rate $Euribor_t := max\{Euribor_t, 0\}$:

$$margin^s_{b,t} = ir^s_{b,t} - Euribor_t \tag{5}$$

The model then is defined as follows:

$$margin^s_{b,t} = \mu^s_b + \alpha^s margin^s_{b,t-1} + \sum_{k=1}^{K} \beta^s_k B_{k,b,t-1} + \sum_{k=1}^{K} \gamma^s_k M_{t-1} + \phi^s HHI^s_{t-1} + \epsilon^s_{b,t} \tag{6}$$

[4]The full pass-through assumption is not binding in our setting because 98% of loans in Lithuania have variable rates. Until 2015, a weighted average of the Vilibor and Euribor reference rates was used, as Vilibor was the reference rate for Litas-denominated loans.

where μ_b^s represents the bank b specific fixed effect, $\text{margin}_{b,t}^s$ is a margin on new loans provided by bank b to sector s, $B_{b,t-1}$ is a vector comprising bank-level variables (such as capital requirements, capital buffers, provisions), M_{t-1} - a vector of macroeconomic variables (such as GDP, HICP, unemployment, house prices), HHI_{t-1}^s - Herfindal-Hirshman index for the loan sector s, $\epsilon_{b,t}^s$ - residuals of the model. The equation is estimated separately for each sector, with bank assets serving as weights. The variables included in each regression are detailed in Table 7.

Table 7: Variables in margin equations

	Variable	*nfc equation*	*hh equation*	*he equation*
$B_{b,t-1}$	$margin_{b,t-1}^s$	+	+	+
	$Prov.ratio_{b,t-1}^s$	+	+	+
	$CARBuffer_{b,t-1}$		-	
	$CR_{b,t-1}$	+		+
M_{t-1}	$\Delta^y GDP_{t-1}$	-		-
	ΔURX_{t-1}		+	+
	$\Delta^y IHX_{t-1}$		-	
	HHI_{t-4}^s	+	+	+

Notes: This table shows the variables included in equation 6 for each private non-financial sector s, specifically non-financial corporations (*nfc equation*), households for house purchases (*hh equation*) and loans to households for consumption (*he equation*). The sign of each estimated coefficient is denoted by + (positive) or - (negative). Provision-to-loan ratio is denoted as $Prov.ratio$, $CARBuffer$ denotes the difference between bank-specific capital adequacy ratio and regulatory requirements, CR - capital requirements, $\Delta^y GDP$ - annual growth of Lithuanian gross domestic product, ΔURX - change in unemployment, $\Delta^y IHX$ - annual growth of house price index, HHI - Herfindahl-Hirschman Index calculated using loans of each sector.

Since banks are assumed to be price setters, loan pricing is primarily influenced by supply factors.[5] The auto-regressive component captures the persistence of banks' pricing strategies.[6] The bank-sector-specific provision ratio, accounting for a credit risk premium to compensate for expected credit losses, is positively correlated with interest margins. Bank-specific capital requirements, which account for the cost of maintaining the required levels of bank capital and compensating shareholders for providing their funds, are also positively related to loan interest margins.[7] If the latter is not statistically significant, we include the bank-specific capital buffer with respect to regulatory requirements. This buffer negatively affects interest margins, as banks are expected to increase loan prices to boost their profitability and avoid capital deficiencies. The deterioration of macroeconomic conditions, proxying the demand for credit, negatively impacts loan portfolio quality, profitability, and the solvency of banks, leading them to raise loan interest margins. Finally, higher market concentration, proxied by sector-specific Herfindahl-Hirschman Index (HHI), positively contributes to loan margins.

[5] In examining the supply factors, we draw inspiration from those outlined by Karmelavičius et al. (2023).

[6] This, among other factors, might reflect operational and other administrative costs associated with issuing and book-keeping loans, as well as banks' funding costs.

[7] These include the Pillar 1 requirement, the institution-specific Pillar 2 requirement, and the combined capital buffer requirements (which include Capital Conservation Buffer (CCoB), the Countercyclical Capital Buffer (CCyB), the Other Systemically Important Institutions (O-SII) capital buffer, and the Pillar 2 Guidance (P2G)).

4.1.3 Calculation of loan interest rates

The interest rates on new loans ($ir^s_{b,t}$) to the private non-financial sector, where $s \in \{nfc, hh, he\}$, are determined as the sum of the modelled margins and the exogenous Euribor rate:

$$ir^s_{b,t} = margin^s_{b,t} + Euribor_t \tag{7}$$

where for mortgages we use the six-month reference rate, and for loans to non-financial corporations, consumer loans and other loans to households we apply the three-month reference rate.

The interest rates on the loan portfolio ($irp^s_{b,t}$) are then calculated as a weighted average of the interest rate from the previous quarter, adjusted by the change in Euribor rate, and the interest rate on newly originated loans:[8]

$$irp^s_{b,t} = \begin{cases} (irp^s_{b,t-1} + \Delta Euribor) \times \frac{Loansgr^s_{b,t-1}(1-d^s_b)}{Loansgr^s_{b,t}} + ir^s_{b,t} \times \frac{NewLoansgr^s_{b,t}}{Loansgr^s_{b,t}} & \text{if } NewLoansgr^s_{b,t} > 0 \\ irp^s_{b,t-1} + \Delta Euribor & \text{if } NewLoansgr^s_{b,t} = 0 \end{cases} \tag{8}$$

where $\frac{Loansgr^s_{b,t-1}(1-d^s_b)}{Loansgr^s_{b,t}}$ represents the share of the loans outstanding from the previous quarter, adjusted by the bank-sector-specific amortization rate d^s_b and $\frac{NewLoansgr^s_t}{Loansgr^s_{b,t}}$ denotes the share of new loans in the loan portfolio (gross carrying amount) at quarter t. In the absence of new loans from bank b for sector s, the loan portfolio interest rate is obtained as $(irp^s_{b,t-1} + \Delta Euribor)$. The volumes of new loans ($NewLoansgr^s_{b,t}$) are obtained as the quarterly change in the loan portfolio volumes adjusted for loan amortization:

$$NewLoansgr^s_{b,t} = \Delta Loansgr^s_{b,t} + d^s_b \times Loansgr^s_{b,t-1} \tag{9}$$

where $\Delta Loansgr^s_{b,t} = Loansgr^s_{b,t} - Loansgr^s_{b,t-1}$, and d^s_b denotes the historical average amortization rate of bank b for each sector $s \in \{nfc, hh, he\}$, calculated over the period from 2015. Finally, to ensure that new loans are non-negative, it is adjusted using the formula $NewLoansgr^s_{b,t} = max(0; NewLoansgr^s_{b,t})$.

4.2 Profitability

4.2.1 Interest income

Interest income is the primary source of revenue for banks derived from loans $ii.loans_{b,t}$ and other interest-bearing assets $ii.other_{b,t}$. Specifically,

$$ii_{b,t} = ii.loans_{b,t} + ii.other_{b,t} \tag{10}$$

Interest income from loans is further broken down into loans to the private non-financial

[8] The former is assumed to be reviewed each quarter.

sector ($ii.loans^{pri}_{b,t}$), loans to general governments ($ii.loans^{g}$), and loans to credit institutions and other financial corporations ($ii.loans^{ff}_{b,t}$):

$$ii.loans_{b,t} = ii.loans^{pri}_{b,t} + ii.loans^{g}_{b,t} + ii.loans^{ff}_{b,t} \tag{11}$$

The interest income on loans to the private non-financial sector $s \in \{nfc, hh, he\}$ is calculated as a sum of products of loan portfolio volumes ($loans^{s}_{b,t}$) and the respective average loan portfolio interest rates $irp^{s}_{b,t}$:

$$ii.loans^{pri}_{b,t} = (Loans^{nfc}_{b,t} \times irp^{nfc}_{b,t}) + (Loans^{hh}_{b,t} \times irp^{hh}_{b,t}) + (Loans^{he}_{b,t} \times irp^{he}_{b,t}) \tag{12}$$

where $Loans^{s}_{b,t} = Loansgr^{s}_{b,t} - Prov^{s}_{b,t}$, $Prov^{s}_{b,t}$ denotes loan loss provisions.

Interest income from loans to general governments, credit institutions and other financial corporations, respectively $s \in \{g, ff\}$, are both calculated as a simple two-quarter moving average:[9]

$$ii.loans^{s}_{b,t} = \frac{\sum_{q=1}^{2} ii.loans^{s}_{b,t-q}}{2} \tag{13}$$

Interest income from other interest-bearing assets encompasses all sources not directly associated with lending activities. It includes interest earned on reserves held at the central bank ($ii.cb_{b,t}$), and income from other financial assets ($ii.fin_{b,t}$), such as investments in securities and money market instruments:

$$ii.other_{b,t} = ii.cb_{b,t} + ii.fin_{b,t} \tag{14}$$

Interest income from the central banks ($ii.cb^{cb}_{b,t}$) is calculated as[10]:

$$ii.cb_{b,t} = BA.cash_{b,t-1} \times ii.cb.ratio^{cb}_{b,t} \tag{15}$$

where $BA.cash_{b,t-1}$ represents the balance sheet item *"cash, cash balances at central banks and other demand deposits"*, and $ii.cb.ratio_{b,t} = ii.cb_{b,t}/BA.cash_{b,t-1}$ approximates an effective interest rate on reserves held at central bank, which is modelled as:

$$ii.cb.ratio_{b,t} = \mu_b + \alpha \times ii.cb.ratio_{b,t-1} + \beta \times DFR_t + \epsilon_{b,t} \tag{16}$$

where μ_b is a bank-specific constant, and DFR_t denotes the ECB deposit facility rate, which is defined as $DFR_t := max\{DFR_t, 0\}$. If $DFR \leqq 0$, then $ii.cb.ratio_{b,t} = 0$.

Finally, interest income from other financial assets is determined as:

$$ii.fin_{b,t} = BA.fin_{b,t-1} \times ii.fin.ratio_{b,t} \tag{17}$$

[9] This simplification is adopted due to the relatively minor proportion of interest income from these loans. A two-quarter average has been calculated to mitigate the impact of one-off occurrences while ensuring that it reflects recent trends.

[10] The income derived by banks from central banks on reserves and from loans and advances cannot be distinctly separated. As the latter represents a relatively minor portion compared to that generated from reserves, we classify this income collectively under the category of earnings from other interest-bearing assets.

where $BA.fin_{b,t-1}$ is bank b specific financial assets, and $ii.fin.ratio_{b,t} = ii.fin/BA.fin_{b,t-1}$ is an effective interest rate on financial assets, given as a ratio between interest income from financial assets and financial assets, modelled as:

$$ii.fin.ratio_{b,t} = \mu_b + \alpha \times ii.fin.ratio_{b,t-1} + \beta \times Euribor_t + \gamma \times \Delta^y GDP_{t-1} + \epsilon_{b,t} \tag{18}$$

where μ_b is a bank-specific constant, $Euribor_t := max\{Euribor_t, 0\}$.[11] If $Euribor_t \leqq 0$, then the equation reduces to: $ii.fin.ratio_{b,t} = \mu_b + \alpha \times ii.fin.ratio_{b,t-1} + \gamma \times \Delta^y GDP_{t-1} + \epsilon_{b,t}$

4.2.2 Interest expenses

Interest expenses (cost of funding) are derived from expenses on deposits $iedepo_t$ and expenses on other liabilities and interest expenses on assets $s \in \{hft, debt, flo, deriv, ieot, ast\}$. Specifically,

$$ie_{b,t} = iedepo_{b,t} + \sum_s ie^s_{b,t} \tag{19}$$

Deposits are the primary source of funding for banks and the primary source of costs. In line with the methodology of Gambacorta (2008) and Holton and Rodriguez d'Acri (2015) the following autoregressive distributed lag specification is applied to the effective interest rate on deposits:

$$\begin{aligned} \Delta iedepo.ratio_{b,t} = \mu_b &+ \sum_{p=1}^{P} \alpha_p \Delta iedepo.ratio_{b,t-p} + \sum_{p=0}^{P} \beta_p \Delta Euribor_{t-p} \\ &+ \delta iedepo.ratio_{b,t-1} + \gamma Euribor_{t-1} \\ &+ \phi Prov.ratio_{t-1} + \theta \Delta Depo.sight.share_{t-1} + \varepsilon_{b,t} \end{aligned} \tag{20}$$

where $iedepo.ratio_t = iedepo_t/Deposits_{t-1}$ denotes the effective interest rate on deposits, $iedepo_t$ is interest expenses on deposits and $Deposits_{t-1}$ is the amount of deposits on the bank's balance sheet at the end of the previous quarter. The change in the bank's b interest rate at time t depends on their past changes, changes in the market rate ($\Delta Euribor_t$) and the long-run relationship between the level of interest rate on deposits ($iedepo.ratio_{b,t-1}$) and the level of market rate ($Euribor_{t-1}$). In addition, $Prov.ratio_{b,t-1}$ accounts for the riskiness of the bank and $Depo.sight.share_{t-1}$ accounts for the share of sight deposits. Bank fixed effects (μ_b) control any additional unobserved bank-specific differences that may affect deposit pricing (see Table 8).

Finally, interest expenses on deposits are calculated as the effective interest rate on deposits times the deposits at the beginning of the period:

$$iedepo_{b,t} = (iedepo.ratio_{b,t-1} + \Delta iedepo.ratio_{b,t}) * Deposits_{b,t-1} \tag{21}$$

The share of sight deposits is modelled separately and depends on the previous value,

[11] Specifically, until 2015 we use a weighted average between the Vilibor and Euribor reference rates, as Vilibor was the primary reference rate for Litas-denominated loans.

Table 8: Variables in the effective interest rate on deposits equation

Variable	Effective interest rate equation
$\Delta iedepo.ratio_{b,t-1}$	+
$\Delta iedepo.ratio_{b,t-2}$	+
$\Delta Euribor_t$	+
$\Delta Euribor_{t-1}$	+
$iedepo.ratio_{b,t-1}$	-
$Euribor_{t-1}$	+
$Prov.ratio_{t-1}$	+
$Depo.sight.share_{t-1}$	-

Notes: The sign of each estimated coefficient is denoted by + (positive) or - (negative).

changes in market interest rate and annual GDP growth (see Table 9):

$$Depo.sight.share_{b,t} = \mu_b + \alpha Depo.sight.share_{b,t-1} + \beta \Delta Euribor_{t-1} + \delta \Delta^y GDP_t + \varepsilon_{b,t} \quad (22)$$

Table 9: Variables in the share of sight deposits equation

Variable	The share of sight deposits equation
$\Delta iedepo.ratio_{b,t-1}$	+
$\Delta Euribor_{t-1}$	-
$\Delta^y GDP_t$	+

Notes: The sign of each estimated coefficient is denoted by + (positive) or - (negative).

The effective interest rate for other liabilities and interest expenses on assets $s \in \{hft, debt, flo, deriv, ieot, ast\}$ is modelled as a simple average of the last two quarters:

$$ie.ratio^s_{b,t} = (ie.ratio^s_{b,t-1} + ie.ratio^s_{b,t-2})/2 \quad (23)$$

where $ie.ratio^s_{b,t} = ie^s_{b,t}/Liab^s_{b,t-1}$ is the effective interest rate for other liabilities. Subsequently, interest expenses are calculated as follows:

$$ie^s_{b,t} = ie.ratio^s_{b,t} * Liab^s_{b,t-1} \quad (24)$$

4.2.3 Net fee commission income

Banks' net fee and commission income (NFCI) is another important revenue component, reflecting their ability to diversify income. NFCI represents the revenue banks earn from services provided to their customers, after deducting related expenses. This includes fees for account maintenance, transactions, loan origination, and commissions from insurance and investment products, but excludes income from loans.

The dynamics of NFCI are modelled as a ratio relative to each bank's assets to account for the varying sizes of banks. The following equation expresses the model:

$$nfci.ratio_{b,t} = \mu_b + \alpha_1 nfci.ratio_{b,t-1} + \alpha_2 \Delta^y GDP_t + \alpha_3 \Delta log(OMX_t) + \alpha_4 \Delta irp_{b,t} + \epsilon_{b,t} \quad (25)$$

where $nfci.ratio_{b,t} = \frac{NFCI_{b,t}}{Assets_{b,t-1}}$ represents the ratio of bank b's NFCI to its assets, μ_b is a bank-specific constant, ΔIRN_t is the change in the average interest rate on new loans granted by MFIs, $\Delta^y GDP_t$ denotes the year-on-year change in Lithuania's real GDP, $\Delta log(OMX_t)$ is the quarterly log change in the stock market index for Vilnius Stock Exchange. Banks' assets are used as weights.

The results presented in Table 10 indicate that NFCI is persistent, as evidenced by the positive and relatively high coefficient. The positive coefficients for real GDP and the OMX index suggest that an increase in economic activity and financial cycle leads to higher demand for banking services, thereby boosting NFCI. The negative coefficient of interest rates implies that banks can diversify their income sources; more specifically, when interest income declines, they compensate by increasing commissions and fees.

Table 10: Variables in NFCI and Opex equations

Variable	*NFCI equation*	*Opex equation*
$AR_{b,t-1}$	+	+
$\Delta^y GDP_t$	+	
$log(OMX_t)$	+	
$irp_{b,t}$	-	
$\Delta log(GDP_t)$		+
$\Delta log(HICP_{t-2})$		+
$\Delta log(URX_{t-1})$		-
$CGap_t$		+

Notes: This table presents the variables included in the net fee and commission income (NFCI) equation 25 and the operating expenses equation 26. The sign of each estimated coefficient is indicated by a + (positive) or - (negative). The autoregressive variable in each equation is denoted as $AR_{b,t-1}$.

4.2.4 Operating expenses

The operating expenses of a bank encompass all costs necessary to sustain its operations. These include costs associated with personnel, technology and IT, administrative functions, and regulatory and compliance requirements, among others. Given the close correlation between operating expenses and bank assets, we analyze the dynamics of operating expenses relative to assets using a panel regression model:

$$\begin{aligned} opex.ratio_{b,t} = \mu_b + \alpha_1 opex.ratio_{b,t-1} + \alpha_2 \Delta log(GDP_t) + \alpha_3 \Delta log(HICP_{t-2}) \\ + \alpha_4 \Delta log(URX_{t-1}) + \alpha_5 CGap_t + \epsilon_{b,t} \end{aligned} \tag{26}$$

where $opex.ratio_{b,t}$ represents the ratio of bank b's operating expenses to its assets at time t, μ_b is a bank-specific constant, $\Delta \log(GDP_t)$ denotes the change in the logarithm of GDP, $\Delta \log(HICP_{t-2})$ represents the change in the logarithm of the Harmonized Index of Consumer Prices lagged by two periods, $\Delta \log(URX_{t-1})$ signifies the change in the logarithm of the unemployment rate lagged by one period, and $CGap_t$ is the credit gap at time t. Banks' assets are used as weights.

The estimated model indicates that all coefficients are positive except for the coefficient on $\Delta\log(URX_{t-1})$, which is negative (see Table 10). This indicates that increased demand for banking services, as indicated by the aforementioned variables, prompts banks to allocate greater resources towards the expansion of their infrastructure, personnel, etc.

4.3 Credit risk

Credit losses experienced by commercial banks have the biggest impact on their asset quality and, accordingly, on their capital adequacy ratio. Therefore, to conduct macroprudential stress testing, credit risk modelling is considered one of the most important elements to assess the potential solvency and operational stability of banks.

Within the domain of credit risk assessment, a prevalent approach involves the quantification of risk parameters such as the probability of default (PD) and loss-given default (LGD). However, in our case, the application of this approach might be limited by the scarcity of historical data pertaining to these risk parameters. In addition, since 2018 new accounting standards IFRS9 were implemented. Under IFRS9, which sets rules for classifying and valuing financial instruments and estimating loan losses, financial assets are grouped into three categories based on their risk of default. The implementation of new accounting standards coincides with a limited historical time series lacking a significant economic downturn. Consequently, the estimation of elasticities under adverse economic scenarios may be challenging. Accordingly, within the credit risk assessment framework, the loss rate experienced by the loan portfolio serves as the dependent variable.

To take into account the peculiarities of different borrowers' activities and econometrically assess their risk more accurately, the loan portfolio for the non-financial private sector is broken down into several segments. Loans to non-financial corporations are divided into 7 parts according to their economic activity: 1) agriculture ($nfc.a$), 2) manufacturing ($nfc.c$), 3) energy ($nfc.de$), 4) construction and real estate activities ($nfc.fl$), 5) trade ($nfc.g$), 6) transportation ($nfc.h$) and 7) other economic activities ($nfc.oth$). Loans to households are also split into two parts: 1) loans for house purchase (hh) and 2) consumer and other loans (he). The net flow of provisions ($NFPro$), which is described in detail below, is used to approximate credit losses for each sector:

$$NFPro_t^i = Prov_t^i - Prov_{t-1}^i + WO_t^i \tag{27}$$

where $Prov_{i,t}$ represents loan provisions at the end of period t, and $WO_{i,t}$ represents write-offs during period t. $NFPro$ is then used to calculate the loan loss rate: $LR.market_t^i = NFPro_t^i/Loansgr_{t-1}^i$, which is our key variable in modelling the credit risk of the loan portfolio.

The initial stage involves estimating the relationships between credit losses experienced by distinct economic sectors and relevant macroeconomic variables. The estimated losses represent the average loss rate ($LR.market_t^i$) incurred within each segment. Following Covas et al. (2014), quantile regression is employed to model credit loss rate:

$$LR.market_t^i(\tau|M_{j,t}) = \alpha^i(\tau) + \sum_{j=1}^{J} \beta_j^i(\tau) M_{j,t} \tag{28}$$

where $LR.market_t^i$ is a loss rate of a segment $i \in \{nfc.a, nfc.c, nfc.de,\ nfc.fl, nfc.g, nfc.h,$ $nfc.oth, hh, he\}$, and $M_{j,t}$ is a vector of macroeconomic variables. $\alpha^i(\tau)$ and $\beta_j^i(\tau)$ are regression coefficients that depend on the percentile τ. Quantile regression can evaluate how the impact of macroeconomic variables on credit losses changes, depending on their empirical distribution function. Certain macroeconomic variables may have a relatively small effect on the median of the credit loss distribution function, but their effect may increase if the 90th quantile is considered. For solvency stress testing, the 50th quantile is used for the baseline scenario and the 75th quantile for the adverse scenario.

Macroeconomic variables, along with their transformation and lag order, were selected by combining statistical selection and expert judgment. Table 11 shows the variables that affect the $LR.market^i$ parameters in the credit risk equations. Key macroeconomic variables are with the expected negative sign. An increase in GDP or its main components, i.e. private consumption PCR, gross fixed capital formation ITR, export XTR, an increase in gross value added GVA, compensation per employee WUN or the housing price index IHX, negatively affects the risk parameters of the loan portfolio. Meanwhile, a higher unemployment rate URX and interest rate ir leads to the opposite effect. Higher economic imbalances, measured by GDP gap $GDPGap$ and credit gap $CGap$, also increase the level of loan portfolio losses.

In the second stage, credit losses are assessed taking into account the structure of a specific bank's loan portfolio. Bank b loss rate is calculated as a weighted amount:

$$LR.bank.w_{b,t} = \sum_{i=1}^{9} LR.market_t^i * wgt_b^i \tag{29}$$

In the third stage, the risk appetite of each bank is assessed. If bank b does not exhibit a propensity for risk, then the actual loss rate ($LR.bank_{b,t}$) should approximate the expected losses ($LR.bank.w_{b,t}$). If such a tendency is nevertheless present, it is appropriate to evaluate it by linear regression:

$$LR.bank_{b,t} = \alpha_b + \beta_b LR.bank.w_{b,t} + \varepsilon_{b,t} \tag{30}$$

The final result is the potential credit loss rate for the non-financial private sector ($LR.pr_{b,t}$) given by the following expression:

$$LR.pr_{b,t} = \max(LR.bank.w_{b,t}, \widehat{LR.bank}_{b,t}) \tag{31}$$

where $\widehat{LR.bank}_{b,t}$ is the fitted value of equation (30). This rule is applied in a conservative manner, given the lack of clarity regarding the most appropriate estimate of the credit loss rate in the context of an adverse scenario.

Based on historical data, the loss rate for other segments of the loans portfolio, i.e. loans

Table 11: Variables in credit risk equations

Variable	*nfc.a*	*nfc.c*	*nfc.de*	*nfc.fl*	*nfc.g*	*nfc.h*	*nfc.oth*	*hh*	*he*
$\Delta\log(GDP_{t-1,2})$	-				-				
$\Delta^y GDP_{t-2}$				-		-			
$\Delta\log(HICP_{t-1,2})$								+	+
$\Delta^y IHX_{t-1,2}$				-				-	
$URX_{t-0,1,2}$	+					+		+	+
$\Delta URX_{t-0,2}$		+	+				+		
Δir^s_t							+		+
$ir^s_{t-0,1,2}$	+	+		+	+	+		+	
$\Delta\log(PCR_{t-2})$			+						
$\Delta^y PCR_{t-2}$							-		-
$\Delta\log(ITR_{t-1,2})$		-	-					-	
$\Delta^y ITR_t$				-	-				
$\Delta\log(XTR_{t-1})$		-							
$\Delta^y XTR_{t-1,2}$	-				-	-			
$\Delta\log(GVA^i_{t-1,2})$	-			-		-			
$\Delta^y GVA^i_{t-0,2}$		-	-		-				
$\Delta\log(WUN_t)$								-	-
$\Delta^y WUN_t$							-		
$GDPGap_{t-4}$				+					
$CGap^s_{t-1}$							+	+	+

Note: The sign of each estimated coefficient is denoted by + (positive) or - (negative).

to the central bank (cb), loans to the government (g) and loans to credit institutions and other financial corporations (ff), are considered to have very low risk, therefore their loss rate is set to zero:

$$LR.market^i_t = 0 \tag{32}$$

where $LR.market^i_t$ is a loss rate of segment $i \in \{cb, g, ff\}$.

4.4 Market risk

Market risk assessment takes into account the volatility of historical net financial asset income (NFAI).[12] We assume that greater volatility leads to increased losses under stressed conditions. This approach is similar to the simplified approach suggested by the European Banking Authority EBA (2014) in 2014. More specifically, net financial asset income for bank b over the stress testing horizon is calculated using the following formula:

$$NFAI_{b,t} = \begin{cases} NFAI^{mean}_b - MR.shock_t * NFAI^{sd}_b & \text{if } t \in \text{MR shock period} \\ NFAI^{mean}_b - 1/3 * NFAI^{sd}_b & \text{if } t \notin \text{MR shock period} \end{cases} \tag{33}$$

[12] In particular, this includes net gains or losses on: i) derecognition of financial assets and liabilities not measured at fair value through profit or loss; ii) financial assets and liabilities held for trading; iii) non-trading financial assets mandatorily at fair value through profit or loss; iv) financial assets and liabilities designated at fair value through profit or loss.

where $NFAI_b^{mean}$ and $NFAI_b^{sd}$ represent the quarterly mean and standard deviation of bank b's NFAI over the previous 12 quarters, and $MR.shock_t$ denotes the shock size, which can be time-varying. The term $NFAI_b^{mean}$ represents the average net income from financial assets, while $MR.shock_t \times NFAI_b^{sd}$ accounts for market risk losses. $NFAI$ is expressed in absolute (currency) units.

The choice of shock size and duration depends on the severity of the scenario. Under the baseline scenario, the bank b's market risk losses are calculated as one-third of the standard deviation of NFAI. These losses are evenly spread across the stress test horizon. Under the adverse scenario, market risk losses are $size = 1.96$ times the standard deviation of NFAI. These losses are applied over two quarters, as historically market losses are not long-lasting. For the remaining stress test horizon, the baseline loss distribution is applied.

4.5 Financial accounts

4.5.1 Balance sheet

This section contains the accounting identities that show how the bank's simplified balance sheet is created.

The total assets of a bank $Assets$ sums up cash, cash balances at central bank $BA.cash$, financial assets $BA.fina$, loans and advances $BA.Loans$ and other assets $BA.other$:

$$Assets_{b,t} = BA.cash_{b,t} + BA.fina_{b,t} + BA.Loans_{b,t} + BA.other_{b,t} \tag{34}$$

Loans and advances include exposures of the non-financial private sector and other sectors $s \in \{cb, g, ff, nfc, hh, he\}$:

$$BA.Loans_{b,t} = \sum_s Loans_{b,t}^s \tag{35}$$

The gross carrying amount of loans to the private non-financial sector of bank b in sector $s \in \{nfc, hh, he\}$ changes according to the estimated results from the loan portfolio dynamics equations (Section 4.1.1)

$$Loansgr_{b,t}^s = Loansgr_{b,t-1}^s * e^{\Delta \log(Loansgr_{b,t}^s)} \tag{36}$$

Meanwhile, the carrying amount of loans of bank b in sector $s \in \{cb, g, ff, nfc, hh, he\}$ is equal to gross carrying amount minus provisions (Section 4.5.3):

$$Loans_{b,t}^s = Loansgr_{b,t}^s - Prov_{b,t}^s \tag{37}$$

Other balance sheet items ($item \in \{cash, fina, other\}$) are kept constant throughout scenario horizon:

$$BA.item_{b,t} = BA.item_{b,t-1} \tag{38}$$

Liabilities of a bank consist of financial liabilities held for trading $BL.hft$, deposits $BL.depo$, debt securities issued $BL.debt$, derivatives - hedge accounting $BL.deriv$, other financial liabilities $BL.flo$ and other liabilities $BL.other$:

$$Liabilities_{b,t} = BL.hft_{b,t} + BL.depo_{b,t} + BL.debt_{b,t} + BL.deriv_{b,t} + BL.flo_{b,t} + BL.other_{b,t} \quad (39)$$

Most of the liabilities items ($item \in \{hft, debt, deriv, flo, other\}$) are kept constant throughout scenario horizon:

$$BL.item_{b,t} = BL.item_{b,t-1} \quad (40)$$

Banks' equity evolves along with the net profit recorded during the period and the dividends paid out:

$$Equity_{b,t} = Equity_{b,t-1} + NP_{b,t} - dividends_{b,t} \quad (41)$$

Finally, given that the main source of financing is deposits and following the 'credit first' view (McLeay et al., 2014), deposits act as a balancing item:

$$BL.depo_{b,t} = Assets_{b,t} - Equity_{b,t-1} - \sum_{item} BL.item_{b,t} \quad (42)$$

4.5.2 Profit and loss account

A simplified profit and loss account statement summarizes the income and expenses incurred by banks according to the behavioural equation. This section presents accounting identities and shows how net profit at the end of the period is derived.

Net interest income NII is equal to the interest income ii (Section 4.2.1) minus interest expenses ie (Section 4.2.2):

$$NII_{b,t} = ii_{b,t} - ie_{b,t} \quad (43)$$

The net fee and commission income $NFCI$ is equal to the $nfci.ratio$ (Section 4.2.3) multiplied by total assets at the beginning of the period:

$$NFCI_{b,t} = nfci.ratio_{b,t} * Assets_{b,t-1} \quad (44)$$

Other operating income $Oth.income$ aggregates the following items from the profit and loss account: dividend income, gains or losses from hedge accounting, gains or losses from exchange differences, gains or losses from on derecognition of non-financial assets, other operating income and other operating expenses. It is assumed that $Oth.income$ is equal to the average of the last four quarters:

$$Oth.income_{b,t} = \left(\sum_{j=1}^{4} Oth.income_{b,t-j} \right) /4 \quad (45)$$

Operating income sums up banks' income streams by adding net interest income, net fee and commission income, net financial assets income and other operating income:

$$OR_{b,t} = NII_{b,t} + NFCI_{b,t} + NFAI_{b,t} + Oth.income_{b,t} \quad (46)$$

Administrative expenses $OPEX$ is equal to the *opex.ratio* (Section 4.2.4) multiplied by total assets at the beginning of the period:

$$OPEX_{b,t} = opex.ratio_{b,t} * Assets_{b,t-1} \tag{47}$$

Depreciation Dep is assumed to be equal to the average of the last four quarters:

$$Dep_{b,t} = \left(\sum_{j=1}^{4} Dep_{b,t-j} \right) /4 \tag{48}$$

Other expenses $Oth.expenses$ is summing up provisions or reversal of provisions, modification gains or losses, impairment or reversal of impairment on financial assets not measured at fair value through profit or loss (financial assets at fair value through other comprehensive income). It is assumed that $Oth.expenses$ is equal to the average of the last four quarters:

$$Oth.expenses_{b,t} = \left(\sum_{j=1}^{4} Oth.expenses_{b,t-j} \right) /4 \tag{49}$$

Impairments on loan portfolio to non-financial private sector or credit losses result from loss rate parameter $LR.pr$ (see Section 4.3) and loan portfolio to the private non-financial sector $Loansgr^{pr}$:

$$Impairl_{b,t} = LR.pr_{b,t} * Loansgr^{pr}_{b,t-1} \tag{50}$$

where $Loansgr^{pr} = \sum_s Loansgr^s$ is a loan portfolio to non-financial private sector $s \in \{nfc, hh, he\}$.

Finally, non-banking income NBP aggregates the following items: share of the profit or loss of investments in subsidiaries, joint ventures and associates, impairment or reversal of impairment of investments in subsidiaries, joint ventures and associates, impairment or reversal of impairment on non-financial assets, profit or loss after tax from discontinued operations. It is assumed that banks will not generate any income or loss from this item:

$$NBP_{b,t} = 0 \tag{51}$$

Banks' gross profit (or profit before tax) is calculated by subtracting administrative expenses, depreciation, other expenses, and impairment on loans from operating income:

$$GP_{b,t} = OR_{b,t} - OPEX_{b,t} - Dep_{b,t} - Oth.expenses_{b,t} - Impairl_{b,t} + NBP_{b,t} \tag{52}$$

A standard corporate income tax rate applicable in Lithuania is 15%. However, from 2020 an additional 5% corporate income tax is applied to profits exceeding €2 million per tax period of credit institutions. A quarterly tax expense Tax is calculated based on the following formula:

$$Tax_{b,t} = \begin{cases} 500 * 0.15 + (GP_{b,t} - 500) * 0.2 & \text{if } GP_{b,t} > 500 \\ GP_{b,t} * 0.15 & \text{if } 0 < GP_{b,t} < 500 \\ 0 & \text{if } GP_{b,t} < 0 \end{cases} \tag{53}$$

Net profit NP, which could be distributed as dividends or added to the capital, is equal to:

$$NP_{b,t} = GP_{b,t} - Tax_{b,t} \tag{54}$$

4.5.3 Provisions

Banks make provisions for loan losses according to the risk parameters estimated in the credit risk part of the model. Based on the estimated loan loss rate parameter, the net flow of provisions for non-financial private sectors $s \in \{nfc, hh, he\}$ is described as follows:

$$NFPro.market^s_{b,t} = LR.market^s * Loansgr^s_{b,t-1} \tag{55}$$

To account for the possibility that individual banks might experience higher losses than the market average, all segments are adjusted proportionally:

$$NFPro^s_{b,t} = Impairl_{b,t} * (NFPro.market^s_{b,t}/NFPro.market^{pr}_{b,t}) \tag{56}$$

where $NFPro.market^{pr}_{b,t} = \sum_s NFPro.market^s_{b,t}$

The evolution of provisions is composed of two parts. The first part is the stock of provisions from the previous quarter that were not written off. The second part is a new net flow of provisions:

$$Prov^s_{b,t} = (1 - WO.rate^s_{b,t}) * Prov^s_{b,t-1} + NFPro^s_{b,t} \tag{57}$$

where $WO.rate^s_{b,t} = WO^s_{b,t}/Prov^s_{b,t-1}$ is a write-off rate.

The rate of write-off also affects the dynamics of provisions. This parameter is not modelled separately but is considered as an average of 4 quarters:

$$WO.rate^s_{b,t} = \left(\sum_{j=1}^{4} WO.rate^s_{b,t-j}\right)/4 \tag{58}$$

Loan loss provisions for other segments $i \in \{cb, g, ff\}$ are kept unchanged:

$$Prov^s_{b,t} = Prov^s_{b,t-1} \tag{59}$$

4.5.4 RWA changes

Total risk-weighted assets RWA consist of RWAs for credit risk, operational risk and market risk. Credit risk makes up the vast majority of risk-weighted assets for Lithuanian banks, therefore this part is modelled in more detail.

$$RWA_{b,t} = RWA.CR^s_{b,t} + RWA.Other_{b,t} \tag{60}$$

where $RWA.CR^s_{b,t}$ is the risk-weighted amount for credit risk of non-financial private sector $s \in \{nfc, hh, he\}$. $RWA.Other_{b,t}$ represent all other risk-weighted amounts.

The risk-weighted amount for credit risk is calculated by multiplying two factors: risk weight for loans to non-financial sector $RW^s_{b,t}$ and exposure at default $EAD^s_{b,t}$:

$$RWA.CR^s_{b,t} = RW^s_{b,t} * EAD^s_{b,t} \tag{61}$$

The risk weight for banks b lending to segment $s \in \{nfc, hh, he\}$ in quarter t is given by:

$$RW^s_{b,t} = RW^s_{b,t-1} + \Delta Prov.ratio^s_{b,t} \tag{62}$$

where $Prov.ratio^s_{b,t} = Prov^s_{b,t}/Loansgr^s_{b,t}$ is provisioning ratio of a corresponding segment.

The change in exposure at default is proportional to the changes in loans:

$$EAD^s_{b,t} = EAD^s_{b,t-1} * Loans^s_{b,t}/Loans^s_{b,t-1} \tag{63}$$

The risk-weighted amount for all other parts of the assets is kept constant:

$$RWA.Other_{b,t} = RWA.Other_{b,t-1} \tag{64}$$

4.5.5 Dividends

The net profit of the bank ($NP_{b,t}$) can be either paid out as dividends to shareholders or retained to increase the bank's capital. The portion of the profit that is distributed as dividends is determined by the Maximum Distributable Amount (MDA) and each bank's internal dividend payment rules ($rule_b$). If a bank meets its combined buffer requirement ($cr.min_b + cr.comb$), it can distribute all its profit as dividends, provided this does not reduce its capital below the required level. However, if a bank does not meet its combined buffer requirement, it must calculate the MDA to determine the maximum amount it can legally distribute as dividends.[13]

Each bank's dividends are calculated as:

$$dividends_{b,t} = NP_{b,t} \times min(B_{b,t}, rule_b) \tag{65}$$

where $NP_{b,t}$ is the bank's net profit after taxes for the given quarter, and B is a factor that depends on the bank's capital position. The B factor depends on the bank's CAR relative to predefined quartiles of the combined buffer requirement. It is determined as follows:

$$B_{b,t} = \begin{cases} 0.6 & \text{if } Q_3 < CAR_b < Q_4 \\ 0.4 & \text{if } Q_2 < CAR_b < Q_3 \\ 0.2 & \text{if } Q_1 < CAR_b < Q_2 \\ 0 & \text{if } CAR_b < Q_1 \end{cases} \tag{66}$$

[13]The MDA represents the maximum amount of profit a bank can distribute as dividends while ensuring adequate capital buffers are maintained. The MDA is calculated quarterly using the formula: $MDA_{b,t} = NP_{b,t} \times B_{b,t}$.

where CAR_b is the bank's capital adequacy ratio. The quartiles Q_n are calculated as follows:

$$Q_n = cr.min_{b,t} + cr.comb_{b,t} \div 4 \times n \tag{67}$$

where $cr.min_{b,t}$ is the bank-specific minimal capital requirements, $cr.comb_{b,t}$ is the combined buffer requirement, and n indicates the quartile number, with $n \in (1, 2, 3, 4)$.

4.5.6 Bank solvency and leverage

Banks' regulatory capital $OwnFunds$ evolves along with the net profit recorded during the period and the dividends paid out:

$$OwnFunds_{b,t} = OwnFunds_{b,t-1} + NP_{b,t} - dividends_{b,t} \tag{68}$$

Similarly, changes in banks' Common Equity Tier 1 capital $CET1$ depends on net profit and dividends as well:

$$CET1_{b,t} = CET1_{b,t-1} + NP_{b,t} - dividends_{b,t} \tag{69}$$

Since 93.3% of own funds are made of CET1 capital, in the SRMS model the main variable describing banks' solvency position is capital adequacy ratio CAR. The nominator of the ratio is own funds and the denominator is the risk-weighted amount (equation 60):

$$CAR_{b,t} = \frac{OwnFunds_{b,t}}{RWA_{b,t}} \tag{70}$$

The CET1 capital ratio $CET1.ratio$ is given by:

$$CET1.ratio_{b,t} = \frac{CET1_{b,t}}{RWA_{b,t}} \tag{71}$$

All banks are subject to capital requirements that they must observe. The total capital requirements $cr.tot$ consist of minimum capital requirements $cr.min$ and additional macroprudential combined buffer requirements $cr.comb$.

$$cr.tot_{b,t} = cr.min_{b,t} + cr.comb_{b,t} \tag{72}$$

The minimum capital requirement is composed of a uniform minimum 8% of the total capital ratio and bank-specific Pillar II requirements $cr.P2R$:

$$cr.min_{b,t} = 8\% + cr.P2R_{b,t} \tag{73}$$

The macroprudential combined buffer requirement is defined as the sum of the capital conservation buffer $cr.ccob$, countercyclical capital buffer $cr.ccyb$, other systemically important institutions buffer $cs.osii$ and sectoral systemic risk buffer $cr.srr$:

$$cr.comb_{b,t} = cr.ccob_{b,t} + cr.ccyb_{b,t} + cr.osii_{b,t} + cr.srr_{b,t} \tag{74}$$

The voluntary capital buffer or surplus/shortfall of capital $CARBuffer$ relative to the total regulatory capital requirements is calculated as follows:

$$CARBuffer_{b,t} = CAR_{b,t} - cr.tot_{b,t} \tag{75}$$

Another variable that allows for the assessment of bank stability is the leverage ratio. This ratio is calculated as the ratio between Tier 1 capital $LEV.equity$ and the total exposure measure of the bank $LEV.assets$:

$$LEV.ratio_{b,t} = \frac{LEV.equity_{b,t}}{LEV.assets_{b,t}} \tag{76}$$

Tier 1 capital capital follows the same rule, where it depends on net profit and dividends:

$$LEV.equity_{b,t} = LEV.equity_{b,t-1} + NP_{b,t} - dividends_{b,t} \tag{77}$$

Meanwhile, $LEV.assets$ evolves according to the changes in banks' assets.

$$LEV.assets_{b,t} = LEV.assets_{b,t-1} + \Delta Assets_{b,t} \tag{78}$$

5 Feedback loop

The macro feedback loop is an important component of the stress testing model, capturing the dynamic interactions between the banking sector and the real economy. This loop examines how shocks transmitted from the macroeconomic environment to banks feed back into the economy, amplifying the initial shocks and creating a more pronounced economic downturn. Understanding and modelling these feedback mechanisms is essential for assessing the banking sector's resilience under stress scenarios and understanding the propagation of systemic risks. This section focuses on how the macro feedback loop is modelled and integrated into the SRMS model.

The SRMS model contributes to the literature on feedback loop integration in stress testing, alongside other approaches such as those proposed by the Bank of Ireland and the ECB. For instance, the Bank of Ireland's model (Morell et al., 2022) focuses on capital deleveraging shocks. In this framework, banks under solvency pressures tighten credit conditions by increasing lending rates and reducing lending volumes. These actions feed back to the real economy within a Structural Vector Autoregression (SVAR) model. The ECB's BEAST model (Budnik et al., 2023) takes a different approach by incorporating non-linear credit supply responses.

The SRMS model builds on these existing frameworks but approaches the feedback loop differently. It focuses on both credit supply and demand shocks within the feedback loop. As macroeconomic conditions worsen, the SRMS model captures how banks dynamically adjust their loan supply and interest margins, not just as a response to solvency concerns but as an interaction with changing economic conditions. These adjustments generate new shocks that feed back to the economy, intensifying the initial macroeconomic disturbances.

The SRMS model approach

The theoretical generation of the macro feedback loop in the SRMS model can be described in several steps, as illustrated in Figure 4. Initially, the economy experiences negative macroeconomic shocks, which lead to worsening macroeconomic conditions such as contracting GDP, falling housing prices, or higher inflation. In this adverse environment, the quality of bank loan portfolios deteriorates, leading to lower profitability and solvency levels for banks. In reaction, banks adjust their loan supply and interest margins to mitigate these adverse conditions and improve their solvency and profitability ratios. These adjustments can generate additional credit supply and demand shocks, which feed back into the real economy and amplify the initial macroeconomic shock.

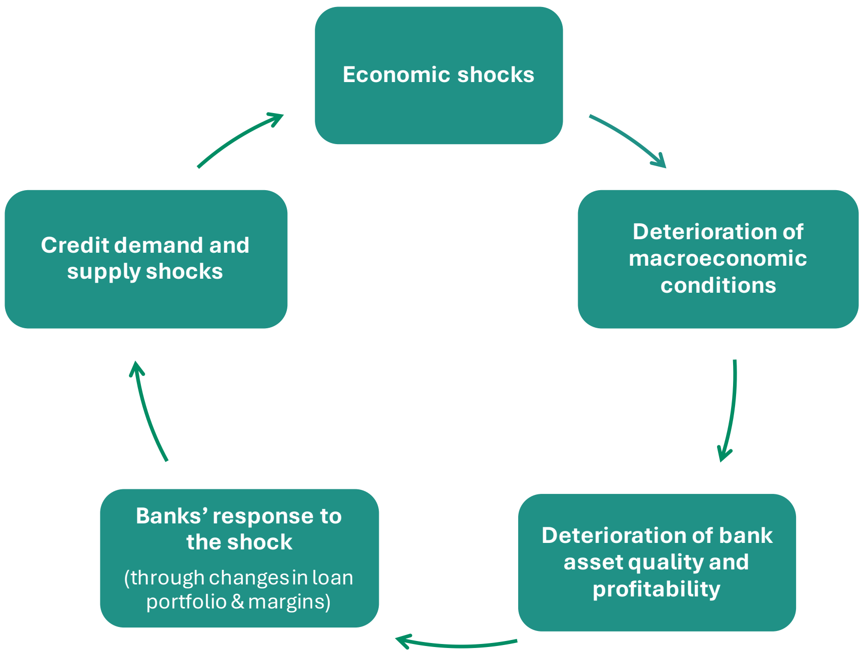

Figure 4: Cycle of feedback loop

Bank-level responses to shocks, however, can vary significantly across banks, reflecting the differences in their financial situation, risk management practices, and alignment with regulatory requirements. For instance, institutions with substantial capital buffers and high asset quality may exhibit greater resilience, extending credit even under adverse conditions. Conversely, banks facing capital adequacy pressures or deteriorating asset quality might need to curtail lending more sharply to maintain solvency and adhere to regulatory capital requirements. The main challenge in modelling the second-round effects lies in translating bank-level responses to shocks into broader macroeconomic impacts.

A graphical representation of the implementation of a macro feedback loop in the SRMS is illustrated in Figure 5. Initially, a macro scenario is generated, and the dynamics of loans and loan interest rates are modelled at the bank level in the satellite models. We then aggregate these individual responses to gauge their cumulative effect on the macroeconomic environment. This aggregation process is pivotal as it allows us to generate credit supply and demand shocks. The updated scenario is then generated by considering these additional shocks, which simultaneously affect bank-level indicators, such as profitability and capital position.

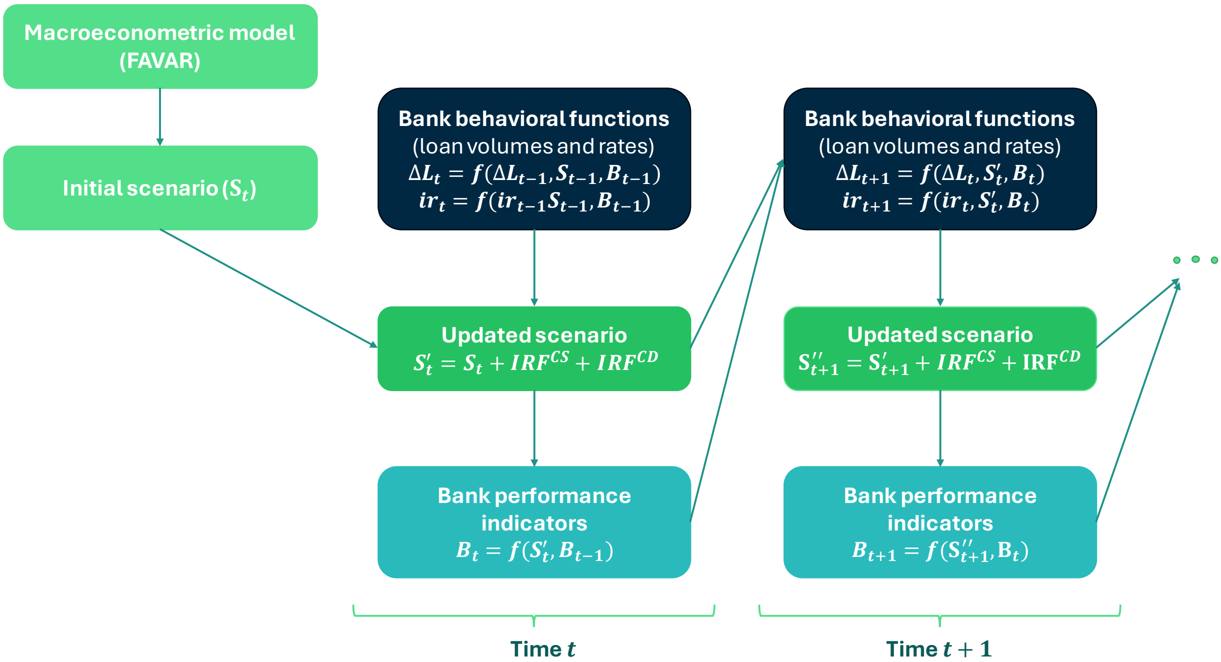

Figure 5: Integration of feedback loop in the SRMS model

The SRMS model operates iteratively at a quarterly frequency, with each iteration composed of three principal steps. Each iteration is initiated by the bank-level reaction to the updated scenario, leading to changes in lending volumes and lending rates. These changes generate additional credit supply and demand shocks, further shaping the scenario and impacting bank-level financial positions. We explain our approach in detail below.

Initial scenario. Let S_{t_0+h} denote an initial adverse macroeconomic scenario, which is generated by producing forecasts using a macroeconomic model presented in Section 3.1. In particular, we use the scenario generation algorithm as detailed in Section 3.2.1, where in the first step conditional forecasts are produced to enable the introduction of assumptions necessary for the implementation of second-round effects.

Two primary assumptions underpin the generation of conditional forecasts:

- *Assumption 1.* Forecasts are produced under the assumption that loan volume growth is zero and lending margins remain constant over the forecast horizon. Additionally, the scenario is conditional on assumptions regarding the Euribor rate.[14]

[14]Typically, we condition the value of the loan interest rate IRN to align with market expectations concerning the Euribor rate dynamics, assuming a constant margin.

- *Assumption 2.* It is assumed that only macroeconomic shocks — aggregate demand and aggregate supply shocks, house price shocks, and unemployment shocks — affect the conditional forecasts. At this stage, credit supply and credit demand shocks are muted, with these shocks being generated separately based on bank-level reactions in the satellite regressions.

Bank behavioural functions. The dynamics of loans and loan interest rates are modelled at the bank level in the satellite models, as detailed in Sections 4.1.1 and 4.1.2. We then aggregate these individual responses to gauge their cumulative effect on the macroeconomic environment within the macro block:

$$\begin{aligned} Loansgr_{t_0+h} &= \sum_s \sum_b Loansgr^s_{b,t0+h} \\ margin_{t_0+h} &= \frac{\sum_s \sum_b margin^s_{b,t_0+h} \times Loansgr^s_{b,t0+h}}{\sum_s \sum_b Loansgr^s_{b,t0+h}} \\ ir_{t_0+h} &= margin_{t_0+h} + Euribor_{t_0+h} \end{aligned} \tag{79}$$

where $Euribor_{t_0+h}$ is exogenous and depends on the assumptions made about the monetary policy.

Scenario update. The updated scenario S'_{t_0+h} is then obtained by adding credit supply and demand shocks to the initial macro scenario S_{t_0+h}:

$$\begin{aligned} S'_{t_0+h} &= S_{t_0+h} + S^{update}_{t_0+h} \\ S^{update}_{t_0+h} &= a_{t_0+h} \times IRF^{CS}_{t_0+h} + b_{t_0+h} \times IRF^{CD}_{t_0+h} \end{aligned} \tag{80}$$

where IRF^{CS} and IRF^{CD} are the impulse responses of all variables to credit supply (CS) and credit demand (CD) shocks, which are identified at the macro level as described in section 3.1.1, and a and b are scale coefficients mapping macro and bank-level responses.

Scale coefficients a and b, mapping the bank-level responses to the macro level, can be obtained from the system of equations:

$$\begin{cases} \Delta \log(Loansgr_{t_0+h}) = a_{t_0+h} \times IRF^{CS}_{CRE} + b_{t_0+h} \times IRF^{CD}_{CRE} \\ \Delta margin_{t_0+h} = a_{t_0+h} \times IRF^{CS}_{IRN} + b_{t_0+h} \times IRF^{CD}_{IRN} \end{cases} \tag{81}$$

where $\Delta \log(Loansgr_{t_0+h})$ is the growth rate of the gross carrying amount of loans and $\Delta margin_{t_0+h}$ is the change in loan margins modelled in the satellite models, which depend on supply and demand factors, as explained in Sections 4.1.1 and 4.1.2; IRF are impulse responses at t_0 of credit IRF_{CRE} or interest rates IRF_{IRN} to credit demand IRF^{CD} or credit supply IRF^{CS} shocks at macro level.

Finally, a and b can be derived as:

$$
\begin{aligned}
a &= \frac{\Delta \log(Loansgr) - b \times IRF_{CRE}^{IR}}{IRF_{CRE}^{CS}} \\
b &= \frac{\Delta margin \times IRF_{CRE}^{CS} - \Delta \log(Loansgr) \times IRF_{IRN}^{CS}}{IRF_{IRN}^{CD} \times IRF_{CRE}^{CS} - IRF_{CRE}^{CD} \times IRF_{IRN}^{CS}}
\end{aligned}
\tag{82}
$$

where all variables are considered at $_{t_0+h}$.

6 Applications

The SRMS model was developed primarily for macroprudential stress testing. In 2024, the model was employed for the first time to assess the financial stability of the Lithuanian banking sector. The findings are documented in the Financial Stability Review 2024. The model also includes features that enable its application in broader macroprudential policy analysis. The following applications demonstrate the capabilities of the SRMS model. The presented results are intended solely for illustrative purposes.

6.1 Stress testing

Lietuvos Bankas employs the SRMS model biannually for stress testing exercises. This application involves a solvency stress test designed to evaluate the capital adequacy of Lithuania's largest financial market participants under adverse economic shocks. The stress test serves a dual purpose: first, it assesses the overall resilience of the banking system, and second, it enhances our understanding of how negative conditions propagate through the system, ultimately raising awareness of potential systemic risks.

One of the main advantages of the SRMS model compared to the previous top-down stress testing model used by the Bank of Lithuania is the inclusion of a feedback loop arising from the interaction between banks and macroeconomic variables. The model also expands the number of institutions tested (from four to ten) and introduces the possibility of applying a dynamic balance sheet assumption[15], allowing the modelling of financial market participants' balance sheet dynamics depending on the scenario used.

Figure 6 illustrates the impact of the new features—a dynamic balance sheet and a feedback loop—on the capital adequacy ratio (CAR) under baseline and adverse economic scenarios. Under the baseline scenario with a static balance sheet assumption, the tested institutions are expected to maintain high profitability over the 2024–2026 testing period, allowing them to raise the already high CAR from 19.42% in Q4 2023 to 23.83% at the end of 2026. A dynamic balance sheet assumption reflects a more realistic dynamic where banks can expand their loan portfolios, resulting in higher RWAs and potentially a lower CAR, estimated to be 21.73% at the

[15] The previous stress test model was based on a static balance sheet assumption. This implied that the natural amortisation of the loan portfolio was counterbalanced by new loans, thereby maintaining a constant composition of the bank loan portfolio throughout the stress test horizon, thus preventing second-round effects.

end of the testing horizon. However, the positive feedback loop enables banks to consistently grow their credit portfolio further to achieve even higher profitability, potentially mitigating the CAR decrease.

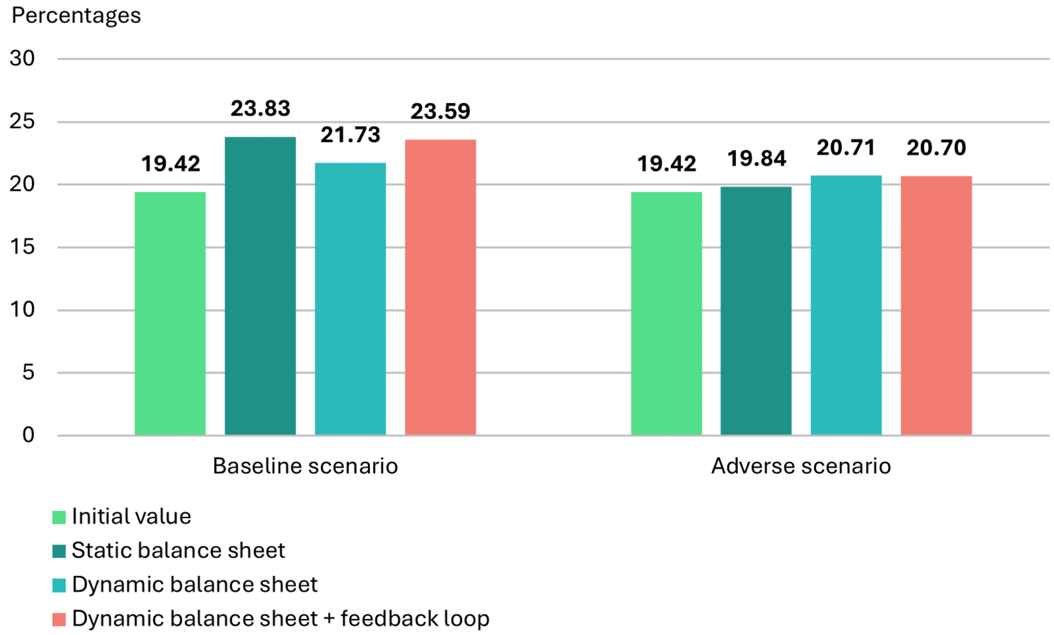

Figure 6: Capital adequacy ratio development under different model assumptions

In contrast, under the adverse scenario, banks maintain a similar CAR level, as the effect is offset by different factors as shown in the CAR decomposition in Figure 7. For instance, under the dynamic balance sheet assumption with a feedback loop, banks are projected to incur higher credit losses (8.2 percentage points) compared to the scenario without it (8.0 percentage points). Under the dynamic balance sheet assumption, banks would reduce their loan portfolio, which is reflected in the impact of RWA changes. Under the static balance sheet assumption, RWA would reduce CAR by 0.4 percentage points. Conversely, with the dynamic balance sheet assumption, the effect of RWA changes is the opposite, increasing CAR by 0.4 percentage points.

Overall, the breakdown of the change in the CAR under the adverse scenario shows that the credit losses are the primary contributor to the decline in the system's solvency, reducing the CAR by over 8.2 percentage points under a dynamic balance sheet with a feedback loop assumption (see bottom middle of Figure 7). Net interest income would be the main source (+16.9 percentage points) allowing the banks to absorb the loss incurred due to the changes in loan quality. In addition, in an adverse economic situation, banks would try to exert stricter control over their administrative costs (-8.2 percentage points) compared to the baseline scenario (-10.2 percentage points).

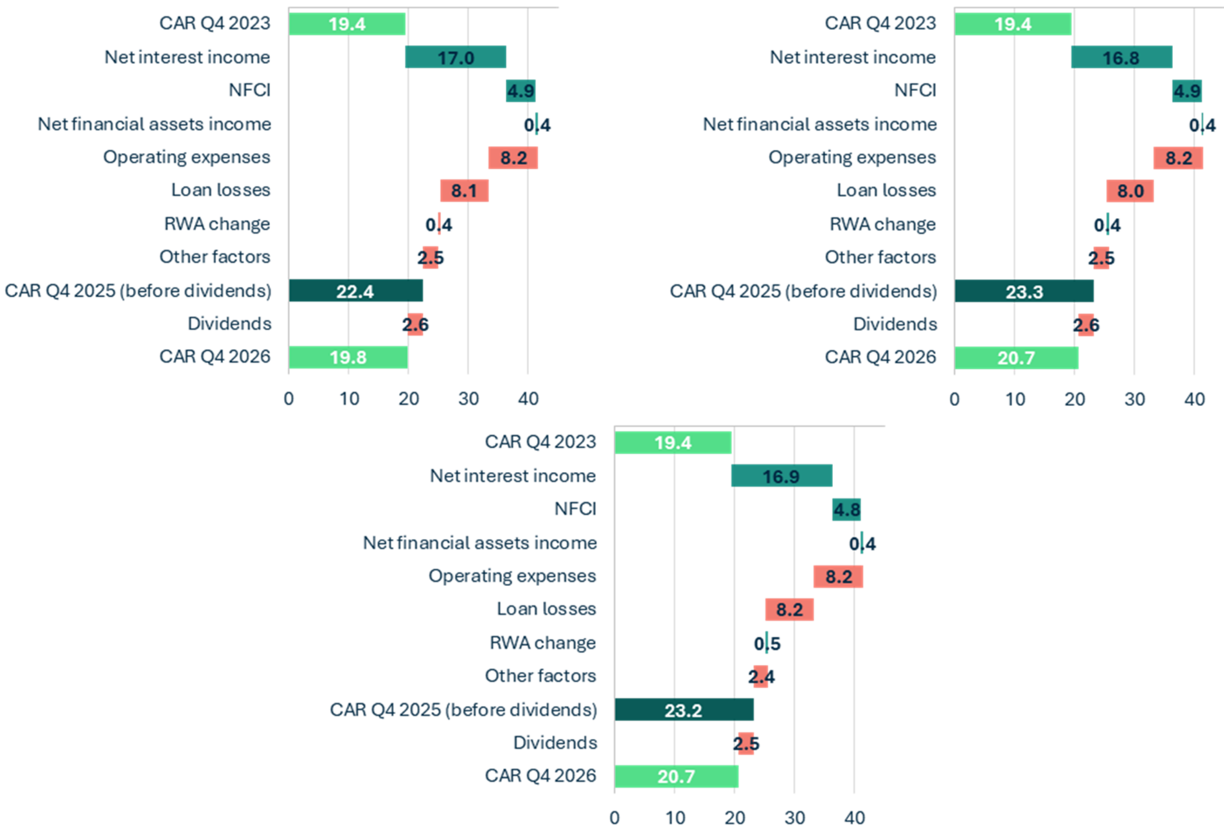

Figure 7: Breakdown of the capital adequacy ratio under adverse scenario
Notes: static balance sheet (top left), dynamic balance sheet (top right) and dynamic balance sheet + feedback loop assumptions (bottom middle)

6.2 Macroprudential policy stance

An important question for macroprudential policymakers is determining their policy effectiveness and assessing its stance. According to ESRB (2021), the macroprudential stance is the balance between systemic risk and resilience relative to financial stability objectives, given implemented macroprudential policies. The stance metric represents residual systemic risk in the financial system, relative to a neutral level of risk considered sustainable in the long run. Building on the work of Adrian et al. (2019), the growth-at-risk (GaR) concept has been employed to empirically assess the macroprudential stance (Škrinjarić, 2024). The resulting stance metric quantifies downside risks to growth distribution, reflecting future impacts of current vulnerabilities and financial system conditions. Furthermore, in addition to the growth-at-risk (GaR) approach, Budnik et al. (2022) proposed a methodology for utilising semi-structural models, based on a macro-micro model which combines macroeconomic dynamics with individual banking data, to assess the macroprudential policy stance, based on a distance-to-tail metric perspective. A main strength of this approach is the endogenous adjustment of bank balance sheets to macroprudential policies following financial shocks or policy implementations – which complements the GaR approach with a separate growth-based metric.

Following Budnik et al. (2022), we employed the SRMS model to evaluate the evolution of the macroprudential policy stance in Lithuania from Q4 2022 to Q4 2023. To measure the macroprudential policy stance, we explore the advantages of the structural FAVAR model which allows running the SRMS model with multiple stochastic simulations and gives the full distribution of GDP and other macroeconomic variables. Figure 8 illustrates the historical GDP growth and the simulated distribution of GDP growth from Q1 2024 to Q4 2028, together with the median and 10th percentile of the distribution and distance-to-tail metric.

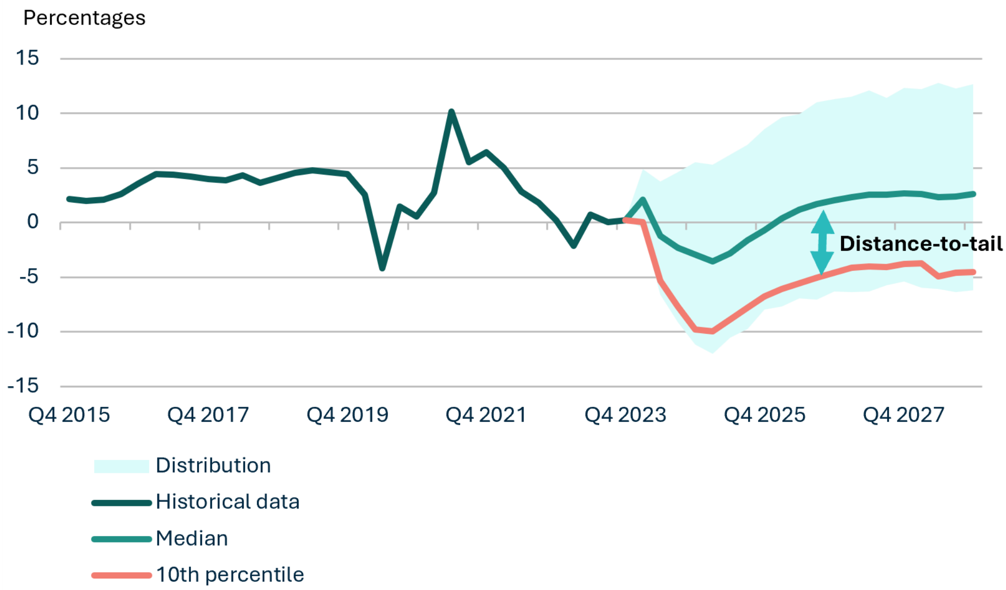

Figure 8: Historical data and forecast distribution of Lithuanian real GDP annual growth rate

The macroprudential policy stance was assessed using the following procedure:

1. Given the initial set of scenarios generated in the macro-block, we ran the SRMS model with a dynamic balance sheet assumption and feedback loop.

2. We calculated the median and 10th percentile of compound GDP growth rate (after the feedback loop) at various time horizons

3. The distance between the median and the 10th percentile of the projected GDP distribution (**distance-to-tail metric**) is used to track the macroprudential policy stance.

The aforementioned procedure was repeated for each period from Q4 2022 to Q4 2023, with recursive out-of-sample forecasts subsequently calculated. In each period, the stance assessment is based solely on the information available up to that moment. Combining macroeconomic and bank-level data we can get the residual systemic risk assessment having the full distribution of GDP (after the feedback loop) and other macroeconomic variables.

Figure 9 shows the median (left-hand side, LHS) and the 10th percentile (right-hand side, RHS) of the compound Lithuanian real GDP growth rate forecasts one to five years ahead. For example, in Q4 2023 the median growth rate was around -3% for one year ahead and around 1% annually for five years ahead. A more stable three to five years ahead annualized GDP growth rate indicates that the model forecasts converge to the long-term trends. In addition, the right-hand side indicates that the tail of the GDP growth distribution shows a strong correlation with the median.

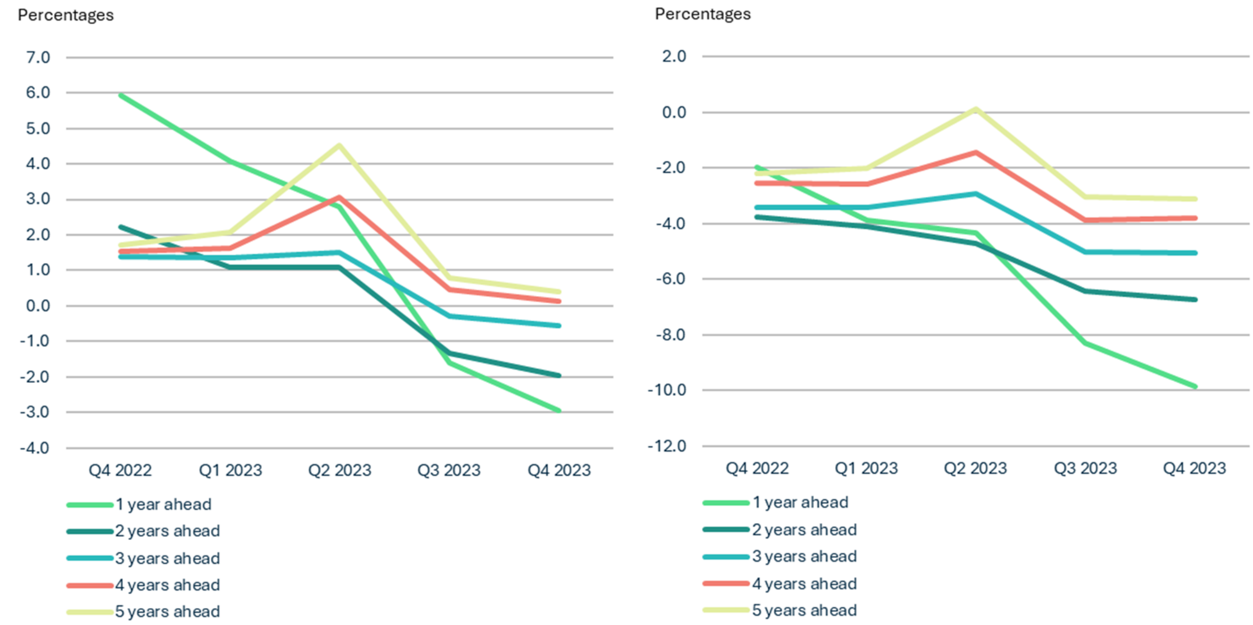

Figure 9: Lithuanian median (LHS) and 10th percentile (RHS) compound annual real GDP growth at different time horizons

Figure 10 shows the evolution of the distance-to-tail metric for Lithuania. For example, a stance measure value of 5% for a three-year horizon in Q4 2022 indicates that the lower tail of the compound annual real GDP growth rate from Q4 2022 to Q4 2025 is projected to be 5 percentage points lower than the median real GDP growth rate anticipated for the same period. An increase in the stance indicator signifies amplified tail risks and a correspondingly looser macroprudential policy stance.

The three-year-ahead distance-to-tail metric is our main measure of the macroprudential policy stance. The stable evolution of the stance measure reflects the fact that no significant policy changes were implemented during this period. Only in Q4 2023 CCyB of 1 percent become applicable for Lithuanian exposures. This episode is reflected in the slight tightening of the stance in the last period.

6.3 Capital-at-risk

One of the macroprudential policy objectives is to strengthen financial sector resilience. A typical stress test provides only point estimates of the resilience of the banking system. A full distribution of the banking system's capital would provide a better understanding of the resilience of the banking system. A stochastic simulation using the SRMS model not only provides a distribution of macroeconomic variables but also a full distribution of bank-level variables, including the capital adequacy ratio.

The full distribution of the banking system's capital adequacy ratio could be used to calculate the CAR-at-risk measure. The Bank capital-at-risk concept proposed by Lang and Forletta (2019) shares conceptual similarities with the "Growth-at-Risk" framework developed by Adrian et al. (2019). Both approaches focus on quantifying downside risks, but Bank capital-at-risk

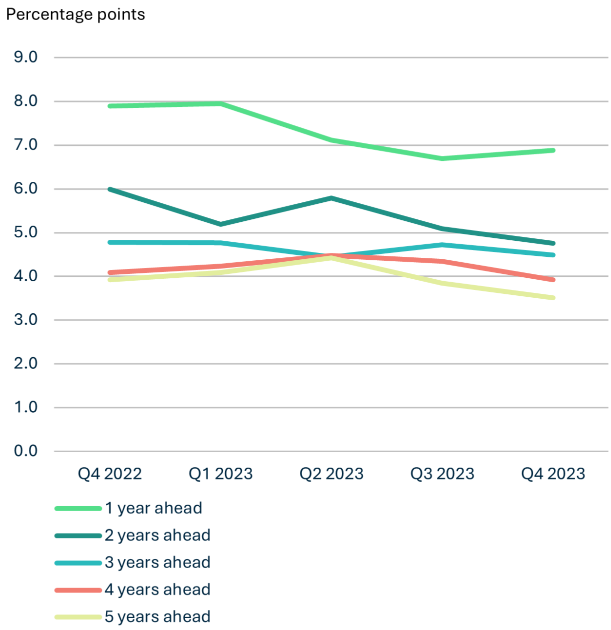

Figure 10: Macroprudential stance development in Lithuania

Notes: The figure shows the distance-to-tail metric, calculated as the difference between the median and the 10th percentile of the compound annual real GDP growth rate for Lithuania over horizons ranging from one to five years. Increasing (decreasing) metric indicates loosening (tightening) macroprudential policy stance.

specifically targets potential future losses in bank capital.

Figure 11 gives a schematic illustration of a CAR-at-risk assessment. Given the available macroeconomic and banking data, a semi-structural model could be used to run multiple stochastic simulations, which gives the development of macroeconomic and banking data under alternative but plausible scenarios. Differently from Lang and Forletta (2019), we do not take the 5th percentile of the CAR distribution but consider the area below capital requirements as a measure of CAR-at-risk. There could be two possible options for this measure: area below total capital requirement (teal shaded area) or area below minimum capital requirement (red shaded area). In other words, the CAR-at-risk measure gives a probability of the banking system going below capital requirements.

The empirical CAR-at-risk measure was estimated using the following procedure:

1. Given the initial set of scenarios generated in the macro-block, we ran the SRMS model with a dynamic balance sheet assumption and feedback loop.

2. We calculated the banking sector‘s CAR distribution at different time horizons.

3. The areas below total and minimal capital requirement are calculated as measures of CAR-at-risk.

Similarly, as in the previous section, we ran the model for each period from Q4 2022 to Q4 2023 and calculated the full distribution of the banking system capital adequacy ratio.

Figure 12 shows banking systems’ CAR distribution at different time horizons, taking information available at Q4 2023. The distribution of CAR is more skewed taking longer forecasting

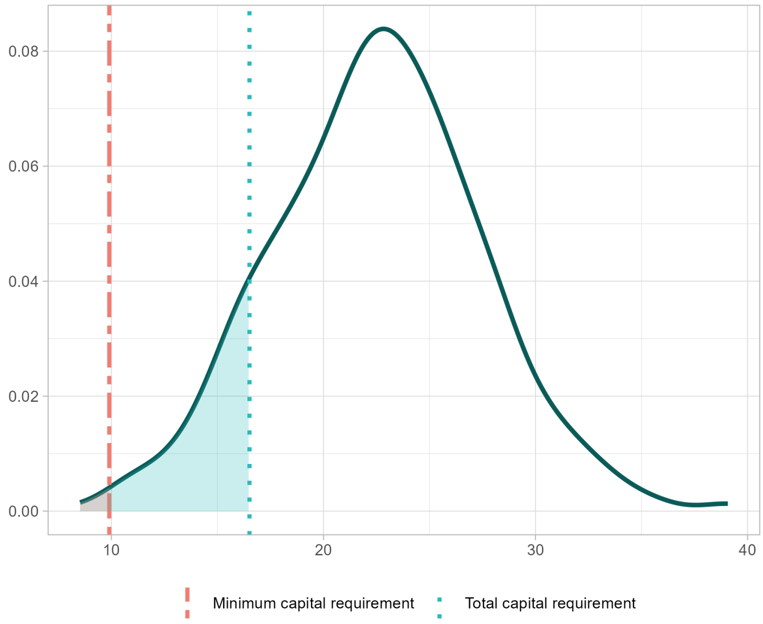

Figure 11: Schematic illustration of CAR-at-risk assessment

horizons. With a one-year time horizon, the CAR distribution exhibits approximate centring around its mean value. However, as the forecasting horizon extends, a pronounced leftward skew emerges in the distribution, with a lengthening and thickening of the left tail. The likelihood of encountering situations that increase capital shortfalls increases, especially over long periods.

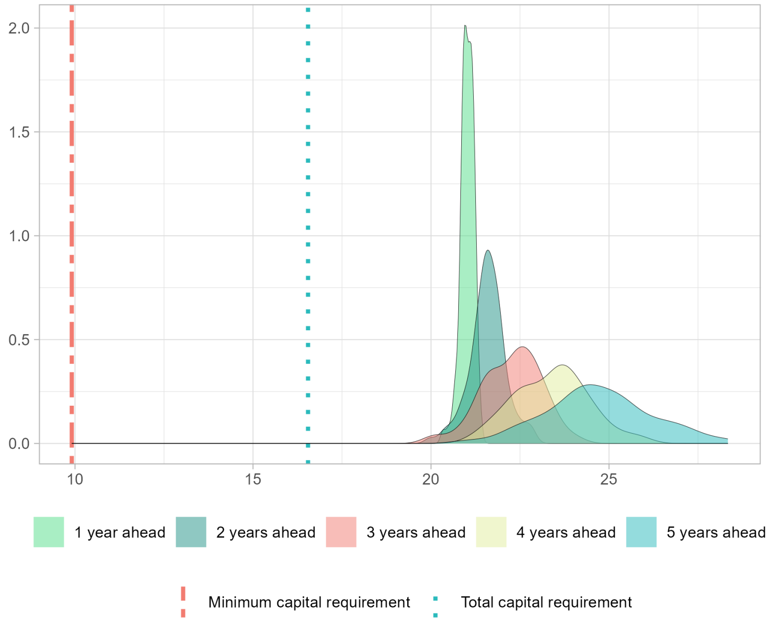

Figure 12: Capital adequacy ratio distribution at different time horizons

The three-year ahead CAR distribution served as the primary variable for calculating CAR-at-risk. Figure 13 summarizes the CAR-at-risk estimates for the Lithuanian banking sector. Depending on the available information from the simulation run, the distributions exhibited variations in both mean and shape. However, it is noteworthy that only one of the simulated distributions breached the total capital requirement threshold in Q4 2025. Consequently, within the confines of this framework, CAR-at-risk remained at zero throughout the past four quarters.

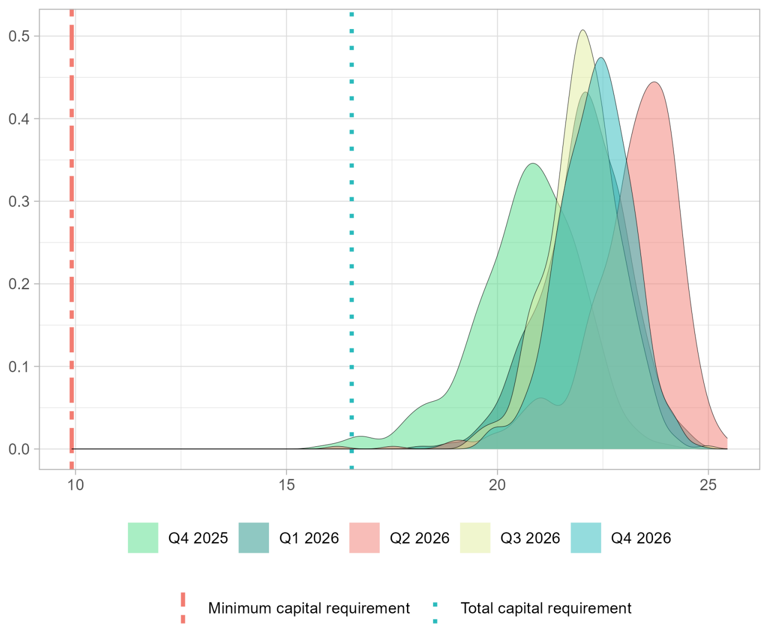

Figure 13: Capital adequacy ratio distribution 3 years ahead

6.4 Macroprudential policy impact

Macroprudential policy authorities have several tools which could be used to address potential vulnerabilities or imbalances in the economy and financial sector. One of them is countercyclical capital buffer (CCyB), which is designed to mitigate the risk of unsustainable growth and secure the banking sector and the economy against a credit boom. Before making any policy changes macroprudential authorities usually try to assess the impact they will have on the banking system and overall economy. The SRMS model could be employed to evaluate the impact of CCyB policy changes.

Taking information available at Q4 2023, the model was used to assess the potential impact of different countercyclical capital buffer policy rates. Three scenarios are explored: (1) No policy change, where the CCyB rate remains at 1% throughout the simulation period (until Q4 2026). (2) Tightening scenario, where the CCyB rate is increased to 2% from Q1 2025 onwards. (3) Loosening scenario, where the CCyB rate is reduced to 0% from Q1 2025 onwards. The impact of each scenario is measured by its deviation from the no-policy-change scenario at the end of the simulation (Q4 2026).

Table 12 summarizes the impact of countercyclical capital buffer policy changes on key bank-level and macroeconomic variables. As expected, a tightening of macroprudential policy (increasing the CCyB) leads to a higher banking system capital adequacy ratio, a contraction (smaller loan portfolio) in credit to the non-financial private sector, and higher interest rates. Interestingly, the impact on median compound annual GDP growth appears slightly stronger than on the tails of the distribution. The impact on both tightening and loosening scenarios appears largely symmetrical.

Table 12: CCyB policy change impact on bank-level and macroeconomic variables

Variable	Tightening	Loosening
CAR	0.17	-0.17
Loans to non-financial private sector	-1.10	1.17
Interest rate for new loans to non-financial private sector	0.04	-0.04
Compound annual real GDP growth (median)	-0.09	0.09
Compound annual real GDP growth (10th percentile)	-0.07	0.07
Macroprudential policy stance	-0.02	0.02

Notes: the impact is illustrated at a 3-year horizon. All variables except loans to the non-financial private sector are expressed as differences from the no-policy-change scenario in percentage points at the end of the horizon. Loans to the non-financial private sector are expressed in percent as the difference between loans portfolio at the end of the horizon.

7 Conclusions

This paper has introduced the Systemic Risk Modelling System (SRMS), a new macroprudential stress testing framework for the Lithuanian banking sector. Building on the previous model by Butkus and Naruševičius (2015), the SRMS model incorporates dynamic balance sheet adjustments and second-round effects, addressing the limitations of traditional static models. By capturing the interactions between banks and the macroeconomic environment, the SRMS is a more accurate and comprehensive tool for the assessment of systemic risks.

One of the SRMS model's significant advancements is the integration of the macro feedback loop, which enhances the understanding of how shocks are transmitted between the banking sector and the real economy. This dynamic interaction is crucial for assessing the resilience of banks under stress scenarios and understanding the propagation of systemic risks. The model's ability to simulate heterogeneous banks' responses to adverse macroeconomic conditions and their subsequent impact on the broader economy is a key innovation, offering valuable insights for regulators.

Beyond stress testing, the SRMS model can also be used for other policy applications. These include the assessment of macroprudential policy stance, capital-at-risk analysis, and the evaluation of macroprudential policy impacts. The SRMS model demonstrated a stable evolution of the macroprudential policy stance in Lithuania from Q4 2022 to Q4 2023, reflecting that no significant policy changes were implemented during this period. Furthermore, within the confines of the proposed capital-at-risk framework, the CAR-at-risk measure remained at zero throughout the past five quarters. Notably, the macroprudential policy impact assessment revealed a non-linear effect on GDP growth, with a slightly stronger impact on median compound annual GDP growth than on the distribution's tails.

While the SRMS model offers significant improvements over the previous Lithuanian top-down stress testing framework, there is potential for further enhancement. Future research could explore additional dimensions of financial stability, such as the impact of climate-related risks. Additionally, integrating more granular data for credit risk assessment or using advanced machine-learning techniques could further improve the model.

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A Appendix

Table 13: Additional macroeconomic variables in the FAVAR

Variable name	Transformation	Definition
PCR	log difference	Real personal consumer expenditure (level, constant prices)
PCN	log difference	Nominal personal consumer expenditure (level, current prices)
GCR	log difference	Real government expenditure (level, constant prices)
GCN	log difference	Nominal government expenditure (level, current prices)
ITR	log difference	Real gross fixed capital formation (level, constant prices)
ITN	log difference	Nominal gross fixed capital formation (level, current prices)
IHR	log difference	Real gross capital formation (dwellings) (level, constant prices)
IHN	log difference	Nominal gross capital formation (dwellings) (level, current prices)
XTR	log difference	Real exports of goods and services (level, constant prices)
XTN	log difference	Nominal exports of goods and services (level, current prices)
MTR	log difference	Real imports of goods and services (level, constant prices)
MTN	log difference	Nominal imports of goods and services (level, current prices)
WUN	log difference	Compensation per employee (level, current prices)
SUR	log difference	Gross operating surplus and mixed income (level, current prices)
SEC_i	log difference	Gross value added by economic activity, $i \in$ (A, B, C, D, E, F, G, H, I, J, K, L, M, N, O, P, Q, R, S, T)
CAB	level	Current account balance (percent of GDP)
PYR	log difference	Disposable income (level, current prices)
YED	log difference	GDP deflator
OMX	log difference	OMX stock market index
CRE_i	log difference	Loans held by other MFIs (outstanding amount at the end of the period), $i \in$ (nfc, hh, he)
IRN_i	level	Interest rate on new loans granted by other MFIs, $i \in$ (nfc, hh, he)