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Abstract

In the presence of adverse macroeconomic shocks, simultaneous capital losses in multiple banks can prompt them to contract their balance sheets. These bank responses generate externalities that propagate in the form of macro-financial feedback loops. This paper develops a credit response and externalities analysis model (CREAM) that integrates a disaggregated banking sector into an otherwise standard macroeconomic structural vector autoregressive model. It shows that accounting for macro-financial feedback loops can significantly affect macroeconomic outcomes and bank-specific stress tests results. The heterogeneity in bank lending responses matters: it determines how each bank fares under adverse conditions and the external effects that banks impose on each other and on economic activity. The model can thus be used to assess the contributions of individual banks to systemic risk along the time dimension.

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I. INTRODUCTION

Recent literature has shown that in the presence of adverse macroeconomic shocks, simultaneous capital losses in multiple banks can prompt them to cut lending and contract their balance sheets. These bank responses can generate externalities that propagate in the form of macro-financial feedback loops. To date, the empirical evidence for these macro-financial effects remains scant, in part reflecting the absence of a general quantitative framework to evaluate them.[1]

This paper develops a credit response and externalities analysis model (CREAM) that integrates a disaggregated banking sector into an otherwise standard macroeconomic structural vector autoregressive (SVAR) model. In this model, exogenous macroeconomic shocks trigger bank losses that erode risk-adjusted capitalization ratios. To mitigate this erosion, banks cut lending in a differentiated manner that depends on their fundamentals. Bank-specific lending cuts in turn weaken GDP growth and undermine the profitability of other banks. A vicious cycle of reduced lending and a weakening economy is generated.

The paper shows that accounting for macro-financial feedback loops can significantly affect the measured impact of shocks on macroeconomic outcomes and bank-specific stress tests results. In addition, the paper shows how CREAM can be used to assess the contributions of individual banks to systemic risk along the time dimension.

More specifically, the empirical framework can address the following questions. First, how does individual and collective bank lending behavior contribute to the propagation of shocks and influence macroeconomic outcomes? Second, how is the propagation of shocks affected by initial bank conditions and heterogeneity? To what extent do stronger bank buffers (e.g.

[1] Recent theoretical studies of adverse macro-financial feedback loops include Farhi and Tirole (2016), Brunnermeier and others (2016), Bocola (2016), and Brunnermeier and Sannikov (2014).

higher capital ratios) mitigate the propagation effects? And third, how does accounting for bank lending behavior and the associated macro-financial feedback loops affect bank-specific stress tests results?

To address the first question, this paper quantifies the contribution of bank *i*'s deleveraging behavior to a macroeconomic downturn following adverse shocks. Bank *i*'s lending behavior is assessed against a no-deleveraging "quasi-static" benchmark in which its balance sheet grows in line with nominal GDP.[2] Its contribution to systemic risk is measured by comparing macroeconomic outcomes under "dynamic" and "quasi-static" balance sheet growth assumptions for the bank. In the same vein, the externality imposed by bank *i*'s deleveraging on bank *j* can be quantified by tracing the effects on bank *j*'s fundamentals (e.g., capitalization, non-performing loan ratios, profitability).

To address the second question, the paper shows how capital surcharges can mitigate the externalities generated by individual banks through their lending behavior. In this way, the paper highlights the use of the framework for evaluation of macroprudential policy interventions.

And to address the third question, the paper highlights the use and relevance of the framework for stress testing. It brings to the fore the drawbacks of applying quasi-static and other ad-hoc bank balance sheet growth assumptions in stress tests. The main difficulty with such commonly used assumptions lies in the distortion that they engender on stress tests results *across* banks. Banks that appear resilient (vulnerable) under a static balance sheet

[2] The use of quasi-static or static balance sheet growth assumptions is commonplace in stress tests coordinated or carried out by policy institutions such as the IMF, the European Banking Authority, and many central banks.

analysis could turn out to be highly vulnerable (resilient) when assessed through a dynamic balance sheet approach.[3]

The model provides a platform to examine macro-financial feedback loops and perform stress testing exercises in a wide range of economies under a common methodology. This is because the model has been designed to rely on publicly available bank data (Fitch/Bankscope),[4] and its flexibility allows it to be adjusted to fit the needs of country-specific applications.

This paper complements recent (theoretical) studies on the role of pecuniary externalities to motivate macroprudential policy, with notable examples including Lorenzoni (2008) and Dávila and Korinek (2018). In these studies, reduced credit provision by a financial intermediary reduces asset prices and tightens price-dependent collateral constraints in other intermediaries, forcing them to also cut credit provision. In contrast, in this paper externalities can take various forms, reflecting a variety of macro-financial transmission channels embedded in the framework. Our analysis suggests that reduced lending by a single systemically important bank i in an adverse scenario exacerbates the credit losses of other banks through the output channel. But the aggregate credit and output contractions lead to lower market interest rates and bond yields, which mitigate other banks' market losses (i.e., profitability). Thus, the impact on other banks' capital ratios is ambiguous and depends on

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[3] Under ad-hoc or static balance sheet growth assumptions the severity of scenarios can be controlled by re-scaling the exogenous shocks. Thus, failure to account for propagation through bank deleveraging should not (necessarily) affect the severity of the tests; however, it does distort the implied mapping between exogeneous shocks and macroeconomic outcomes, affecting the narrative and communication of stress testing exercises. Note that, in practice, the shortcomings of imposing ad-hoc assumptions must be balanced against the capacity of stress testers to accurately estimate the behavioral responses of banks. The use of ad-hoc assumptions may be the best course of action when such responses cannot be properly estimated for lack of data or other reasons.

[4] However, for stress testing purposes, access to granular supervisory bank data must always be considered a superior option which would also allow a more refined application of the framework presented in this paper.

bank-specific exposures and estimated sensitivities of losses to changes in macroeconomic factors. Similarly, bank i's deleveraging can result in crowding-in or crowding-out effects on the credit of other banks, depending on bank-specific conditions.

Policymakers have recognized the need for enhancing the "realism" of stress tests and hence their "relevance" for policy decision-making, pointing out that allowing for differentiated bank responses and accounting for macrofinancial feedback effects are key areas for improvement.[5] The studies by Budnik and others (2019) and Krznar and Matheson (2017) represent concrete first steps to bring these proposals to fruition.

A number of studies, such as Meh and Moran (2010) and Gerali and others (2010), have also tried to capture macro-financial feedback effects using dynamic stochastic general equilibrium (DSGE) models with a banking sector. The "truly" structural DSGE modeling approach is appealing and has some well-known advantages, but a realistic description and behavior of banks is not one of them. Since these studies model the behavior of a representative and overly simplistic bank, they cannot capture heterogeneity in individual bank deleveraging behavior, which is highlighted in this paper as a key source of cross-bank externalities and shock propagation, and a key determinant of bank-level stress tests results.

To demonstrate how CREAM can be used to address the questions posed above, this paper provides an illustrative application to the case of Indonesia. It is organized as follows: section II describes the macro-financial framework; section III discusses how to take the model to the data; section IV presents the application to the case of Indonesia and section V concludes.

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[5] See a recent keynote speech by Andrea Enria (2019), Chair of the Supervisory Board of the European Central Bank. Also, during the global financial crisis, Andrew Haldane (2009) had highlighted the need to include second-round effects in stress testing exercises to enhance their realism and relevance.

II. The Credit Response and Externalities Analysis Model

CREAM is a semi-structural macro-financial econometric model that captures the two-way linkages between banks and the economy (depicted in Figure 1). The model consists of two broad sets of equations. The first set of equations specifies a macroeconomic (SVAR) block where aggregate bank lending and the lending rate are exogenous. The second set of equations determines individual bank behavior and conditions, reflecting the influence of idiosyncratic and macroeconomic factors on bank profits, capital, and lending. Individual bank decisions are then aggregated to determine bottom-up measures of lending and the lending rate for the banking sector. The macro-financial feedback loop is closed by plugging the aggregated banking sector decisions into the macroeconomic block. CREAM thus incorporates a disaggregated banking sector into an otherwise standard SVAR model.

The equations characterizing the model are presented in Appendix I and variable definitions and notation are summarized in Table 1.

The remainder of this section proceeds as follows. Sub-section A describes the macroeconomic (SVAR) block and sub-section B describes the equations that characterize the disaggregated banking sector. The subscript i differentiates bank-specific variables from macroeconomic variables and, to simplify notation, time subscripts have been suppressed. Note that references to equations follow the numbering of Appendix I rather than the order in which they appear in the text.

A. Macroeconomic Block

The macroeconomic block consists of structural vector autoregressive (SVAR) equations expressed in reduced form and defined over the external and domestic macroeconomic variables included in $\tilde{z}$ (Eq. 1). The dynamics of $\tilde{z}$ is influenced by the evolution of financial conditions ($\tilde{\boldsymbol{f}}$). These are defined by aggregate real bank lending (L^R) and the nominal lending rate (i^L) and treated as exogenous in the SVAR block.

The external variables included in $\tilde{z}$ have potential effects on the domestic economy through trade or financial channels and comprise the following: real GDP of trading partners ($RGDP^*$), commodity prices (P^{COMM}), and the nominal U.S. policy interest rate (i^{US}). The domestic variables included in $\tilde{z}$ are the following: real GDP ($RGDP$), inflation (*INF*), the real effective exchange rate ($REER$), and the nominal policy interest rate (i^0). Thus, in Eq. 1, $\tilde{z}$ and $\tilde{\boldsymbol{f}}$ are defined as:

$$\tilde{z} = \left[RGDP^*, P^{COMM}, i^{US}, RGDP, INF, REER, i^0 \right]^{'} \text{ and } \tilde{\boldsymbol{f}} = \left[L^R, i^L \right]^{'}.$$

All the variables except for nominal interest rates (i^{US}, i^0 and i^L) and inflation (*INF*) are expressed in logs and a time trend is included explicitly in the SVAR, with trend coefficients allowed to differ across equations.

The choice of variables and structure is guided by theory and empirical literature on SVAR models applied to small open economies.[6] To identify the structural parameters of the SVAR and capture the "small open economy" assumption, a set of restrictions is imposed on the contemporaneous and lagged relations. On the *contemporaneous* relations, the reduced form errors are orthogonalized by Cholesky decomposition as in Sims (1980), with the external

[6] VARs with restrictions on lagged relations can be derived from New Keynesian models (see Dungey and Pagan 2009). However, we follow Sim's (1980) principle of imposing a minimal number of restrictions on lagged relations—"block exogeneity" restrictions that are consistent with the small open economy assumption. The block exogeneity approach in structural VAR models has been used in the literature that studies the effects of external shocks on macroeconomic fluctuations in both developed and developing countries. For example, Cushman and Zha (1997), Dungey and Pagan (2000, 2009), Hoffmaister and Roldós (2001) and Sosa (2008) applied this approach to various countries, including Australia, Brazil, Canada, Korea, and Mexico.

variables "preceding" the domestic variables. The relation between reduced form ($\boldsymbol{\mu}^z$) and structural ($\boldsymbol{\varepsilon}^z$) errors is given by $\boldsymbol{\mu}_t^z = \mathrm{B} \cdot \boldsymbol{\varepsilon}_t^z$, where $\boldsymbol{\varepsilon}_t^z \sim \left(0, \Sigma_{\boldsymbol{\varepsilon}^z}\right)$ and $\Sigma_{\boldsymbol{\varepsilon}^z}$ is diagonal. On *lagged* relations, block exogeneity restrictions are imposed to preclude lagged effects of domestic shocks on external variables.[7] These restrictions, when combined, imply that external variables can affect the domestic economy both contemporaneously and with lags. In contrast, changes in domestic variables do not have contemporaneous or lagged effects on external variables.

Note that the SVAR defined in Eq. 1 includes a single domestic interest rate, the nominal policy rate i^0. However, a broader set of interest rates is needed to adequately capture the transmission of macroeconomic shocks to the banking sector. In particular, corporate and government bond yield curves are needed to price securities portfolios held by banks. Also, through their role as benchmark rates, government bond yields influence the determination of banks' funding costs and lending interest rates.

In this regard, we collect aggregate interest rates in the vector $\boldsymbol{ir}$ (Eq. 7) and introduce a second VAR (Eq. 2) to map trajectories of the domestic policy rate (i^0) to 10-year (40 quarters) government bond yields ($Y^{G,40}$) and both short and 10-year corporate bond yields ($Y^{C,0}$ and $Y^{C,40}$). The corresponding yield curves are obtained through linear interpolation between short and 10-year rates (Eq. 28).[8]

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[7] Block exogeneity restrictions can be removed in applications of CREAM to "large economies"—those where sizable changes in domestic conditions have a meaningful impact on the world economy (as defined in a technical sense following standard terminology in the open economy macroeconomics literature). It is commonly understood that only the four or five largest economies would satisfy this requirement.

[8] It could be advantageous to include all interest rates in the main SVAR jointly with other domestic macroeconomic variables. An obvious drawback of having a separate VAR for interest rates is that domestic variables such as real GDP, the real exchange rate, and inflation are not influenced directly by bond markets' term and credit spreads. However, some practical obstacles imply that there are also advantages of analyzing

B. Banks

Balance sheet

Bank i's assets (A_i) are comprised of gross loans (L_i) net of loan loss provisions (PR_i), portfolios of government and corporate bonds (B_i^G and B_i^C), cash assets (M_i), and other assets (OA_i).[9] Liabilities are divided into those that qualify as regulatory capital (K_i) and other liabilities (D_i) (Eq. 20). Bonds are booked as "marked-to-market" (MTM) or held-to-maturity (HTM), depending on whether valuation effects triggered by changes in market conditions are recognized as profits (Eq. 21).

Profits

Bank i generates net profits (Π_i) from various sources (Eq. 10). Interest income from loans (II_i^L) and interest expense (IE_i) are generated by portfolios of loans and interest-bearing liabilities, respectively. "Loan losses" (LL_i) are defined as credit losses in loan portfolios. Returns on securities portfolios (R_i^G and R_i^C) reflect interest income associated with bond coupon payments and gains or losses triggered by repricing of marked-to-market securities due to shifts in yield curves. "Other net profits" (O_i) collects all remaining items, such as net fee and commission income and operational and tax expenses.

Financial ratios

interest rates separately, through the introduction of an additional VAR. For instance, available historical bond yield series are shorter than macroeconomic series for many countries, and inclusion of multiple interest rates in the main SVAR can substantially increase the number of parameters to be estimated.

[9] The stock of gross loans (L_i) excludes interbank loans, which are included in other assets (OA_i) along with other asset items (e.g., fixed assets, intangibles). Thus, in this paper, reduced bank lending in an adverse scenario implies a decline in the provision of loans to corporations, households and the government. Interbank exposures, however, are assumed to remain constant according to Eq. (29)—there is no freezing or abrupt disruption of the interbank market.

Bank-specific capital, liquidity, and loan loss ratios play key roles in the model and are collected in the vector $\boldsymbol{x}_i$ (Eq. 8). In the definition of bank i 's "capital adequacy ratio" (Eq. 9), risk-weighted assets RWA_i are defined as the sum of the products of average risk weights ($\Theta_i^L, \Theta_i^G, \Theta_i^C$) for different asset portfolios and the corresponding exposure amounts (Eq. 31).[10] The "liquidity ratio" ($LATA_i$) is defined as the ratio of liquid assets (LA_i) to total assets (A_i), where liquid assets consist of cash and bonds (Eq. 9). The "loan loss ratio" (LLR_i) is defined as the ratio of loan losses to gross loans (Eq. 17).

Determination of profits

Profits of individual banks are affected by macroeconomic conditions. The transmission of changes in macroeconomic conditions to bank profits varies across banks, depending on their financial health and sensitivity to shocks. The key channels of transmission of macroeconomic shocks to the banking sector are shown in Figure 1 (left-hand side, "macro-to-banking transmission").

First, changes in macroeconomic conditions cause shifts in government bond yields which are transmitted to bank deposit and lending rates, thereby impacting interest income and expenses. For any bank i , interest rates on rolled-over deposits and other debt (i_i^{ND}) adjust not only to reflect the full impact of changes in government bond yields but also predetermined and idiosyncratic changes in cost of funding (Eq. 16), where the idiosyncratic

[10] Note that loan loss provisioning has an impact on profitability *and* on RWAs. The framework is flexible and can be extended to increase the granularity of asset and liability portfolios. It can also be adjusted to incorporate internal ratings-based formulas for specific banks and exposures. Also, the parameter ρ_i^{ORWA} represents the share of other risk-weighted assets (corresponding to operational and other risks) in the total risk-weighted assets of bank *i*.

component is a spread (spr_i) that depends on bank-specific fundamentals and exogenous shocks (Eq. 5).

The pass-through effect of bank funding costs onto lending rates corresponding to newly extended loans (i_i^{NL}) is partial and determined by the parameters ψ_i^G and ψ_i^{spr} (Eq. 13). The transmission to overall (average) deposit and other debt rates (i_i^D) and lending rates (i_i^L) is, in turn, protracted and reflects gradual re-setting of interest rates given laddered maturity structures of deposits and other debt and loan portfolios (Eq. 12 and Eq. 15). More specifically, fractions π_i^D and π_i^L of bank i's deposits and other debt, and loans, mature and can re-set their interest rates in every quarter. Also, interest income is adversely impacted by any deterioration in credit quality of loan portfolios, as interest associated with non-performing loans (NPL) is neither collected nor accrued (Eq. 11).

Second, changes in macroeconomic conditions affect loan defaults in different ways. A slowdown in real GDP growth triggers loan defaults, increasing non-performing loan ($NPLR_i$) and loan loss ratios (LLR_i). Also, bank-specific increases in lending rates (associated with the pass-through interest rate effects described above) can increase borrowers' debt service burden, triggering additional defaults.

In the model, loan losses LL_i are obtained from Eqs. 3 and 17. The former is an estimated dynamic panel used to forecast the evolution of loan loss ratios LLR_i based on macroeconomic and bank-specific conditions.[11] Note that a logistic transformation of LLR_i introduces non-linearity in the relation between the loan loss ratio and its determinants. It

[11] Real GDP growth, inflation, and changes in exchange rates are typically included as macroeconomic determinants of bank credit losses associated with loan defaults. Bank-specific determinants include lending rates and capital ratios.

also implies that dynamic responses of loan loss ratios to shocks are bank-specific (affected by the fixed effect term and the financial ratios of each bank). The model thus allows for differentiated sensitivity of bank loan losses to macroeconomic shocks.[12]

The returns on securities R_i^G and R_i^C reflect changes in the values of HTM and MTM bond portfolios (Eqs. 25 and 26 respectively). These returns are driven by (full) re-investment of coupon payments received and gains or losses associated with the repricing of MTM portfolios due to changes in yields. Repricing of MTM bonds is based on modified duration formulas (Eq. 26) where changes in yields are evaluated at the points of the corresponding yield curves given by the durations. Coupon payments received, in turn, adjust over time as interest rates in the economy change (Eq. 27). Other net profit O_i remains constant (Eq. 19).

Determination and dynamic evolution of balance sheet items

Bank i's stock of gross loans and its evolution over time is determined using a dynamic panel set of equations (Eq. 4); we refer to these equations as the "lending block." The stocks of provisions are driven by recognition of loan losses (Eq. 23).

All banks are assumed to implement reinvestment strategies that preserve the initial structure of their bond portfolios. More specifically, the composition of the bond portfolios (mix between corporate and government) and their average duration are assumed to remain

[12] To some extent, cross-bank differences in the sensitivity of loan loss ratios to changes in macroeconomic conditions capture unobserved differences in loan portfolio characteristics, which could be further investigated using more granular data (e.g. loan level data). In this paper, however, it is assumed that credit losses are estimated using portfolio level data. Note that in Eq. (3) coefficients other than fixed effects are common across banks; whether this should be the case, however, must be tested empirically and adjustments must be made if necessary.

unchanged over time.[13] Regarding cash balances, bank i targets a constant ratio of cash to deposits and other debt liabilities (m_i), according to Eq. 24.

The evolution of bank capital is given by Eq. 30, where the expression in square brackets is the retention ratio, div_i denotes the dividend payout ratio when bank profits are positive, and $\mathbf{1}_+(\Pi_{i,t})$ is an indicator function that takes the value 1 when profits are positive (and 0 otherwise).[14] External capital injections, as a ratio of risk-weighted assets, are captured by $kir_{i,t}$.

In addition to the main balance sheet items, Eq. 22 tracks the evolution of nonperforming loans (NPL_i); as noted above, this is necessary because only performing loans are assumed to earn interest income. Loan losses LL_i can be mapped into stocks of non-performing loans NPL_i only under specific assumptions about loan write-off activity—otherwise the relation is indeterminate. To visualize the full impact of stress on credit losses and non-performing loan ratios, Eq. 22 is derived under a zero loan write-off rate assumption in the projection period.[15]

[13] If banks do not continuously rebalance their bond portfolios, their remaining maturity would decline over time, until eventually all bonds mature. Thus, the implicit assumption in the model is that banks engage in reinvestment and trading to keep the composition and duration of bond portfolios constant.

[14] General model simulations assume that no capital injections or stock repurchases take place in the projection period. The impact of capital injections or surcharges is assessed in specific simulations discussed below.

[15] Note that (realized) loan losses and the evolution of non-performing loans (NPLs) are related through the following formula: $NPL_{i,t} = (1-\omega_{i,t}) \cdot NPL_{i,t-1} + PD_{i,t} \cdot \left(L_{i,t-1} - NPL_{i,t-1}\right)$, where $\omega_{i,t}$ is the loan write-off rate and $PD_{i,t}$ stands for the fraction of defaulting loans. Loan losses are given by: $LL_{i,t} = PD_{i,t} \cdot \left(L_{i,t-1} - NPL_{i,t-1}\right) \cdot LGD_i$, where LGD_i is the loss given default. Combining these equations, we obtain Eq. 22 in the model, which tracks the evolution of NPLs under a zero loan write off assumption ($\omega_{i,t} = 0$).

The variable "deposits and other debt liabilities" (D_i) acts as a residual and adjusts to ensure that the balance sheet identity (Eq. 20) is satisfied. Figure 2 illustrates how the components of the balance sheet would adjust to generate deleveraging. First, macroeconomic shocks reduce bank profitability through various channels: lower economic growth increases non-performing loans and triggers loan losses; net interest income declines because loan defaults reduce interest income and higher costs of funding increase interest expenses; and higher yields reduce the valuation of securities portfolios. Second, banks respond by cutting gross loans and repaying debt liabilities; cash balances also decline to maintain cash-to-debt ratios constant.

Aggregation

Gross aggregate bank lending in nominal terms (L) results from aggregation of bank-specific lending decisions (Eq. 32). The aggregate nominal lending rate (i^L) is calculated as a weighted average of bank specific lending rates (i_i^L), where the weights are given by the ratio of individual banks' performing loans to the total amount of performing loans in the banking system (Eq. 33).

Case of "Quasi-static" Bank Balance Sheet Growth

In the framework above, banks adjust their balance sheets in a differentiated and "dynamic" manner, according to Eq. 4. To perform simulations under a "quasi-static" bank balance sheet growth assumption, Eq. 4 should be replaced by $\Delta \ln L_{i,t} = \Delta RGDP_t + INF_t$ for all i. In this case, the stock of gross loans for each bank grows at the rate of nominal GDP so that aggregate lending remains unchanged as a percentage of GDP.[16]

Individual Bank Contributions to Systemic Risk

The contribution of bank *i* to systemic risk along the time dimension is quantified by comparing results when a *dynamic* balance sheet assumption is imposed on all banks (including bank *i*) against results obtained when only bank *i* adjusts its balance sheet *quasi-statically*. More precisely, the benchmark where all banks adjust their balance sheets dynamically is compared to the case where bank *i* lending behavior is given by $\Delta \ln L_{i,t} = \Delta RGDP_t + INF_t$ while the lending behavior of all other banks ($j \neq i$) is described by Eq. 4.

III. Taking the Model to the Data: Numerical Parameterization and Stress Simulation

Two steps are required to operationalize the framework. The first step consists of assigning numerical values to parameters and initial conditions; the second step consists of simulating macro-financial stress triggered by the realization of adverse shocks.

Numerical Parameterization

Coefficients in Eq. 1 are estimated using standard VAR regression techniques, while those in Eqs. 2-5 are estimated using dynamic panel data techniques.[17] Other parameters in the model

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[16] Under a "static" balance sheet growth assumption $\Delta \ln L_{i,t} = 0$ for all i. Static or quasi-static assumptions are common in stress tests implemented by policy institutions in the U.S. and Europe, as well as in stress tests performed under the IMF Financial Sector Assessment Program (FSAP).

[17] In country applications, the credit risk block can be defined using the loan loss rate (LLR_i) or the non-performing loans ratio ($NPLR_i$) as the dependent variable in Eq. 3. The choice must be guided by the availability of historical data. In section IV, for the case of Indonesia, we estimated a model based on $NPLR_i$.

are calibrated to match the latest observed individual bank data available from Fitch (Bankscope), as described in Table 2.[18]

In Table 2, 8 of the 18 parameters measure durations of balance sheet items (dur) and related fractions of outstanding balances maturing in every quarter (π). These parameters are calibrated in two steps for portfolios of loans, government and corporate securities, and deposits and other debt liabilities.[19] First, Fitch reports on amounts maturing in the following time bands: "less than 3 months," "3 to 6 months," "1 to 5 years," and "longer than 5 years." Mid-point duration values are assigned to the different time bands (0.5 quarter for "less than 3 months"; 2.5 quarters for "3 to 6 months"; 12 quarters for "1 to 5 years"; and 30 quarters for "longer than 5 years") and used to calculate the portfolio duration parameter as a weighted average.

Second, the fraction of balances repricing every quarter is calculated as the inverse of the portfolio duration parameter: $\pi_i = (1/dur_i)$. Specifically, balances are assumed to mature at a constant quarterly rate π_i , and hence, the quarterly maturity structure of the loan portfolio is given by: π_i ; $\pi_i \cdot (1-\pi_i)$; $\pi_i \cdot (1-\pi_i)^2$; $\pi_i \cdot (1-\pi_i)^3$; .... Thus, it follows that the duration of the portfolio can be expressed as: $dur_i = \sum_{t=1}^{\infty} t \cdot \pi_i \cdot \left(1-\pi_i\right)^{t-1} = \left(1/\pi_i\right)$.

Bank-specific risk weights comprise 4 of the 19 parameters in Table 2. Fitch reports risk weighted asset amounts by asset portfolio type. Precise calibration of portfolio-level average

[18] The calibration of some parameters could be further refined by using more detailed supervisory information (unpublished). Likewise, the recovery values could be set to match country-specific publicly available information; for instance, the World Bank's doing business database provides estimates of recovery values and LGDs (loss given defaults) for a large set of countries.

[19] In the rest of the paragraph, super-scripts are omitted to emphasize the use of a common approach to calibration for different balance sheet items.

risk weights can therefore be determined—dividing for each portfolio the risk-weighted assets by the outstanding amount in the balance sheet. The calibration of three remaining parameters is straightforward: the fraction of checking deposits in total deposit and debt liabilities (ch_i) and the cash-to-debt ratio (m_i) are directly observed from the latest balance sheet data while the other net income to total assets ratio (Ξ_i) is calibrated based on average flows of "other net income" for the last 4 quarters.

But the calibration of four parameters merits further discussion. The interest rate pass-through parameters (ψ_i^G and ψ_i^{spr}) cannot be calibrated using Fitch data and must be determined by other means—such as country- and/or bank-specific empirical studies of interest rate pass-through. The simulations for Indonesia (section IV) assume pass-through parameters of 0.6.

Also, bank-specific LGD_i data is not reported by Fitch and must be assumed—but, if available, it could be obtained directly from supervisory sources in specific country applications. Finally, dividend payout rates are available from Fitch and could be used to calibrate the parameter div_i on a bank-by-bank basis. However, it is standard practice to conduct the stress tests under common dividend distribution assumptions. Such assumptions ensure that bank capital ratios under stress scenarios reflect losses rather than cross-bank differences in dividend payouts. In the simulations below, we assume a common dividend rate equal to 0.3.

Stress Simulations

The numerical stress simulations integrate the estimated blocks of equations with the rest of the model. For given parameter values, initial conditions, and sequences of adverse macroeconomic structural shocks (applied in the SVAR block) and bank-specific cost of funding shocks, a stress simulation solves for consistent paths of macroeconomic and bank-specific variables that satisfy all the equations of the model (Appendix I).

Note that a stress simulation solves *simultaneously* for bank-specific and macroeconomic outcomes, ensuring micro-to-macro consistency. Thus, in CREAM, there is no sequential separation between the scenario design and bank stress calculation steps. Such separation is only feasible if financial-to-macro feedbacks are ignored, as is common in standard stress testing exercises.[20]

Appendix II describes the stress simulation algorithm. The algorithm is flexible and can accommodate different types of bank lending behavior. It can be used to compute "quasi-static" solutions where all banks behave quasi-statically; "dynamic" solutions where all banks behave dynamically; or "mixed" runs where some banks behave dynamically while others follow quasi-static behavior. As noted in section II, particular cases of mixed runs can be used to measure individual bank contributions to systemic risk. In country-specific applications, such as the one presented in Section IV, we conduct the four types of simulations shown in the Table below.

Simulation	Model-based (iterated/consistent) ?	Bank Behavior
Dynamic	Yes	Dynamic for all banks
Quasi-static	Yes	Quasi-static for all banks
Initial	No	Quasi-static for all banks
Mixed (Bi-QS)	Yes	Quasi-static for bank i Dynamic for all other banks

[20] A significant drawback of stress tests based on ad-hoc balance sheet growth assumptions is that ex-post outcomes for banks, once aggregated, do not coincide with assumptions made at the scenario design stage.

The simulation labeled “Initial” essentially replicates the sequential and quasi-static stress testing approach commonly used in policy institutions. A multi-year scenario is constructed, and then bank stress tests are performed based on these scenarios. There is an ex-post inconsistency between banks’ desired lending responses and the availability of credit assumed under the initial adverse scenario, and there is no account of macro-financial loops in the simulation. To highlight these inconsistencies, we include paths for aggregate lending and lending rates in the “initial” scenarios shown in Section IV. (By doing so, this scenario can also be used to kick-start iterated simulations that exhibit ex-post consistency under the model.)

In the “Dynamic” and “Quasi static” simulations, macroeconomic and bank-specific results are outcomes of the analysis, ex-post consistency between aggregate and bottom-up lending behavior is ensured by application of the model, and *all* banks exhibit dynamic or quasi-static behavior. In mixed simulations labeled $Bi-QS$, an individual bank i is the only bank that behaves quasi-statically, while all other banks exhibit dynamic lending behavior.

IV. COUNTRY APPLICATION: INDONESIA

This section applies the framework described in sections II and III to the case of Indonesia. Quarterly macroeconomic data series are obtained from various sources and span from 1990:Q1 to 2018:Q2, covering both the Asian and the global financial crises. Banking data is

obtained from Fitch (Bankscope). The dynamic panel regressions cover the entire banking system (118 banks) and are performed using quarterly data from Q1:2001 to Q1:2015.
The stress simulation analysis is performed on 12 small and large banks that jointly account for 70 percent of the banking system's assets. Details on data sources are presented in Appendix III.
Subsection A presents a baseline macroeconomic scenario and an "initial adverse scenario." Subsection B presents the estimates of dynamic panel models for the bank credit risk and lending blocks. Subsection C contains the main empirical results for the CREAM application to Indonesia, including the stress simulation analysis and the assessment of individual banks' contributions to systemic risk.

A. Baseline and "Initial Adverse Scenarios"

Impulse Responses

Figures 3 and 4 show impulse responses of macroeconomic variables to single structural shocks obtained from a VAR model that includes equations for aggregate credit (L^R) and the lending rate (i^L). The impulses consist of one standard deviation (positive) structural shocks that are applied for one quarter and trigger endogenous dynamic responses of macroeconomic variables spanning over 20 quarters. Figures 3 and 4 also depict confidence bands corresponding to (.16,.84) intervals. The following observations are noteworthy:

- A shock to real GDP of Indonesia's main trading partners (U.S., China, and the EU) triggers an increase in commodity prices due to high intensity of commodity demand from these economies. Increased demand for Indonesian exports boosts domestic real GDP and appreciates the rupiah in real terms. Inflation declines, possibly reflecting pass-through from a nominal appreciation of the rupiah, while the policy interest rate adjusts downward.

- Similarly, a positive shock to commodity prices boosts domestic real GDP, since Indonesia is a commodity exporter (e.g. palm oil, natural gas, coal).
- A positive shock to the U.S. federal funds rate reduces Indonesian real GDP, as the rise in interest rate differentials triggers capital outflows and a depreciation of the rupiah in nominal and real effective terms.
- In response to a positive shock to domestic real GDP, inflation rises with the policy interest rate following suit.
- Importantly, the banking sector plays a crucial role in the transmission of shocks. For instance, the real GDP expansion associated with stronger demand for Indonesian exports is fueled by expansion of bank lending—at a much faster rate than real GDP—and reduced lending rates.
- Note that a positive shock to the lending rate triggers a decline in real bank credit and GDP; it can thus be interpreted as an adverse credit supply shock. On the other hand, a positive shock to real bank credit triggers an increase in the lending rate—consistent with a positive shock to credit demand.[21]

Baseline and Initial Adverse Scenarios

Table 3 shows the structural shocks that jointly generate the (combined) responses presented in Figure 5. These responses are used to produce the "initial adverse scenario" that is presented in Table 4, along with the baseline scenario.

[21] In the stress simulations presented below, however, the market for bank credit is not a source of shocks and only acts as a conduit for the propagation of macroeconomic shocks (i.e., identification of credit supply and demand drivers is not a concern and lies beyond the scope of this paper).

Government bond yield series available for Indonesia are significantly shorter than other macroeconomic series; thus, we estimated a separate two-equation SVAR to evaluate the relationship between the domestic policy rate (i^0) and the 10-year government bond yield ($Y^{G,40}$).[22] The model was then used to compute the impulse response of $Y^{G,40}$ to a given shock in i^0. Due to the lack of sufficiently long data series for Indonesian corporate bond yields, we assumed that corporate yields follow the movements of government yields amplified by 30 percent, i.e., a 100 basis point (parallel) shift in the government yield curve results in a 130 basis point shift in the corporate yield curve. The amplification parameter can be varied to assess the robustness of results to this assumption.[23]

B. Dynamic Panel Estimates

Table 6 (a) presents results for the dynamic panel model of credit risk. The logistic transformation of bank non-performing loan ratios ($NPLR_i$) is regressed on lags of the dependent variable, macroeconomic variables, and bank-specific capital ratios. In Table 6 (a), lagged coefficients of explanatory variables are added up to simplify the interpretation of results.

The determinants have the expected effects on non-performing loan ratios. The signs of estimated coefficients indicate that slower real GDP growth or increases in the policy interest

[22] This SVAR was estimated using quarterly data for the period 2004:Q1 to 2018:Q3, with interest rates calculated as averages of monthly observations within each quarter. The specification contains two lags and the deterministic part includes a constant and a linear trend.

[23] The iteration algorithm described in Appendix II relies on impulse responses of 10-year government yields ($Y^{G,40}$) and short- and 10-year corporate bond yields ($Y^{C,0}$ and $Y^{C,40}$) to shocks in the policy rate (i^0). We estimated the impulse responses of $Y^{G,40}$ but had to impose ad-hoc assumptions on the responses of the corporate rates as data on these rates are unavailable in Indonesia. Specifically, for the short and long corporate rates ($Y^{C,0}$ and $Y^{C,40}$), the responses are 1.3 times the responses of the corresponding government bond rates.

rate lead to higher $NPLR_i$; also, higher bank-specific capital ratios (CAR_i) are associated with lower $NPLR_i$.

Note that the model exhibits non-linearities due to the logit transformation applied to $NPLR_i$ and the presence of a quadratic real GDP growth term. The non-linear features of the model imply that estimated elasticities of $NPLR_i$ with respect to changes in macroeconomic determinants vary depending on initial conditions—increasing as $NPLR_i$ rises and $\Delta RGDP$ declines. Table 6 (b) reports selected elasticities calculated for different initial conditions.

Table 7 presents results for the dynamic panel model of bank lending. The estimates correspond to an augmented autoregressive distributed lag (ARDL) framework, which was first proposed in a panel data context by Pesaran and Smith (1995) and Pesaran (2006). The model separates the determinants of bank lending that affect the long-run growth path from those that only influence the transitional dynamics around this path and was applied to Indonesia banking data by Catalán, Hoffmaister, and Harun (2019).[24]

C. Accounting for Macrofinancial Feedback Loops: Results

Macroeconomic Outcomes and Bank Stress Tests Results

Figure 6 depicts the numerical paths of macroeconomic variables under "Initial", "Dynamic," and "Quasi-static" simulations. Figure 7 presents the evolution of aggregate bank balance

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[24] In the regression, bank capitalization is measured as the amount of capital that a bank holds in excess of its minimum regulatory requirements ("capital ratio distance" or *CARD*). The data details the minimum capital requirements prevailing for each bank over time and thus captures the complexities and shifts in regulatory regimes during the sample period. Banks are currently subject to a minimum common equity tier 1 capital ratio (CET1) (4.5 percent) and a total capital ratio (8 percent). In addition, all banks must hold capital to cover a capital conservation buffer that is defined in terms of CET1 and Pillar II add-ons ranging from 1 to 3 percentage points that are expressed in terms of total capital. Finally, four categories of domestic systemically important banks are subject to capital surcharges (equivalent to 1, 1.5, 2, and 2.5 percent of CET1 capital). The capital requirement measure used in this paper incorporates not only the common minimum total capital-to-risk weighted assets ratio of 8 percent, but also the bank-specific Pillar II add-on.

sheet items, profits, and selected financial ratios under the different simulations. Figure 8 compares the evolution of aggregate bank balance sheets under the quasi-static and dynamic simulations, highlighting the extent of deleveraging that takes place in the latter simulation.

The “Initial” simulation reflects the one-way impact of the initial adverse macroeconomic scenario on banks. It assesses the ability of banks to withstand stress without deleveraging given that bank balance sheets grow in line with nominal GDP. In this simulation, there is an ex-post inconsistency between the bottom-up and aggregate paths of credit because nominal GDP growth significantly outpaces the nominal credit growth projected under the scenario. (Note that for the “Initial” simulation, Figure 6 shows the real stock of loans projected under the scenario—not the one resulting from a bottom-up aggregation of bank loans.)

In contrast, in the “Quasi-static” and “Dynamic” simulations, the aggregate credit paths are consistent with individual bank lending behaviour. This consistency is achieved by explicitly accounting for macro-financial feedback loops.[25] Figure 6 shows how bank deleveraging amplifies the impact of weaker trading partners’ activity, adverse terms of trade shocks, and higher world interest rates on the domestic economy: the paths of real GDP and stock of loans are lower in the “Dynamic” than in the “Quasi-static” simulation. The contractionary effect of deleveraging on activity, however, is cushioned by its effects on interest rates: lending and policy rates, and corporate and government bond yields are lower in the “Dynamic” than in the “Quasi-static” simulation.

[25] As discussed in Appendix II, the initial adverse macro scenario is revised to reflect the bottom-up aggregation of the lending rate and credit paths (bank lending responses to stress under the initial adverse scenario). In turn, this revised adverse scenario is used to re-compute bank-specific financials in a second-round iteration. These second-round bank-specific financials are then used to once again compute bottom-up credit and lending rate paths, further revise the adverse scenario, and re-compute bank financials in the third round. The iteration process continues until the paths of credit and the lending rate in the adverse macro scenario are consistent with those obtained from the bottom-up aggregation.

Note that there is a delayed and persistent response of real lending and the lending rate under the ”Dynamic” simulation relative to the “Initial” adverse scenario, and that these features of the responses are transmitted to the policy interest rate and to bond yields. Under the model, lending rates adjust gradually, reflecting the current composition and maturity structure of loan portfolios. Thus, the delayed response of lending and interest rates in the “Dynamic” simulation could reflect differences between the current and historical maturity structure of loan portfolios or changes in the share of loans with adjustable interest rates.[26]

Figure 7 compares the evolution of individual balance sheet and profit items under the different simulations, highlighting the role of deleveraging in the “Dynamic” simulation. Reflecting the stress-response adjustment mechanism described in Figure 2, the paths of loans, cash balances, and deposits and other debt are significantly lower in the “Dynamic” simulation than in the “Initial” and “Quasi-static” simulations. The valuations of securities portfolios mirror the differentiated paths of yields across simulations. In particular, market losses are larger in the “Quasi-static” than in the “Dynamic” case, and the wide fluctuations in yields under the “Initial” scenario result in significant market losses in the first 2 years and sharp market gains in the last three years.

In terms of profitability, deleveraging reduces both interest income on loans and interest expense on deposits and other debt—note that the paths of these items are significantly higher in the “Initial” and “Quasi-static” simulations than in the “Dynamic” simulation. Similarly, deleveraging mitigates the rise in total loan losses under the “Dynamic” simulation. And the valuations of securities portfolios reflect the dynamics of yields,

[26] The share of loans with adjustable interest rates is not reported in Fitch. Hence, we do not account for the presence of such loans in the simulations presented in this paper. It would be straightforward to adjust the framework to include them, if supervisory data were used as input and a proper calibration of bank-specific shares of adjustable rate loans in overall loan portfolios were feasible.

declining in the first 2-3 years of the stress scenario and increasing in the last 2-3 years, as yields decline.

The panel on selected financial ratios in Figure 7 shows that deleveraging initially helps banks cushion the impact of the adverse shocks on their capital adequacy ratios. However, as time evolves, second-round effects of widespread deleveraging on the economy materialize and are transmitted back to banks in the form of losses, with impact on capital ratios. Capital ratios are lower in the "Quasi-static" case than in the "Dynamic" case, as the additional credit provision assumed in the "Quasi-static" case requires higher levels of risk-weighted assets.

Figure 9 compares changes in capital adequacy ratios for individual banks under the three simulations discussed above to illustrate the heterogeneity of bank-specific results.

The top panel compares results corresponding to the "Dynamic" simulation against those obtained under the "Initial" and "Quasi-static" simulations. Capital adequacy ratio (CAR) changes are computed as differences between CAR values at the beginning and at the end of the 5-year projection period. A point above the 45-degree line indicates that the decline in a bank's CAR is smaller in the "Dynamic" than in the alternative simulation (initial or quasi-static). The middle panel, in turn, shows the results when CAR changes are computed as differences between CAR values at the outset of stress and the minimum values reached during the projection period.

The scatter plots show that some banks perform better in the "Dynamic" than in the "Initial" simulations, while others perform worse.

Also, "Quasi-static" stress tests results—obtained in a framework that ensures full consistency between macroeconomic and aggregated bottom-up conditions—are always dominated by "Dynamic" stress tests results—all points lie above the 45-degree line in the top-right and middle-right panels of Figure 9. This result confirms that all banks lend more in the quasi-static simulation and have higher levels of risk-weighted assets.

What is most important, however, is that explicitly accounting for macro-financial feedback loops can change the *relative* ordering of assessed vulnerabilities across banks. A bank that is deemed “resilient” under the standard approach to stress testing (“Initial” simulation) could be considered less resilient relative to other banks when evaluated under alternative behavioral assumptions. This fact is made explicit in the bottom panel of Figure 9, which compares bank rankings (from 1 to 12) across simulations based on CAR changes. (For example, a bank that ranks 2^{nd} in the “Initial” simulation ranks 1^{st} in the “Dynamic” simulation; a bank that ranks 9^{th} in the “Quasi-static” simulation ranks 6^{th} when evaluated in a “Dynamic” simulation.)

The key finding of our analysis is that accounting for macro-financial loops can affect the *cross-sectional pattern of stress tests results*. Increasing the severity of the ‘initial” adverse scenario by applying larger structural shocks would make all banks worse-off without changing the bank vulnerability ranking. Thus, this option cannot be considered an adequate substitute for macro-financial stress analysis that accounts for heterogeneous bank deleveraging.

Externalities Analysis

Figure 10 shows the effects of deleveraging by selected banks on macroeconomic outcomes. These outcomes are measured by deviations of real GDP, the real stock of credit, and the nominal policy interest rate from baseline projections. In particular, Figure 10 compares the “Dynamic” simulation results against those corresponding to a “Mixed ($Bi-QS$)” simulation in which bank i behaves quasi-statically while all other banks exhibit dynamic lending behavior. The analysis is performed for three large banks (numbered 1, 2, and 4) that offer loans at different lending rates.

Consider the macroeconomic effects of a credit expansion by Bank 1 (top panel of Figure 10). Bank 1 is characterized by offering loans at a lending rate that is well above the average for the system. As the bank is large, its initial action boosts aggregate lending, but it also increases the aggregate lending rate significantly. Once cross-bank externalities and macro-financial feedback effects are accounted for, the economy ends up with higher interest rates and yields that offset the expansionary effect on output of Bank 1's additional lending. The higher level of interest rates also exacerbates market losses and reduces the profitability of other banks, which contribute to nullify the expansionary effect on output of Bank 1's action.

In contrast, Bank 2's lending rate is close to the average for the system. The upward pressure on interest rates associated with Bank 2's credit expansion (middle panel of Figure 10) is less intense, and hence the output effect is larger than when Bank 1 expands credit.

Bank 4 is smaller (in terms of assets and loans) than Banks 1 and 2, but it provides credit at lending rates that are well below the average rate for the system. Therefore, despite its smaller size, the impact of its lending decisions on GDP is larger than that of Bank 1.

In the middle panel of Figure 10, the area A+B measures the 5-year cumulative loss of output in the "Dynamic" simulation, when all banks engage in deleveraging. The area A measures the cumulative loss of output when Bank 2 behaves quasi-statically and all other banks follow dynamic behavior. Thus, the area B (between the two red lines) is the 5-year cumulative loss of output associated with Bank 2 deleveraging. It follows that the contribution of each bank's deleveraging to the total decline in real GDP is measured by $B/(A+B)$.

Despite the fact that Banks 1 and 2 have a somewhat similar size (in terms of assets and credit), they differ in terms of *systemic importance*—the GDP impact of their lending decisions, as reflected in the $B/(A+B)$ measure.

The results illustrate a general principle. The systemic importance of a bank along the time dimension depends crucially on factors that include not only its size but also its exposures, the sensitivities of its exposures to shocks, its buffers, and the intensity of its behavioral responses to shocks in terms of both credit (quantity) and lending interest rate (price).

Figure 11 shows cross-bank externalities triggered by individual bank's deleveraging. Each panel presents the results for an individual bank under the "Dynamic" and 12 "Mixed ($Bi-QS$)" simulations—measured in terms of changes in CAR and real loan growth rates.

Consider the case of Bank 3. Under the dynamic simulation, Bank 3's loans decline by more than 30 percent in real terms and its CAR declines 7 percentage points (first pair of dots shown in the left-hand side). When Bank 3 is the only bank behaving quasi-statically ($B3-QS$ simulation), its lending expands 25 percent in real terms, with adverse impact on the bank's CAR, which now declines by 10 percentage points. Quasi-static behavior by Bank 1 generates a negative externality on Bank 3 ($B1-QS$ simulation), as Bank 3's capital ratio falls 9 percentage points (2 percentage points more than in the "dynamic" simulation). As the higher level of interest rates associated with Bank 1's quasi-static behavior adds stress on Bank 3, the latter bank cuts real lending by almost 40 percent, more aggressively than in the "Dynamic" run. Similarly, comparisons between the "Dynamic" run against the other mixed simulations capture the impact on Bank 3 from no deleveraging behavior in each of the other 11 banks. Banks are ordered from the largest to the smallest (within the group); in general, however, externalities reflect not only bank size (share of loans) but also the sensitivity of lending responses and other sources of cross-bank heterogeneity.

Finally, Figure 12 shows how individual banks' CARs are affected by their own lending decisions and by the collective lending decisions of other banks.

The declines in CARs of individual banks due to stress are smaller when all banks exhibit dynamic lending behavior (compared to the case of collective quasi-static lending behavior). Observe that a single bank would able to mitigate the impact of stress on its capital ratio by deleveraging individually when all other banks are behaving quasi-statically.

Note also that deleveraging by other banks mitigates the impact of stress on individual banks. As noted earlier, externalities associated with deleveraging are transmitted through various channels. And the quantitative analysis indicates that the negative externalities generated by other banks' deleveraging behavior, which reduced aggregate credit and output, are more than offset by the positive externalities stemming from the downward pressure on interest rates and bond yields. Overall, Figure 12 suggests that complementarity among banks' decisions can generate perverse dynamics where deleveraging by individual banks encourages other banks to cut lending as well.

Figure 13 compares the macroeconomic effects of the "Dynamic" simulation described above to those from a new simulation in which all banks receive capital injections equivalent to 3 percentage points of CAR over a two-year period (equally spread across 8 quarters). The effect of the capital injections on aggregate credit is significant but it takes time to materialize. The impact on other macroeconomic variables (e.g., output), however, is found to be modest and meaningful only with a significant time lag.

V. Concluding Remarks

This paper presents a general framework for empirical evaluation of macro-financial feedback loops and individual bank contributions to systemic risk along the time dimension. The credit response and externalities analysis model (CREAM) integrates a disaggregated banking sector into an otherwise standard macroeconomic structural vector autoregressive model. The systemic importance of a bank depends on its size, its exposures, the sensitivities of its exposures to shocks, its buffers, and its lending behavior. As the framework is sufficiently rich and embeds various sources of heterogeneity, it provides a platform for stress testing and calculation of systemic risk contributions.

In line with traditional approaches to stress testing, the framework disentangles the channels through which macroeconomic shocks impact bank losses. Separate estimates were made for three types of losses: credit (loan portfolios), market (securities portfolios), and net interest income, and were found to vary across banks. Also, and importantly, bank lending responses are heterogeneous and dependent on bank capitalization ratios.

The paper shows that accounting for heterogeneous bank deleveraging and macro-financial loops can affect the cross-sectional pattern of stress tests results. Country-specific applications of the framework can uncover the relevance of different types of bank heterogeneity and risk transmission channels for macroeconomic outcomes, cross-bank externalities, and stress tests results.

Table 1. Variables: Definitions and Notation[1]

Bank Balance Sheet and Financial ratios			
$A_{i,t}$	Total assets	$L^R_{i,t}$	Real stock of gross loans
$L_{i,t}$	Stock of gross loans	$NPL_{i,t}$	Stock of non-performing loans
$PR_{i,t}$	Provisions (stock)	$NPLR_{i,t}$	Ratio of non-performing loans to gross loans
$M_{i,t}$	Cash balance	$RWA_{i,t}$	Risk weighted assets
$B^G_{i,t}$	Government bonds	$LA_{i,t}$	Liquid assets
$B^C_{i,t}$	Corporate bonds	$CAR_{i,t}$	Capital adequacy ratio
$B^{G,HTM}_{i,t}$	Government bonds, held-to-maturity	$CARD_{i,t}$	Capital adequacy ratio (distance)
$B^{G,MTM}_{i,t}$	Government bonds, marked-to-market	$LATA_{i,t}$	Liquidity ratio
$B^{C,HTM}_{i,t}$	Corporate bonds, held-to-maturity	$LLR_{i,t}$	Loan loss ratio
$B^{C,MTM}_{i,t}$	Corporate bonds, marked-to-market	$\boldsymbol{x}_{i,t}$	Vector of bank ratios (capital, liquidity, and loan loss ratio)
$OA_{i,t}$	Other assets	$kir_{i,t}$	Ratio of external capital injections to risk weighted assets
$K_{i,t}$	Capital		
$D_{i,t}$	Deposits and debt securities		
Bank Profit and Loss			
$\Pi_{i,t}$	Total profit	$i^L_{i,t}$	Interest rate on loans
$II^L_{i,t}$	Interest income from loans	$i^{NL}_{i,t}$	Interest rate on new loans
$IE^D_{i,t}$	Interest expense on deposits and debt securities	$i^D_{i,t}$	Interest rate on deposits
$LL_{i,t}$	Loan losses	$i^{ND}_{i,t}$	Interest rate on new deposits
$R^G_{i,t}$	Return on government bond portfolio	$i^G_{i,t}$	Current yield on government bonds
$R^C_{i,t}$	Return on corporate bond portfolio	$i^C_{i,t}$	Current yield on corporate bonds
$O_{i,t}$	Other net profit	$spr_{i,t}$	Funding (credit) spread
Aggregate Variables			
$\tilde{\boldsymbol{z}}_t$	Vector of macroeconomic variables (transformed)[2]	$\tilde{\boldsymbol{f}}_t$	Vector of aggregate banking variables (transformed)[2]
$\boldsymbol{z}_t$	Vector of macroeconomic variables (non-transformed)	$\tilde{\boldsymbol{f}}$	Vector of aggregate banking variables (non-transformed)
$RGDP^*_t$	Real GDP of trading partners	L^R_t	Real aggregate stock of gross loans in the banking system
P^{COMM}_t	Commodity prices	i^L_t	Nominal lending interest rate in the banking system (average)
i^{US}_t	Nominal policy interest rate in the US	L_t	Nominal aggregate stock of gross loans in the banking system
$RGDP_t$	Real GDP	P_t	Price level
$REER_t$	Real effective exchange rate	$\boldsymbol{ir}_t$	Vector of domestic interest rates
INF_t	Inflation rate	$Y^{G,40}_t$	Long-term government bond yield (10 years or 40 quarters)
i^0_t	Nominal policy interest rate	$Y^{C,0}_t$	Short-term corporate bond yield
		$Y^{C,40}_t$	Long-term corporate bond yield (10 years or 40 quarters)

Notes. 1/ With the exception of bank-specific ratios, all variables are expressed in nominal terms, unless otherwise indicated with the label "real"; yields, interest rates and funding (credit) spreads are expressed in annual (nominal) terms; the inflation rate is expressed as a quarterly rate.
2/ All aggregate variables except for interest rates and inflation are expressed in logs.

Table 2. Notation and Numerical Calibration of Bank-specific Parameters

Calibrated Parameters		
Symbol	Definition	Source
ψ_i^G	Pass-through of changes in government bond yields to lending interest rates (Eq. 13)	Set at 0.6 for all banks.
ψ_i^{spr}	Pass-through of cost of funding spread to lending interest rates (Eq. 13)	Set at 0.6 for all banks.
dur_i^L	Duration of loan portfolio (Eq. 13)	The duration parameter is calculated from data on remaining time-to-maturity structure of bank loan portfolios reported by Fitch. The duration parameter is then used to calculate the fraction, of loans in the portfolio that (on average) are repriced every quarter. For further details, see the footnote.[2/]
π_i^L	Fraction of loan portfolio repricing every quarter (Eq. 12)	
dur_i^D	Duration of debt and deposit liabilities (Eq. 16)	The parameters corresponding to duration and fraction of debt and deposits repricing every quarter are calculated in a similar manner as those corresponding to loan portfolios (see footnote 2).
π_i^D	Fraction of debt and deposit liabilities repricing every quarter (Eq. 15)	
Ξ_i	Other net income to total assets (Eq. 19)	Set to match the average of the last 4 quarters. Other income is calculated as follows: Dividend Income + Net Insurance Income + Net Fees and Commissions + Other Operating Income - Personnel Expenses - Other Operating Expenses - Securities and Other Credit Impairment Charges + Non-recurring Income - Non-recurring Expense + Change in Fair Value of Own Debt + Other Non-operating Income and Expenses - Tax expense + (Conprehensive - Net income).
LGD_i	Loss given default (Eq. 22)	Set to be constant at 0.5 for all banks.
m_i	Cash-to-debt ratio (Eq. 24)	Set to match the last observation. The cash balance includes the following items: cash and dues from banks, reverse repos and cash collateral, and loans and advances to other banks.
dur_i^G	Duration of government securities portfolio (Eq. 26)	The parameters corresponding to duration and fraction of government securities repricing every quarter are calculated in a similar manner as those corresponding to loan portfolios (see footnote 2).
π_i^G	Fraction of government securities portfolio repricing every quarter (Eq. 27)	
dur_i^C	Duration of corporate securities portfolio (Eq. 26)	The parameters corresponding to duration and fraction of corporate securities repricing every quarter are calculated in a similar manner as those corresponding to loan portfolios (see footnote 2).
π_i^C	Fraction of corporate securities portfolio repricing every quarter (Eq. 27)	
div_i	Dividend distribution ratio (Eq. 30)	Set to be constant and equal to 0.3 for all banks.[3/]
Θ_i^L	Risk weight of loans (Eq. 31)	The parameters reflect portfolio averages. They are calculated as ratios of reported risk weighted assets for each type of asset portfolio divided by the size of the corresponding portfolio.
Θ_i^G	Risk weight of government securities (Eq. 31)	
Θ_i^C	Risk weight of corporate securities (Eq. 31)	
ρ_i^{ORWA}	Share of other risk weighted assets in total risk weighted assets (Eq. 31)	Set to match the last observation.

Notes. 1/ For each bank, parameters are calibrated based on data available from Fitch (Bankscope).
2/ First, Fitch reports loan amounts maturing in time bands: "less than 3 months", "3 to 6 months", "1 to 5 years", and "longer than 5 years." A mid-point duration value is assigned to each time band (0.5 quarter for "less than 3 months"; 2.5 quarters for "3 to 6 months"; 12 quarters for "1 to 5 years", and 30 quarters for "longer than 5 years") and these values are used to calculate the loan portfolio duration parameter as a weighted average. Second, the fraction of loans repricing every quarter is calculated as the inverse of the loan portfolio duration parameter: $\pi_i^L = (1/dur_i^L)$. Specifically, if loans mature at a constant quarterly rate π_i^L, the quarterly maturity structure of the loan portfolio is given by: $\pi_i^L;\ \pi_i^L \cdot (1-\pi_i^L);\ \pi_i^L \cdot (1-\pi_i^L)^2;\ \pi_i^L \cdot (1-\pi_i^L)^3;\ \ldots$.

The duration of the portfolio is then given by: $dur_i^L = \sum_{t=1}^{\infty} t \cdot \pi_i^L \cdot \left(1-\pi_i^L\right)^{t-1} = \left(1/\pi_i^L\right)$.

3/ Historical bank dividend payout rates vary across banks. However, forward-looking stress analysis is carried out under common payout rates to eliminate the impact of differentiated profit retention rates on capital ratios and stress tests results. With differentiated payout rates, capital ratios are not fully accounted for by losses associated with shocks and their transmission, which hampers the cross-bank comparability of stress tests results.

Table 3. Indonesia—Structural Macroeconomic Shocks

(in standard deviations)

Quarter	$RGDP^*$	P^{COMM}	i^{US}	i^L	L^R	$RGDP$	INF	$REER$	i^0
1	-2.50	-1.50	2.00	0	0	-0.50	0	0	0
2	-2.00	-0.75	1.50	0	0	-0.75	0	0	0
3	-1.50	-0.50	1.00	0	0	-1.00	0	0	0
4	-0.50	-0.25	0.50	0	0	-0.50	0	0	0
5	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0

Table 4. Indonesia—Paths of Macroeconomic Variables Under the "Initial Adverse" Scenario

(in percent, unless otherwise indicated)

		Paths in Stress Period				
	2017	2018	2019	2020	2021	2022
Real GDP growth						
Baseline	5.1	5.3	5.5	5.6	5.6	5.6
Initial adverse	5.1	4.6	0.6	1.8	5.6	7.8
Inflation, y-o-y change						
Baseline	3.8	3.4	3.7	3.7	3.6	3.6
Initial adverse	3.8	4.0	9.6	12.8	3.4	-1.0
Real effective exchange rate index (2014=100)						
Baseline	100.0	94.2	94.0	94.0	94.0	94.0
Initial Adverse	100.0	92.1	77.2	78.5	88.6	94.0
Nominal effective exchange rate, y-o-y change						
Baseline	-0.4	-6.7	-1.1	-1.2	-1.4	-1.5
Initial adverse	-0.4	-10.1	-23.7	-9.6	11.4	9.2
Nominal interest rate (BI policy rate), percent per annum						
Baseline	4.5	5.0	5.3	5.3	5.3	5.3
Initial adverse	4.5	5.7	11.6	12.4	5.7	2.2
International interest rate (Fed Funds Rate)						
Baseline	1.0	2.0	3.1	3.7	3.2	2.9
Initial adverse	1.0	2.3	4.7	5.6	4.7	3.8
Trading partners' growth						
Baseline	8.4	4.9	5.8	5.7	5.7	5.7
Initial adverse	8.4	3.6	1.8	6.5	6.4	6.0
Commodity prices (2007=100)						
Baseline	113.5	130.5	131.5	131.5	131.5	131.5
Initial adverse	113.5	114.6	71.5	90.0	108.2	118.7
Real bank credit to the private sector growth						
Baseline	3.7	5.2	5.0	5.3	5.3	5.3
Initial adverse	3.7	3.0	-9.5	-22.7	-20.6	12.3
Nominal bank credit to the private sector growth						
Baseline	7.5	8.5	8.6	9.0	8.9	8.9
Initial adverse	7.5	7.0	0.1	-9.8	-17.2	11.3
Bank lending rate						
Baseline	11.1	10.5	10.5	10.5	10.5	10.5
Initial adverse	11.1	10.8	13.1	13.8	11.1	8.7

Note. The model is not used to produce baseline quarterly paths. These reflect projections in the 2017 *World Economic Outlook*. Impulse responses are used to produce quarterly paths for the "initial adverse scenario." The quarterly paths are then used to generate the annual numbers presented in the Table.

Table 5. Indonesia—Bank-specific Cost of Funding Shocks

(annual rates)

Horizon (quarters)	Bank												
	1	2	3	4	5	6	7	8	9	10	11	12	13
1	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025
2	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013
3	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006
4	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
5	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
6	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
7	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
10	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
11	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
15	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
16	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
17	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
18	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
19	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
20	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 6. Indonesia—Bank Credit Risk Block: Dynamic Panel Estimates

a) Regression results

Dependent variable: $\ln\left(\frac{NPLR_{i,t}}{1-NPLR_{i,t}}\right)$	Lags included: s	Sum of coefficients	F-statistic	Marginal significance
Lagged dependent variable				
NPL ratio, logit transformation: $\ln\left(\frac{NPLR_{i,t-s}}{1-NPLR_{i,t-s}}\right)$	1 to 2	0.85		
Macroeconomic variables				
Real GDP growth: $\Delta RGDP_{t-s}$	2 to 5	-12.33	14.08	0.000
Real GDP growth squared: $\Delta RGDP^2_{t-s}$	2 to 5	105.05	2.20	0.066
Change in the nominal policy interest rate: Δi^0_{t-s}	2 to 5	3.52	5.38	0.000
Bank-specific variables				
Capital adequacy ratio: $CAR_{i,t-s}$	4	-0.16	-2.04	0.041
R-squared		0.85		
Number of observations		5,497		

b) Elasticities of the non-performing loan ratio with respect to changes in macroeconomic variables

Long-run elasticity with respect to a permanent 1 percentage point change in quarterly (annual) rates of:	$NPLR_i$ = 0.02	$NPLR_i$ = 0.05
Real GDP growth:		
when initial $\Delta RGDP = 0.01$	-1.3 (-0.3)	-3.2 (-0.8)
when initial $\Delta RGDP = 0.00$	-1.6 (-0.4)	-3.9 (-1.0)
Change in the nominal policy interest rate: Δi^0_{t-s}	0.46 (0.11)	1.11 (0.28)

Notes. 1/ Estimates in (a) correspond to regressions that include bank-specific fixed effects (not reported). Model estimates are summarized by the sum of each regressor's coefficients. The F-statistic corresponds to the null hypothesis that all the coefficients for a specific regressor equal zero. The marginal significance indicates the statistical significance level for which the null hypothesis is rejected; for instance, rejecting the null at a 5 percent level requires the marginal significance to be less than 0.05. 2/ Let β^1_l and β^2_l denote the regression coefficients for different lags l corresponding to the regressors $\Delta RGDP$ and $\Delta RGDP^2$ respectively and let λ_1 and λ_2 denote the coefficients corresponding to the lagged dependent variable terms included as regressors. The long-term elasticity of the $NPLR_i$ with respect to a one percentage point increase in the *quarterly* rate of real GDP growth is calculated as follows:

$$\frac{\partial NPLR_{i,\infty}}{\partial \Delta RGDP} = \left[\left(\sum_{l=2}^{5}\beta^1_l\right) + 2\cdot\left(\sum_{l=2}^{5}\beta^2_l\right)\cdot \Delta RGDP\right]\cdot\left(NPLR_i\right)\cdot\left(1-NPLR_i\right)\cdot\left(\frac{1}{1-\lambda_1-\lambda_2}\right).$$

By dividing the previous expression by 4, we obtain the long-term elasticity of $NPLR_i$ with respect to a one percentage point increase in the *annual* rate of real GDP growth—shown in parentheses in (b). Similarly, the long-term elasticity of $NPLR_i$ with respect to a one percentage point increase in the policy interest rate in each quarter is given by $\frac{\partial NPLR_{i,\infty}}{\partial \Delta i^0} = \left(\sum_{l=2}^{5}\beta^3_l\right)\cdot\left(NPLR_i\right)\cdot\left(1-NPLR_i\right)\cdot\left(\frac{1}{1-\lambda_1-\lambda_2}\right)$, where β^3_l are the regression coefficients corresponding to Δi^0.

Table 7. Indonesia—Bank Lending Block: Dynamic Panel Estimates

Dependent variable: Real loan growth: $\Delta \ln L^{R}_{i,t}$	Lags included: s	Sum of coefficient estimates	Hypothesis tests: Sum equals zero (p-value)	Hypothesis tests: Exclusion test (p-value)
Short-run dynamic effects				
Lagged dependent variable				
Real loan growth: $\Delta \ln L^{R}_{i,t-s}$	1 to 4	**0.302**	12.9 (0.00)	57.8 (0.00)
Change in bank specific fundamentals				
Change in non-performing loan ratio: $\Delta NPLR_{i,t-s}$	1 to 5	**-0.667**	-4.5 (0.00)	8.5 (0.00)
Change in liquid assets ratio: $\Delta LATA_{i,t-s}$	1 to 5	**-0.024**	-1.0 (0.32)	0.3 (0.93)
Change in capital ratio distance: $\Delta CARD_{i,t-s}$	1 to 5	**-0.437**	-3.6 (0.00)	5.4 (0.00)
Change in capital ratio distance squared: $\Delta CARD^{2}_{i,t-s}$	1 to 5	**0.026**	0.3 (0.75)	1.1 (0.35)
Change in macroeconomic variables (common effects)				
Change in policy rate: Δi^{0}_{t-s}	0 to 4	**-0.690**	-1.8 (0.07)	5.3 (0.00)
Change in real GDP growth: $\Delta RGDP_{t-s} - \Delta RGDP_{t-s-1}$	0 to 4	**-6.833**	-2.2 (0.03)	16.8 (0.00)
Change in inflation rate: ΔINF_{t-s}	0 to 4	**-2.918**	-3.4 (0.00)	14.6 (0.00)
Long-run effects				
Bank-specific				
Non-performing loan ratio: $NPLR_{i,t-1}$	1	**-0.076**	-2.3 (0.02)	5.1 (0.02)
Liquid assets ratio: $LATA_{i,t-1}$	1	**0.033**	4.8 (0.00)	22.6 (0.00)
Capital ratio distance: $CARD_{i,t-1}$	1	**0.193**	7.0 (0.00)	49.4 (0.00)
Capital ratio distance squared: $CARD^{2}_{i,t-1}$	1	**-0.082**	-4.3 (0.00)	18.6 (0.00)
Macroeconomic (common)				
Real GDP growth: $\Delta RGDP_{t}$	0	**5.266**	5.3 (0.00)	27.9 (0.00)
Adjusted R^2		0.152		
Standard error of the regression		0.113		
Number of observations		5,863		

Note. Estimates correspond to fixed effects and are based on an unbalanced panel of quarterly data from 2001:Q1 to 2015:Q1 for 118 banks operating in Indonesia at end-2015. The estimated augmented ARDL models contain the contemporaneous and lagged observations for the regressors as indicated; with the exception of the long-run effect of regressors, coefficient estimates have been summarized by their sum. In this regard, two null hypothesis tests are reported for each regressor: (1) the sum of coefficients equals zero, and (2) every coefficient equals zero. In all cases, the null hypothesis is rejected at the 5 (10) percent significance level whenever the p-value (marginal significance level) is less than 5 (10) percent.

Figure 1. Macrofinancial Feedback Loops

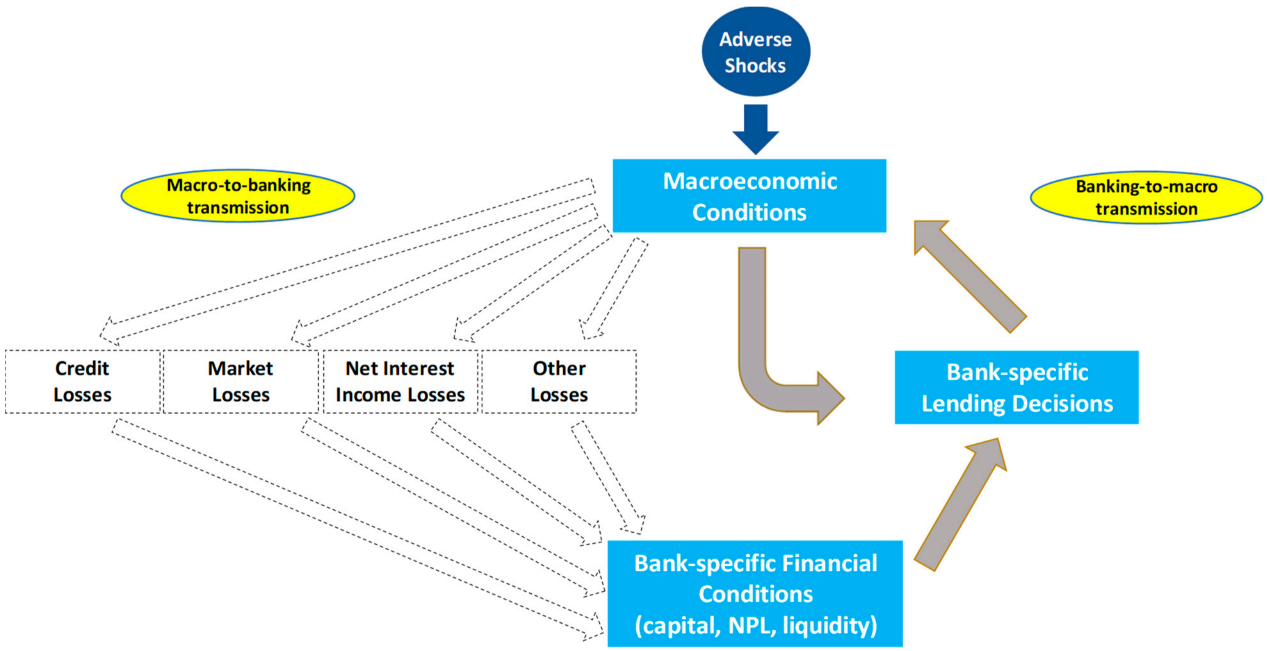


Figure 2. Bank Stress-Response Diagram

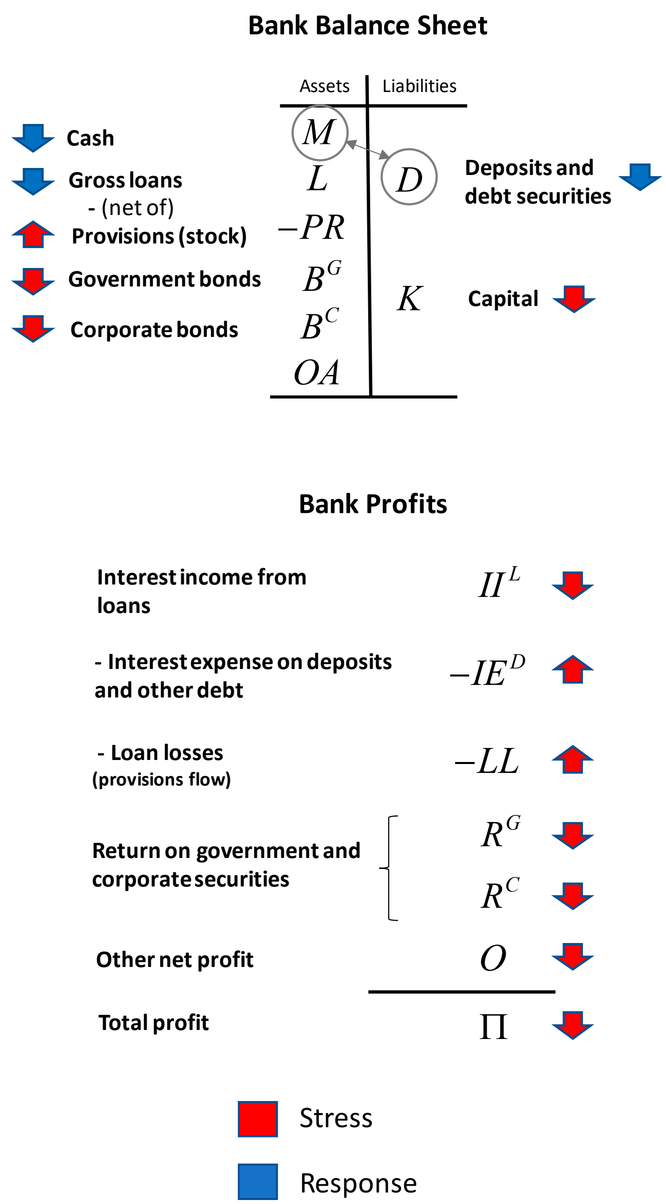


Figure 3. Indonesia—Impulse Responses of External Variables: Unconditional (2 lags)

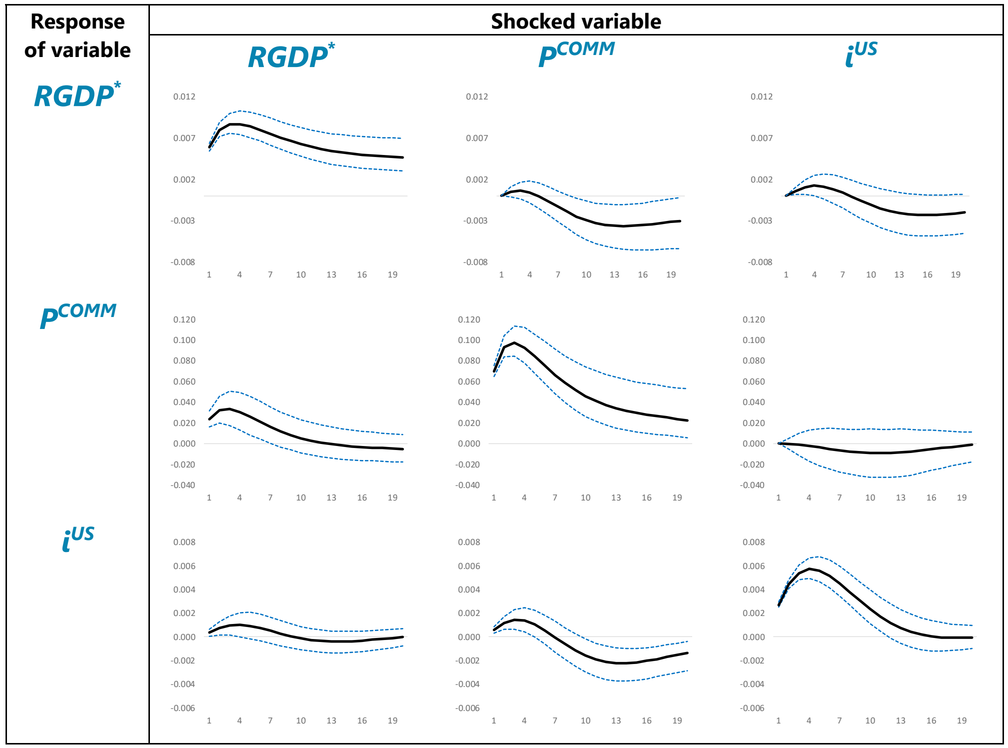


Figure 4. Indonesia—Impulse Responses of Domestic Variables: Unconditional (2 lags)

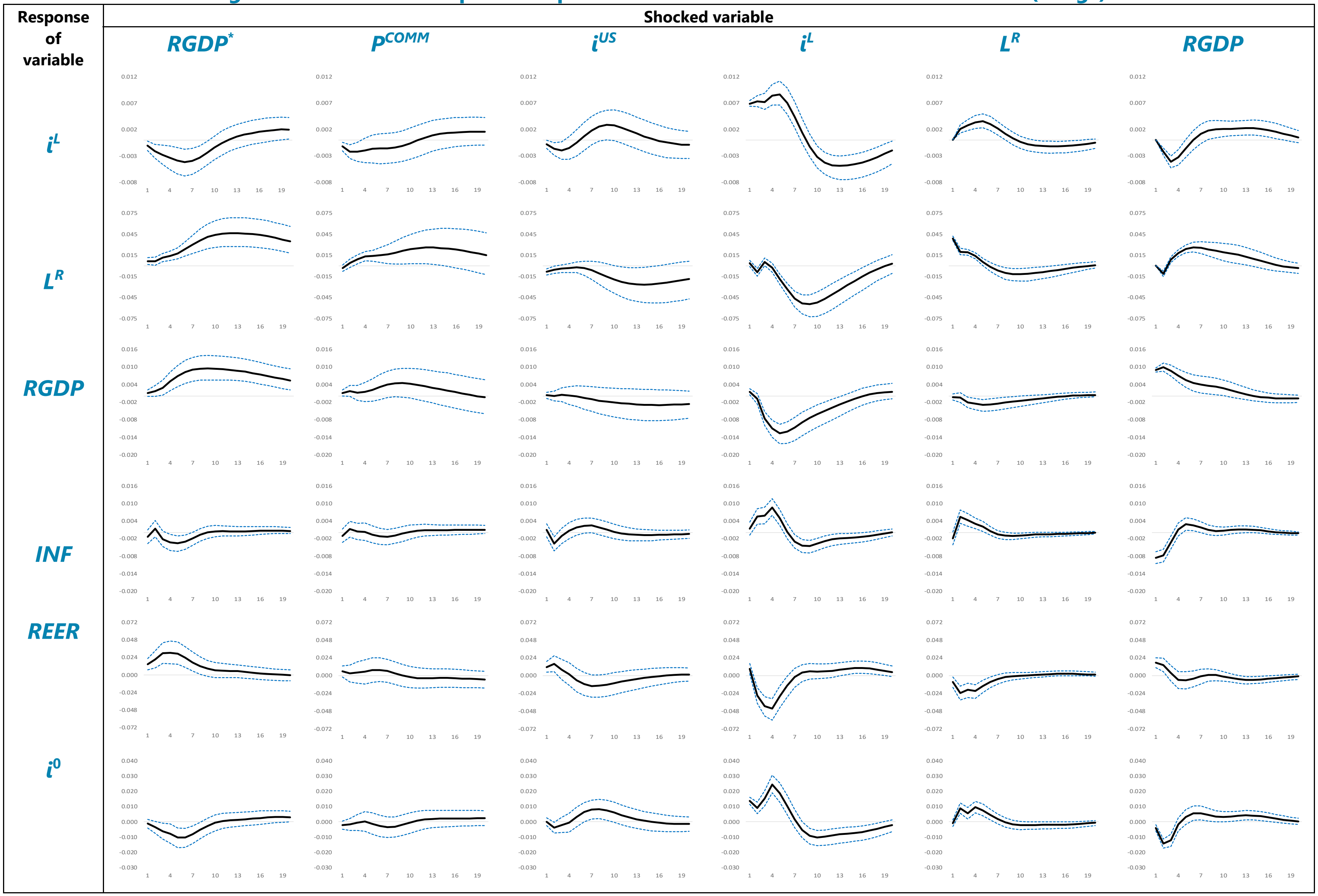


Figure 5. Indonesia—Responses of External and Domestic Macroeconomic Variables to Combined Structural Shocks

(responses to shocks presented in Table 3)

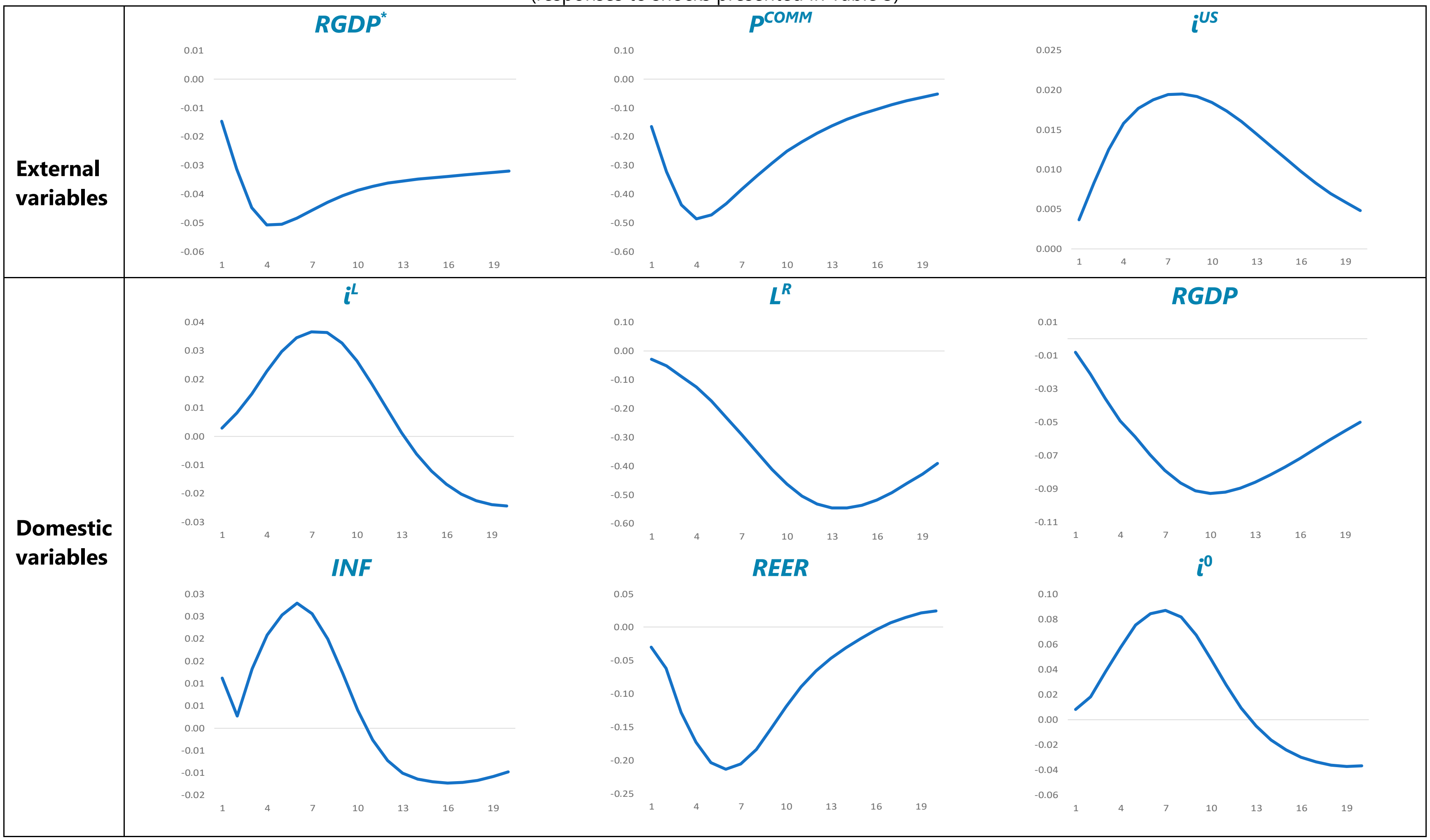


Figure 6. Indonesia—Stress Simulation: Macroeconomic Results

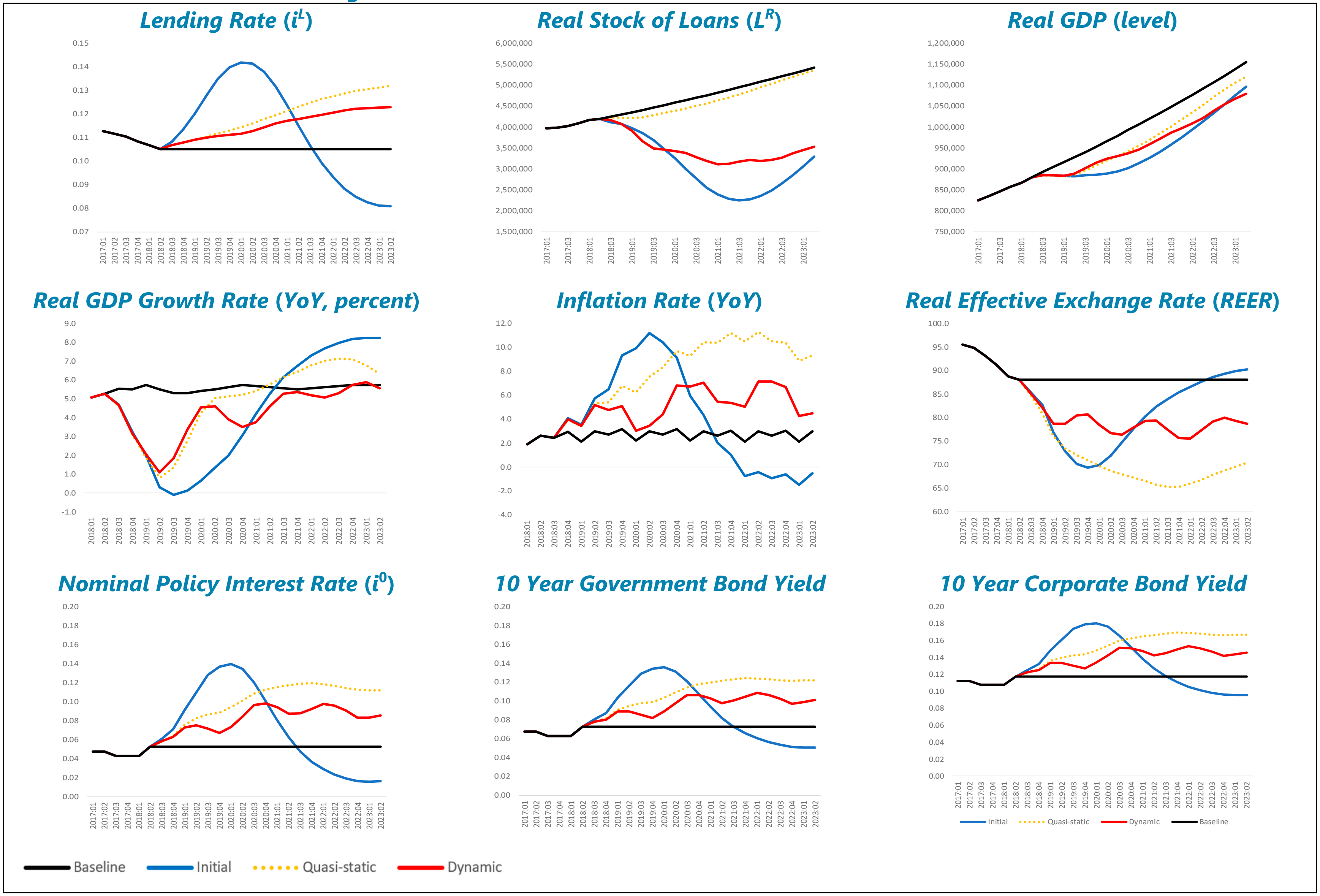


Figure 7. Indonesia—Aggregate Bank Results: *Balance Sheet Items*

(all variables are expressed in real terms)

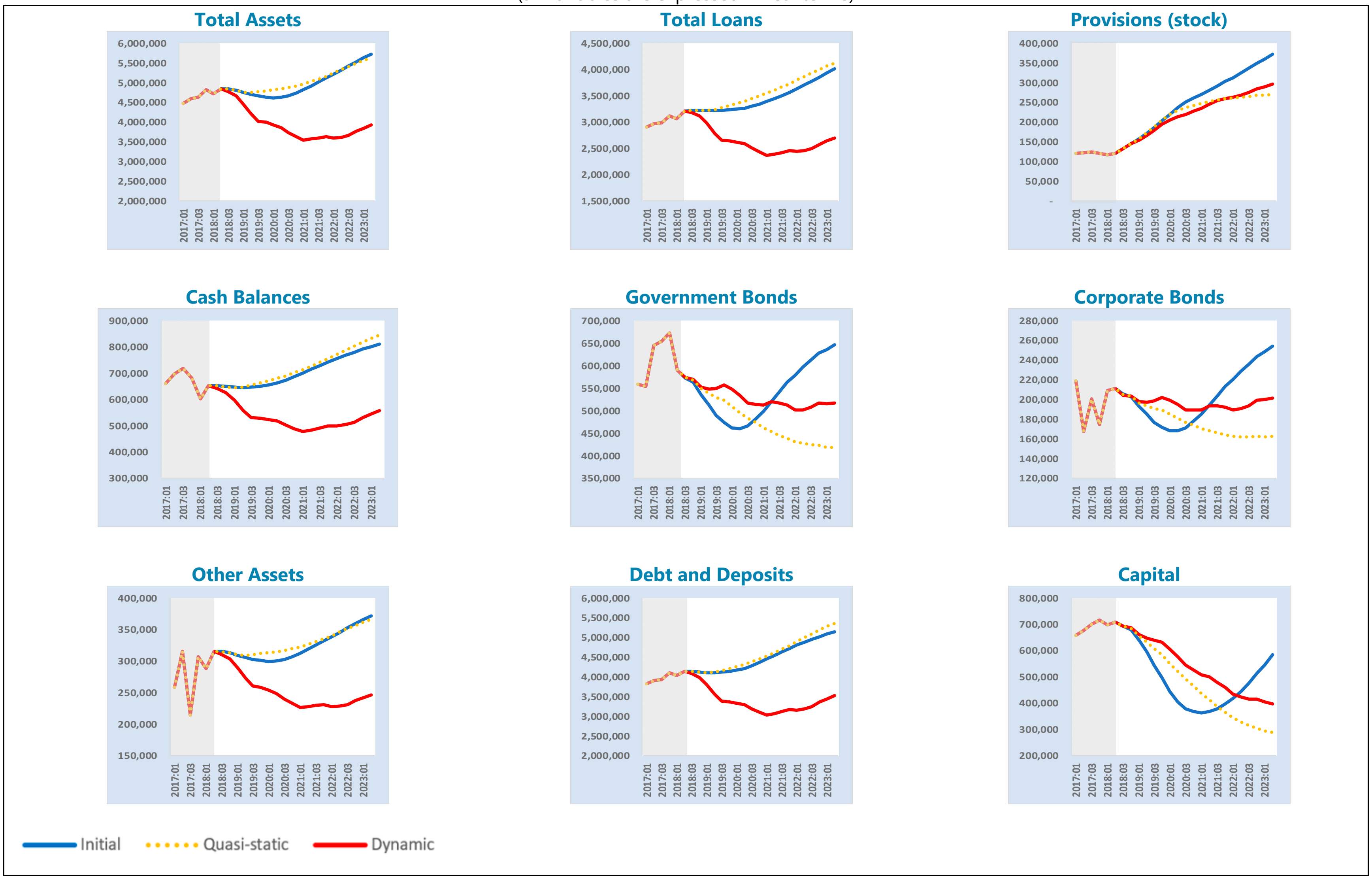


Figure 7 (cont.). Indonesia—Aggregate Bank Results: *Profit Items*

(all variables are expressed in real terms)

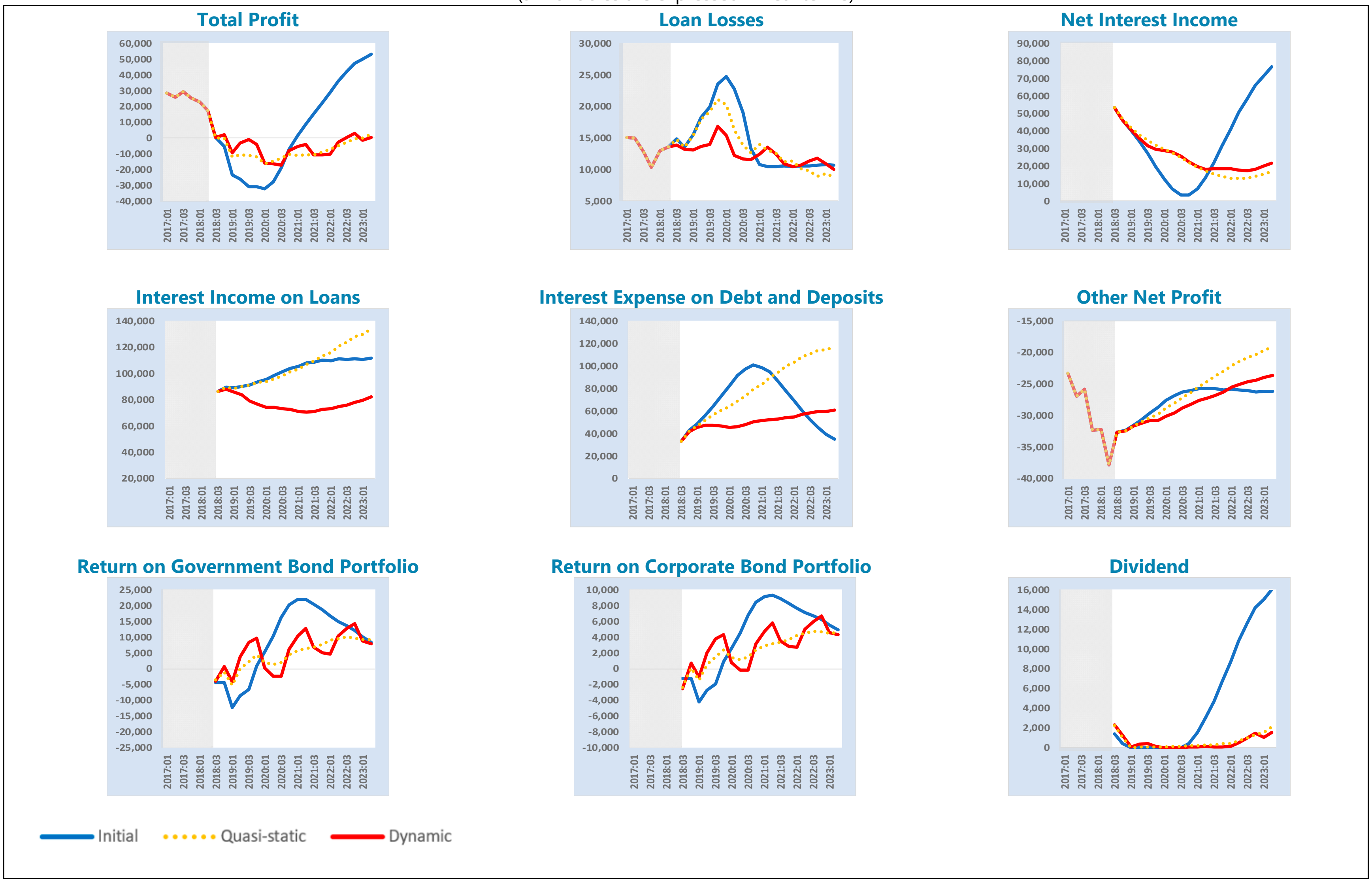


Figure 7 (cont.). Indonesia—Aggregate Bank Results: *Selected Financial Ratios and Interest Rates*

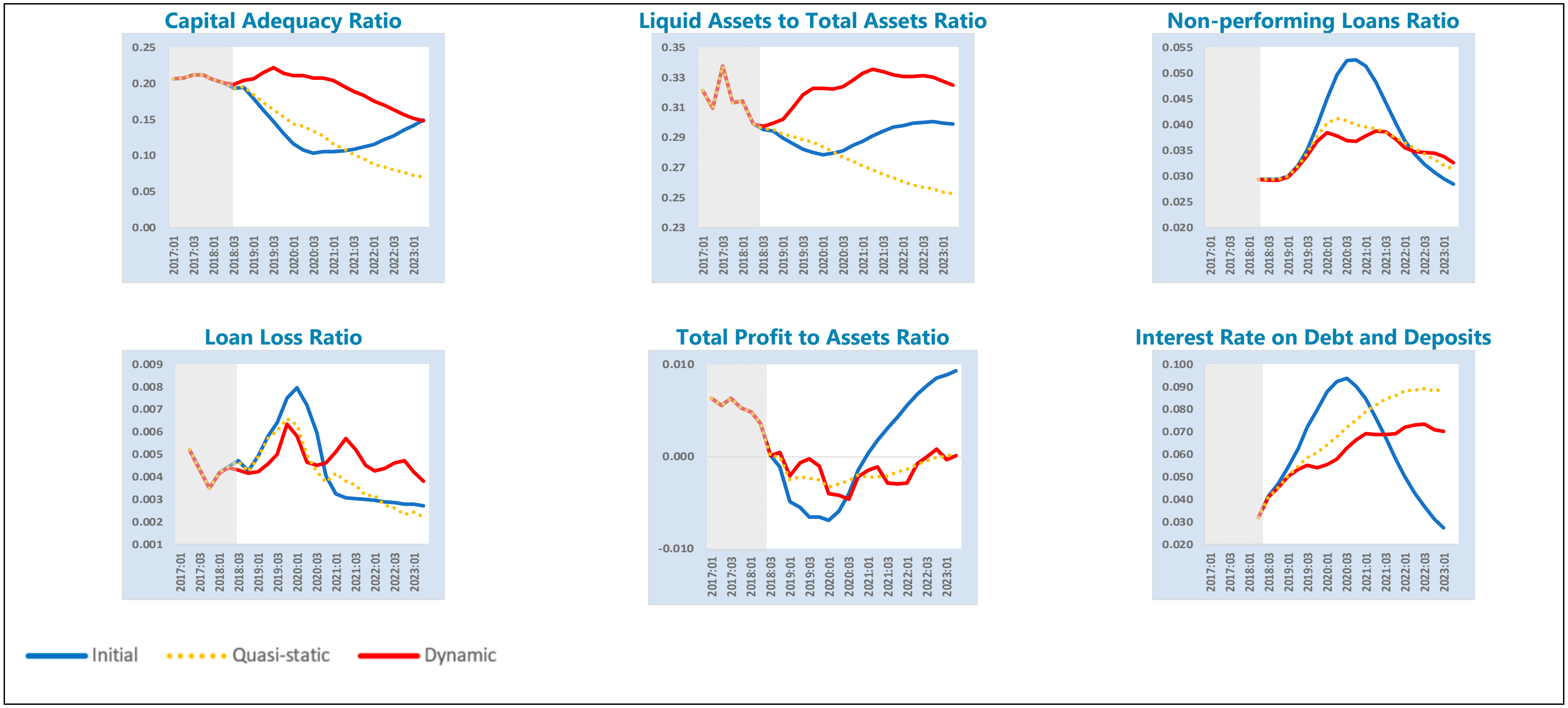
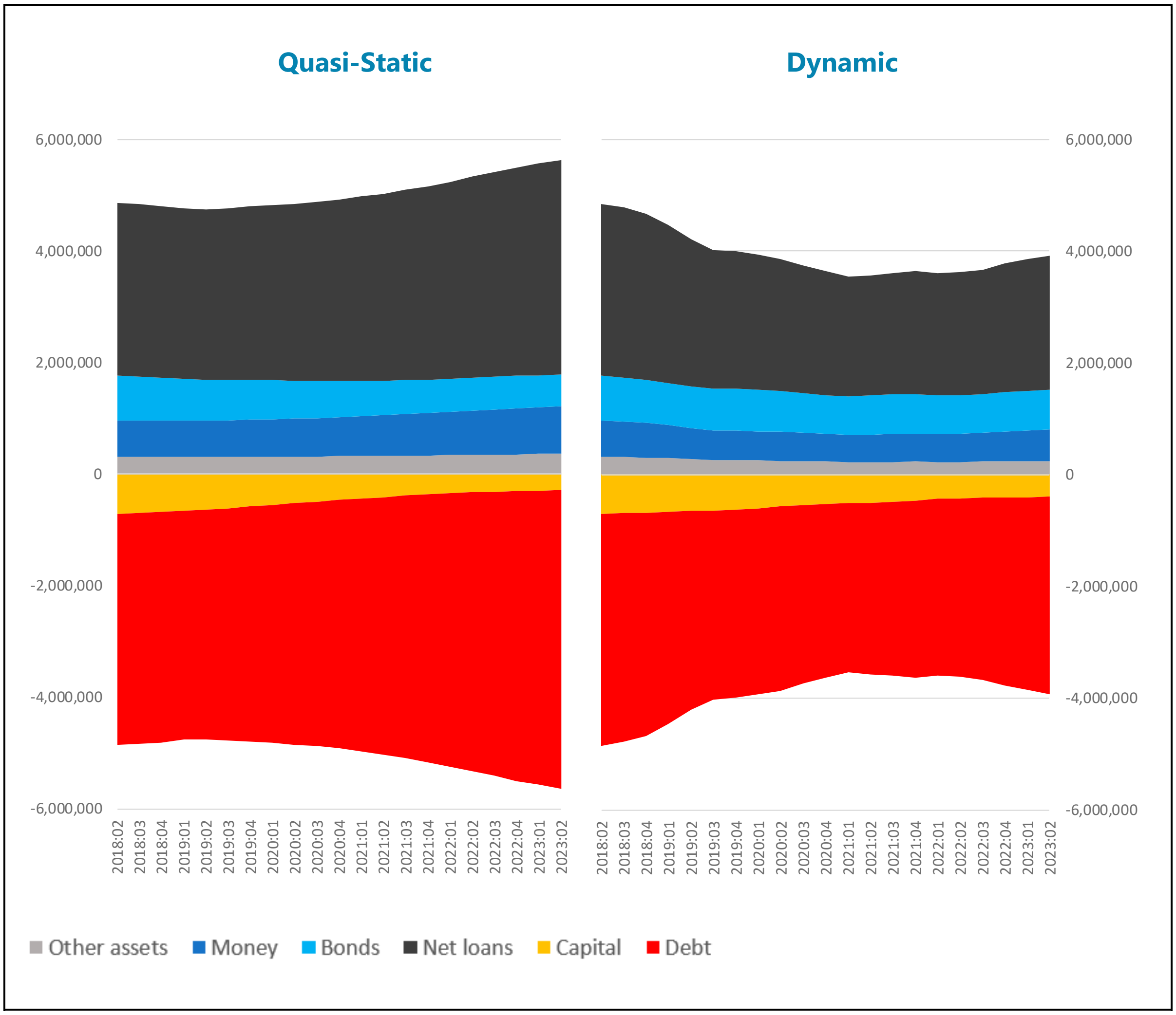


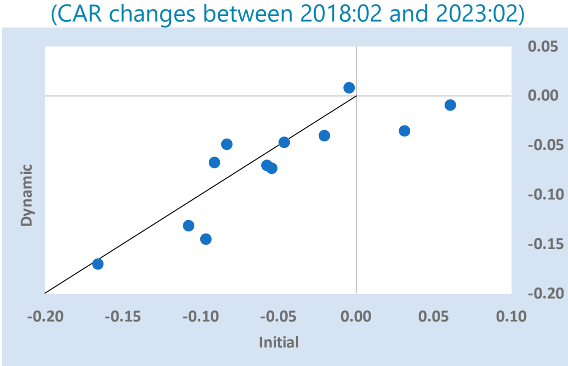
Figure 8. Evolution of Aggregate Balance Sheets in the Quasi-static and Dynamic Simulations
(balance sheet components, in real terms)



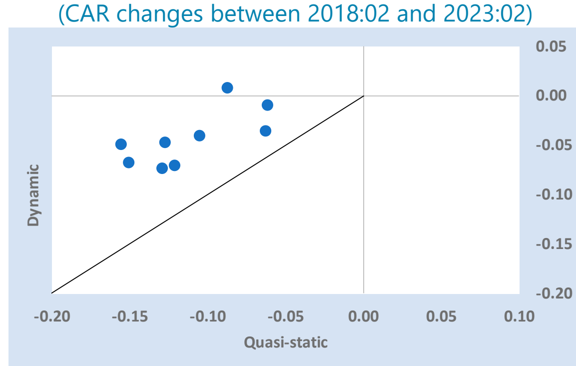
Note. The figure shows the evolution of the sum of balance sheet components across all banks. Net loans is the difference between gross loans and the stock of provisions.

Figure 9. Indonesia—Stress Simulation: Bank-specific Results
Changes in Capital Adequacy Ratios (CAR)

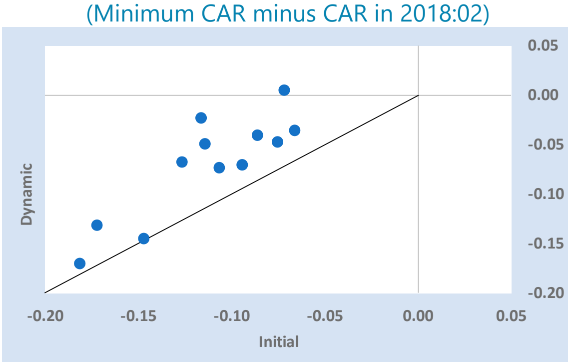
Dynamic versus Initial Simulations
(CAR changes between 2018:02 and 2023:02)



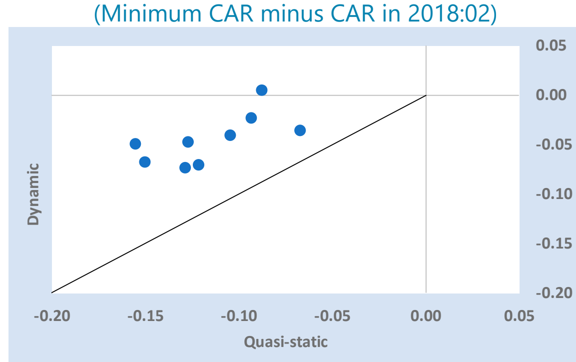
Dynamic versus Quasi-Static Simulations
(CAR changes between 2018:02 and 2023:02)



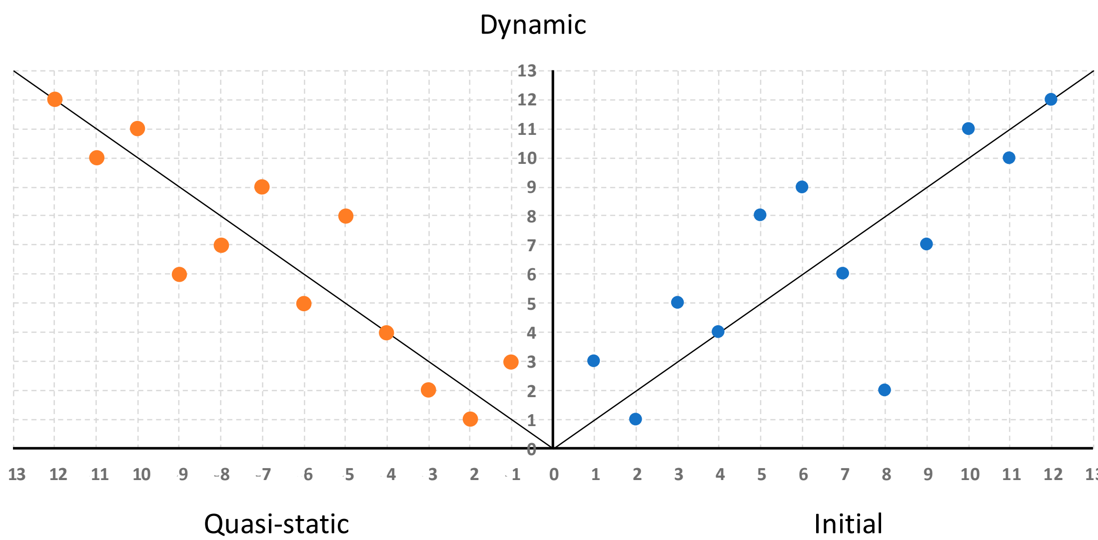
Dynamic versus Initial Simulations
(Minimum CAR minus CAR in 2018:02)



Dynamic versus Quasi-Static Simulations
(Minimum CAR minus CAR in 2018:02)

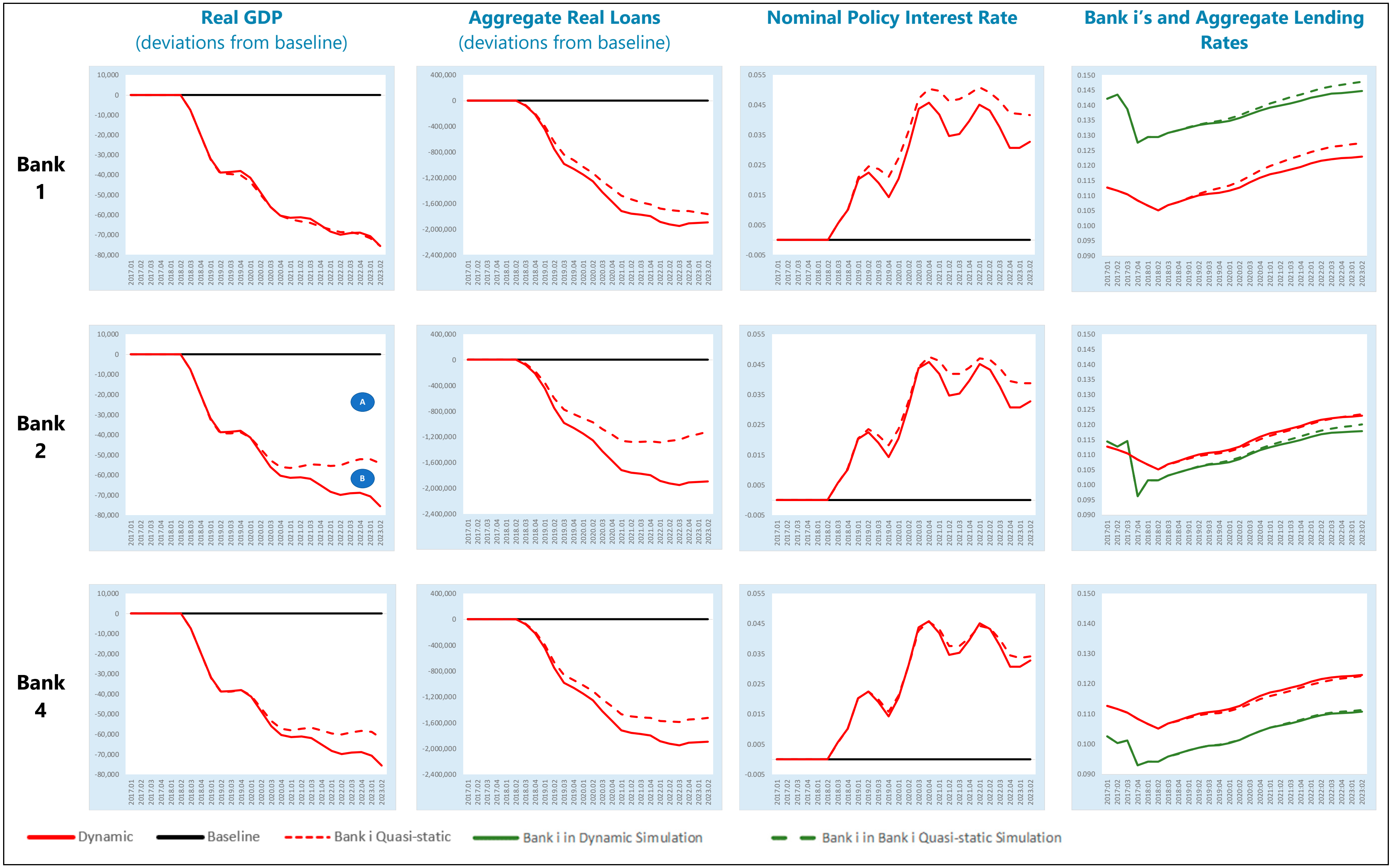


Stress Tests Results: Bank Rankings Based on CAR Changes[1]



Note. 1/ Banks are ranked based on CAR changes (minimum CAR minus CAR in 2018:02). A higher rank indicates a smaller decline in capital ratio due to stress.

Figure 10. Indonesia—Stress Simulation: Effect of Individual Bank De-leveraging on Macroeconomic Outcomes

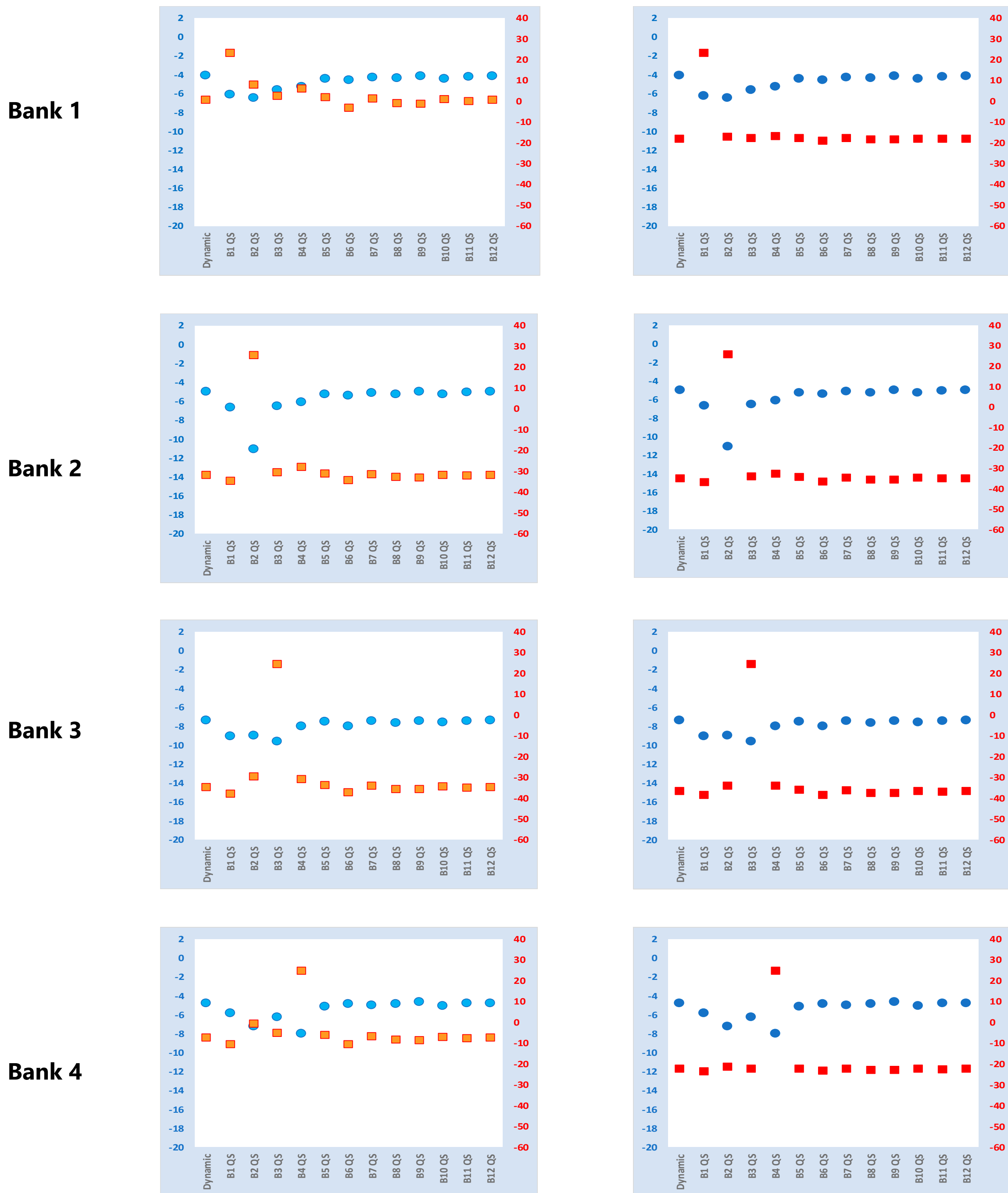


Note. Area A is the cumulative output loss when all banks (except bank 2) deleverage. Area B shows the output loss associated with bank 2's deleveraging behavior.

Figure 11. Indonesia—Stress Simulation: Cross-bank Externalities Associated with Individual Bank De-leveraging

Changes in Capital Adequacy Ratios (CAR) and Real Loan Growth Rates:
Dynamic Simulation and Simulations in which Bank i behaves Quasi-statically (Bi QS)

CAR changes and Real Loan Growth Rates between 2018:02 and 2023:02 | **CAR changes and Real Loan Growth Rates between 2018:02 and Minimum Level**



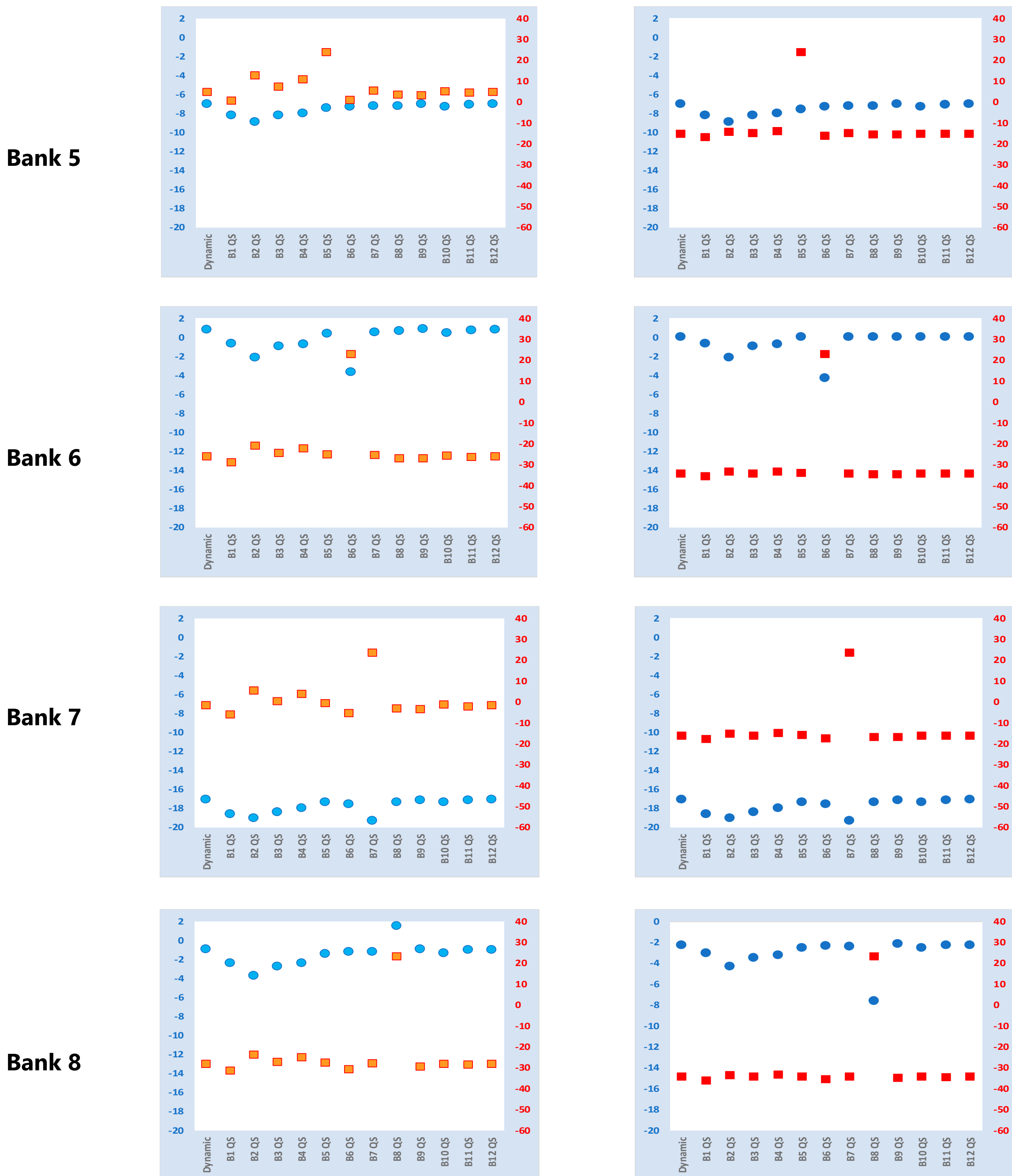
● Change in CAR (2018:02 to end of period, percentage points) ■ Real Loan Growth (2018:02 to end of period, percent, right axis)
● Change in CAR (2018:02 to minimum, percentage points) ■ Real Loan Growth (2018:02 to minimum, percent, right axis)

Figure 11 (cont.). Indonesia—Stress Simulation: Cross-bank Externalities Associated with Individual Bank De-leveraging

Changes in Capital Adequacy Ratios (CAR) and Real Loan Growth Rates: Dynamic Simulation and Simulations in which Bank i behaves Quasi-statically (Bi QS)

CAR changes and Real Loan Growth Rates between 2018:02 and 2023:02

CAR changes and Real Loan Growth Rates between 2018:02 and Minimum Level

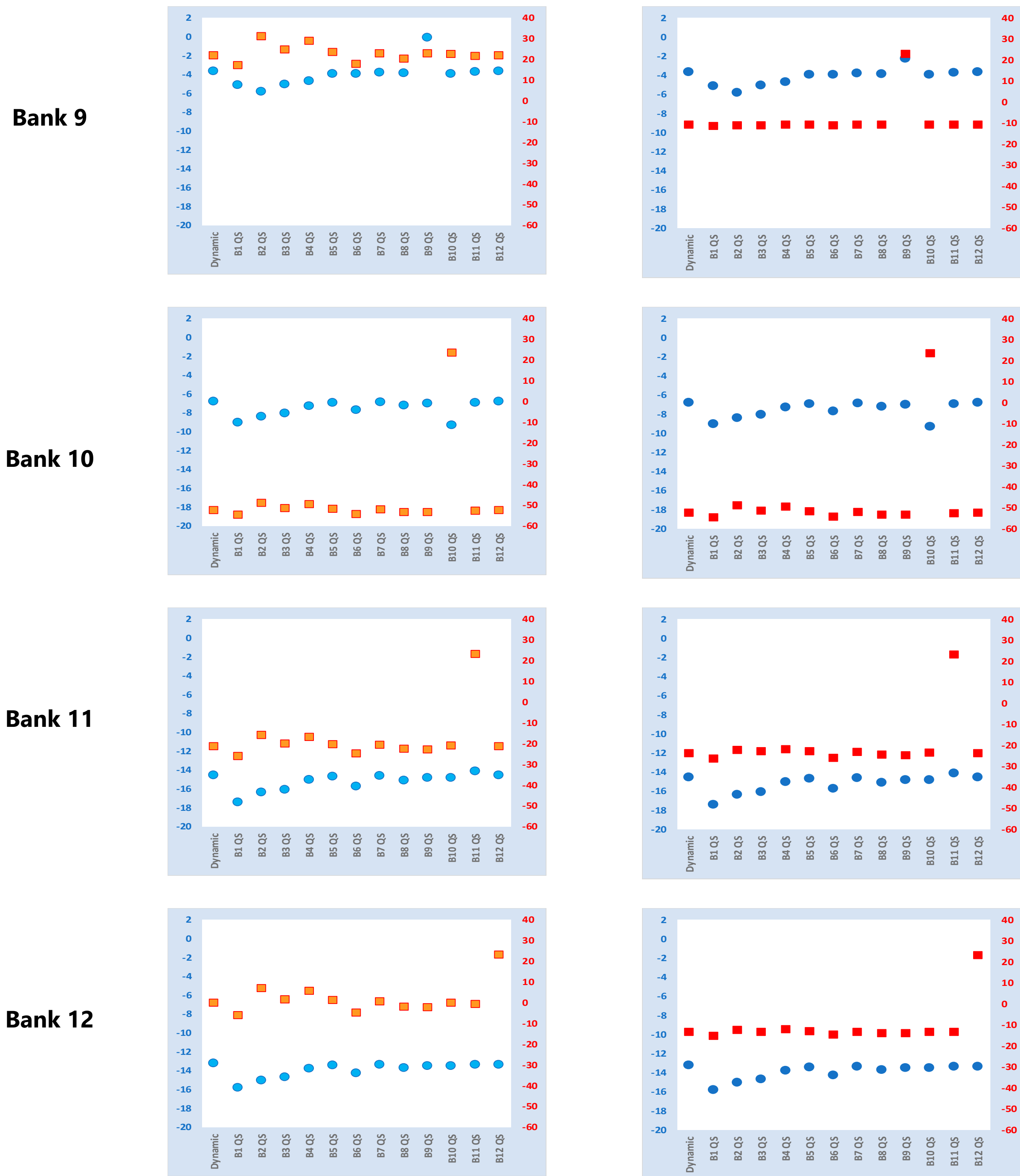


● Change in CAR (2018:02 to end of period, percentage points)
■ Real Loan Growth (2018:02 to end of period, percent, right axis)
● Change in CAR (2018:02 to minimum, percentage points)
■ Real Loan Growth (2018:02 to minimum, percent, right axis)

Figure 11 (cont.). Indonesia—Stress Simulation: Cross-bank Externalities Associated with Individual Bank De-leveraging

Changes in Capital Adequacy Ratios (CAR) and Real Loan Growth Rates: Dynamic Simulation and Simulations in which Bank i behaves Quasi-statically (Bi QS)

CAR changes and Real Loan Growth Rates between 2018:02 and 2023:02 | **CAR changes and Real Loan Growth Rates between 2018:02 and Minimum Level**



Change in CAR (2018:02 to end of period, percentage points)
Real Loan Growth (2018:02 to end of period, percent, right axis)
Change in CAR (2018:02 to minimum, percentage points)
Real Loan Growth (2018:02 to minimum, percent, right axis)

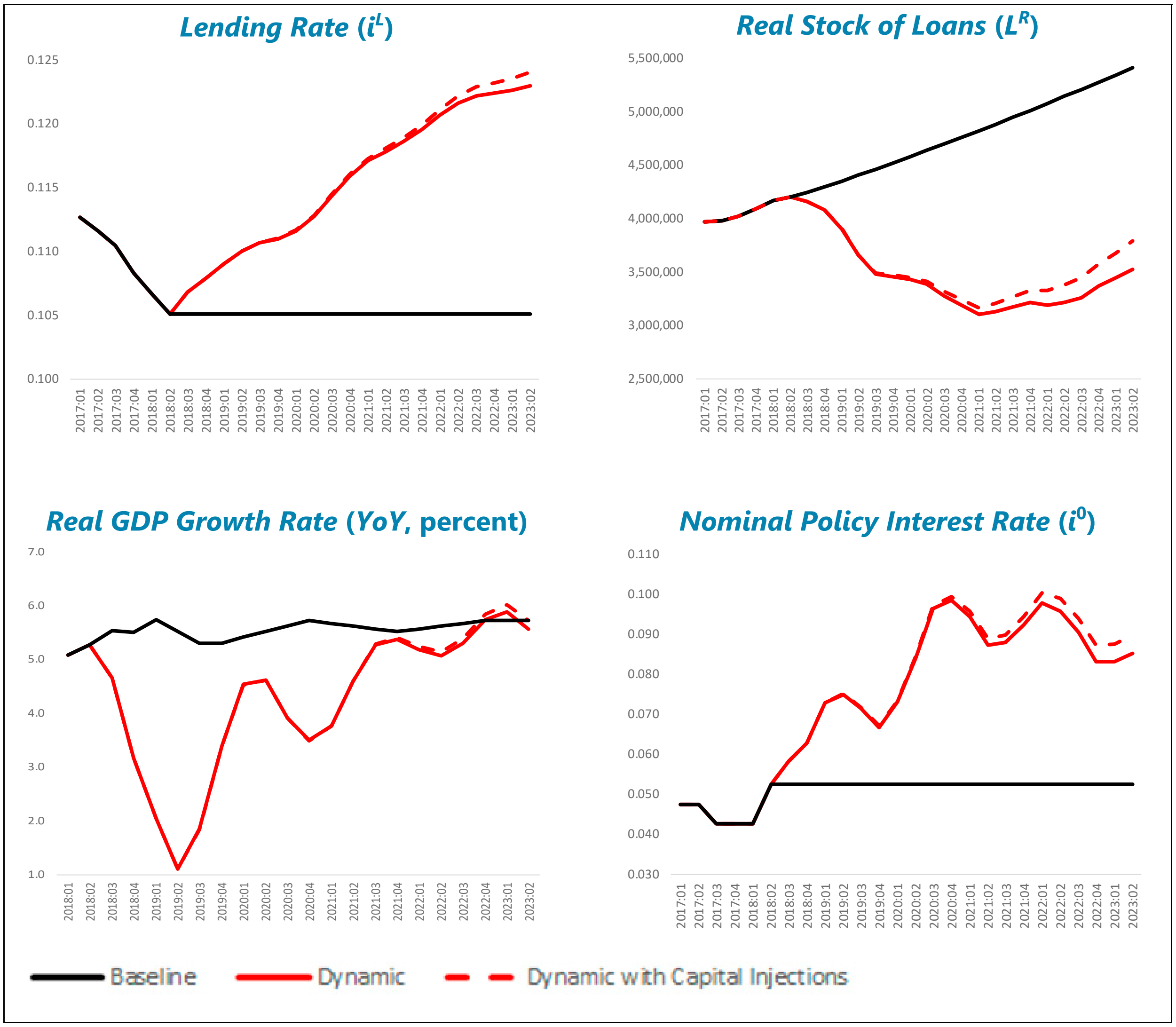
Figure 12. Indonesia—Externalities Analysis: Changes in Banks' Capital Adequacy Ratios (CAR) Depending on their Own and Other Banks' Behaviors

Changes in CAR of Bank i

(2008:02 to minimum, in percentage points)

		Other banks	
		Quasi-static	Dynamic
Bank 1	Quasi-static	-10.5	-6.2
	Dynamic	-9.9	-4.1
Bank 2	Quasi-static	-15.5	-11.0
	Dynamic	-11.0	-5.0
Bank 3	Quasi-static	-12.9	-9.6
	Dynamic	-12.4	-7.4
Bank 4	Quasi-static	-12.7	-8.0
	Dynamic	-10.7	-4.7
Bank 5	Quasi-static	-12.1	-7.6
	Dynamic	-12.4	-7.1
Bank 6	Quasi-static	-8.8	-4.3
	Dynamic	-6.8	0.0
Bank 7	Quasi-static	-25.0	-19.4
	Dynamic	-23.2	-17.1
Bank 8	Quasi-static	-9.3	-7.7
	Dynamic	-8.0	-2.3
Bank 9	Quasi-static	-6.7	-2.3
	Dynamic	-10.1	-3.7
Bank 10	Quasi-static	-15.0	-9.4
	Dynamic	-13.8	-6.8
Bank 11	Quasi-static	-20.5	-14.2
	Dynamic	-22.5	-14.5
Bank 12	Quasi-static	-20.6	-13.4
	Dynamic	-20.9	-13.2

Figure 13. Macroeconomic Effects of System-wide Capital Injections
(equivalent to 3 percentage points of CAR over two years for all banks)



APPENDIX I. EQUATIONS OF THE MODEL

The equations are organized as follows. Estimated equations are presented first (1 through 5). Next are the definitions and transformations needed to integrate the output from these equations to the rest of the model (6 through 9). These are followed by blocks of equations that determine banks' net profit items (10 through 19) and the dynamic evolution of their balance sheets (20 through 31). The last set of equations aggregates bank lending decisions, computes the lending interest rate (32 to 33), and describe initial conditions as well as variables with pre-determined paths (34 to 43).

A) Estimated Blocks

Macro block (SVAR)

$$\tilde{\boldsymbol{z}}_t = \mathbf{C}_z + \mathbf{C}_{ztr} \cdot t + \sum_{s=1}^{p_M} \mathbf{A}_s \cdot \tilde{\boldsymbol{z}}_{t-s} + \sum_{s=0}^{p_M} \boldsymbol{\varphi}_s \cdot \tilde{\boldsymbol{f}}_{t-s} + \boldsymbol{\mu}_t^z \tag{1}$$

Macro block (ir)

$$\boldsymbol{ir}_t = \mathbf{C}_{ir} + \sum_{s=1}^{p_M} \mathbf{B}_s \cdot \boldsymbol{ir}_{t-s} + \sum_{s=1}^{p_M} \mathbf{h}_s \cdot i_{t-s}^0 + \boldsymbol{\mu}_t^{ir} \tag{2}$$

Bank credit risk block

$$\ln\left(\frac{LLR_{i,t}}{1-LLR_{i,t}}\right) = \alpha_i + \sum_{s=1}^{p_{LL}} \lambda_s \cdot \ln\left(\frac{LLR_{i,t-s}}{1-LLR_{i,t-s}}\right) + \sum_{s=0}^{p_{LL}} \boldsymbol{\beta}_s \cdot \Delta \boldsymbol{z}_{t-s} + \sum_{s=1}^{p_{LL}} \boldsymbol{\gamma}_s \cdot \Delta \boldsymbol{x}_{i,t-s} + \mu_{i,t}^{LL} \tag{3}$$

Bank lending block

$$\Delta \ln L_{i,t}^R = \xi_i + \boldsymbol{\theta}_1 \cdot \boldsymbol{z}_t + \boldsymbol{\theta}_2 \cdot \boldsymbol{x}_{i,t-1} + \sum_{s=1}^{P} \eta_s \cdot \Delta \ln L_{i,t-s}^R + \sum_{s=0}^{P} \boldsymbol{\delta}_s \cdot \Delta \boldsymbol{z}_{t-s} + \sum_{s=1}^{P} \boldsymbol{\rho}_s \cdot \Delta \boldsymbol{x}_{i,t-s} + \mu_{i,t}^l$$

$$\text{where} \quad L_{i,t}^R = L_{i,t} / P_t \tag{4}$$

Bank funding cost block

$$spr_{i,t} = \mathrm{v}_i + \vartheta(\boldsymbol{z}_t, \boldsymbol{x}_{i,t}) + \mu_{i,t}^{spr} \tag{5}$$

Definitions and transformations of variables related to estimated blocks:

$$\tilde{\boldsymbol{z}}_t \to \boldsymbol{z}_t ; \tilde{L}_t \to L_t \tag{6}$$

$$\tilde{\boldsymbol{z}}_t = \left[RGDP_t^*, P_t^{COMM}, i_t^{US}, RGDP_t, REER_t, INF_t, i_t^0 \right]' \text{ where } INF_t = \ln P_t - \ln P_{t-1} \tag{7}$$

$$\tilde{\boldsymbol{f}}_t = \left[L_t^R \quad i_t^L \right]' \text{ where } L_t^R = \sum_{i=1}^{I} L_{i,t}^R , \; \boldsymbol{ir}_t = \left[Y_t^{G,40} \quad Y_t^{C,0} \quad Y_t^{C,40} \right]'$$

$$\boldsymbol{x}_{i,t} = \left(CAR_{i,t}, LATA_{i,t}, LLR_{i,t} \right) \tag{8}$$

$$CAR_{i,t} = \frac{K_{i,t}}{RWA_{i,t}}, \; LATA_{i,t} = \frac{LA_{i,t}}{A_{i,t}} = \frac{M_{i,t} + B_{i,t}^G + B_{i,t}^C}{A_{i,t}} \tag{9}$$

B) **Bank Profit and Loss Block**

Definition of total profit

$$\Pi_{i,t} = II_{i,t}^L - IE_{i,t}^D - LL_{i,t} + R_{i,t}^G + R_{i,t}^C + O_{i,t} \tag{10}$$

Interest income on loans

$$II_{i,t}^L = 0.25 \cdot \left(L_{i,t-1} - NPL_{i,t-1} \right) \cdot i_{i,t-1}^L \tag{11}$$

$$i_{i,t}^L = \left(1 - \pi_i^L \right) \cdot i_{i,t-1}^L + \pi_i^L \cdot i_{i,t}^{NL} \tag{12}$$

$$i_{i,t}^{NL} = i_{i,t-1}^{NL} + \psi_i^G \cdot \left(Y_t^{G,dur_i^L} - Y_{t-1}^{G,dur_i^L} \right) + \psi_i^{spr} \cdot \left(spr_{i,t} - spr_{i,t-1} \right) \tag{13}$$

Interest expense on deposits and debt

$$IE_{i,t}^D = 0.25 \cdot D_{i,t-1} \cdot i_{i,t-1}^D \tag{14}$$

$$i_{i,t}^D = \left(1 - \pi_i^D \right) \cdot i_{i,t-1}^D + \pi_i^D \cdot i_{i,t}^{ND} \tag{15}$$

$$i_{i,t}^{ND} = \left(1 - ch_i \right) \cdot \left(Y_t^{G,dur_i^D} + spr_{i,t} \right) \tag{16}$$

Loan losses

$$LL_{i,t} = LLR_{i,t} \cdot L_{i,t-1} \tag{17}$$

Securities return

$$R_{i,t}^h = B_{i,t}^h - B_{i,t-1}^h , \; h \in \{ G, C \} \tag{18}$$

Other net income

$$O_{i,t} = \Xi_i \cdot A_{i,0} \tag{19}$$

C) Bank Balance Sheet Dynamics

Balance sheet

$$A_{i,t} = \left(L_{i,t} - PR_{i,t}\right) + M_{i,t} + B_{i,t}^{G} + B_{i,t}^{C} + OA_{i,t} = K_{i,t} + D_{i,t} \tag{20}$$

$$B_{i,t}^{h} = B_{i,t}^{h,HTM} + B_{i,t}^{h,MTM} \quad \text{for } h \in \{G, C\} \tag{21}$$

Dynamics of non-performing loans

$$NPL_{i,t} = NPL_{i,t-1} + \frac{1}{LGD_i} \cdot LL_{i,t} \tag{22}$$

Dynamics of provisions

$$PR_{i,t} = PR_{i,t-1} + LL_{i,t} \tag{23}$$

Cash balances

$$M_{i,t} = m_i \cdot D_{i,t} \tag{24}$$

Dynamics of securities portfolios

$$B_{i,t}^{h,HTM} = \left(1 + 0.25 \cdot i_{i,t-1}^{h}\right) \cdot B_{i,t-1}^{h,HTM} \quad \text{for } h \in \{G, C\} \tag{25}$$

$$B_{i,t}^{h,MTM} = \left[1 - \frac{0.25 \cdot dur_i^h}{\left(1 + Y_{t-1}^{h,dur_i^h} \cdot 0.25\right)} \cdot \left(Y_t^{h,dur_i^h} - Y_{t-1}^{h,dur_i^h}\right) + 0.25 \cdot i_{i,t-1}^{h}\right] \cdot B_{i,t-1}^{h,MTM} \quad \text{for } h \in \{G, C\} \tag{26}$$

$$i_{i,t}^{h} = \left(1 - \pi_i^h\right) \cdot i_{i,t-1}^{h} + \pi_i^h \cdot Y_t^{h,dur_i^h} \quad \text{for } h \in \{G, C\} \tag{27}$$

$$Y_t^{G,s} = LINT(s, i_t^0, Y_t^{G,40}); \; Y_t^{C,s} = LINT(s, Y_t^{C,0}, Y_t^{G,40}) \tag{28}$$

Other assets

$$OA_{i,t} = OA_{i,0} \tag{29}$$

Dynamics of capital

$$K_{i,t} = K_{i,t-1} + \Pi_{i,t} \cdot \left[1 - div_i \cdot \mathbf{1}_{+}(\Pi_{i,t})\right] + kir_{i,t} \cdot RWA_{i,t-1} \tag{30}$$

Risk-weighted assets

$$RWA_{i,t} = \left[\Theta_i^L \cdot \left(L_{i,t} - NPL_{i,t}\right) + \left(NPL_{i,t} - PR_{i,t}\right) + \Theta_i^G \cdot B_{i,t}^G + \Theta_i^C \cdot B_{i,t}^C\right] \cdot \left(\frac{1}{1-\rho_i^{ORWA}}\right) \tag{31}$$

D) Aggregation

Aggregate lending

$$L_t = \sum_{i=1}^{I} L_{i,t} \tag{32}$$

Aggregate lending interest rate

$$i_t^L = \sum_i i_{i,t}^L \cdot \omega_{i,t} \quad \text{where}\, \omega_{i,t} = \left(L_{i,t} - NPL_{i,t}\right) / \sum_i \left(L_{i,t} - NPL_{i,t}\right) \tag{33}$$

E) Initial conditions and variables with a predetermined path

Macroeconomic data

$$\boldsymbol{z}_0, \boldsymbol{z}_{-1}, \boldsymbol{z}_{-2}, \ldots;\, L_0, L_{-1}, L_{-2}, \ldots;\; \boldsymbol{ir}_0, \boldsymbol{ir}_{-1}, \boldsymbol{ir}_{-2}, \ldots;\; P_0, P_{-1}, P_{-2}, \ldots \tag{34}$$

Bank-specific data

$$LLR_{i,0}, LLR_{i,-1}, LLR_{i,-2}, \ldots \tag{35}$$

$$\boldsymbol{x}_{i,0}, \boldsymbol{x}_{i,-1}, \boldsymbol{x}_{i,-2}, \ldots \tag{36}$$

$$\begin{aligned}&\left\{L_{i,0}, PR_{i,0}, M_{i,0}, B_{i,0}^G, B_{i,0}^C, OA_{i,0}, K_{i,0}, D_{i,0}\right\}, \left\{L_{i,-1}, PR_{i,-1}, M_{i,-1}, B_{i,-1}^G, B_{i,-1}^C, OA_{i,-1}, K_{i,-1}, D_{i,-1}\right\},\\ &\left\{L_{i,-2}, PR_{i,-2}, M_{i,-2}, B_{i,-2}^G, B_{i,-2}^C, OA_{i,-2}, K_{i,-2}, D_{i,-2}\right\}, \ldots\end{aligned} \tag{37}$$

$$A_{i,0} = \left(L_{i,0} - PR_{i,0}\right) + M_{i,0} + B_{i,0}^G + B_{i,0}^C \tag{38}$$

$$B_{i,0}^h = B_{i,0}^{h,HTM} + B_{i,0}^{h,MTM} \quad \text{for } h \in \{G, C\} \tag{39}$$

$$NPL_{i,0} \tag{40}$$

$$i_{i,0}^{NL}, i_{i,-1}^{NL}, i_{i,-1}^{L}, i_{i,-1}^{D} \tag{41}$$

$$\mu_{i,0}^{spr},\, \mu_{i,-1}^{spr} \tag{42}$$

Variables with a predetermined path (shocks to Eqns. 1, 2 and 5)

$$\boldsymbol{\varepsilon}_t^z,\ \boldsymbol{\mu}_t^{ir},\ kir_{i,t} \text{ and } \mu_{i,t}^{spr} \text{ given for all } i \text{ and } t = 1, 2, \ldots, \text{ where } \boldsymbol{\varepsilon}_t^z = \mathbf{B}^{-1} \cdot \boldsymbol{\mu}_t^z \tag{43}$$

APPENDIX II. DESCRIPTION OF THE STRESS SIMULATION ALGORITHM

The stress simulation algorithm consists of the following steps:

Step 1. Define a baseline macroeconomic scenario.

Step 2. Specify a sequence of adverse macroeconomic structural shocks $\boldsymbol{\varepsilon}_t^z$ for $t = 1, 2, ...$

Step 3. Produce an "initial adverse scenario" using an auxiliary VAR model that includes equations for aggregate credit and the lending interest rate. The auxiliary VAR model treats aggregate credit and the lending interest rate as endogenous and is defined over the vector $\left[RGDP^*, P^{COMM}, i^{US}, i^L, L^R, RGDP, INF, REER, i^0\right]'$.[27] Importantly, the "initial scenario" reflects the effects of the shocks $\boldsymbol{\varepsilon}_t^z$ and includes initial "guesses" for the paths of aggregate credit and the lending interest rate.

Step 4. The algorithm enters a main iteration loop (indexed by *ii*) that will remain active until convergence is achieved between the aggregate paths of credit and lending interest rates from the previous iteration, and those obtained from a bottom-up aggregation of individual bank results in the current iteration. More specifically,

- A nested bank-by-bank loop (indexed by *bb*) produces forecasts of individual bank results—losses, stress, and lending responses—conditional on the paths of macroeconomic variables.
- Once the *bb* loop ends, bank-specific variables are aggregated, and convergence (or lack thereof) for aggregate credit and lending interest rate paths between the previous and the current iterations can be verified.

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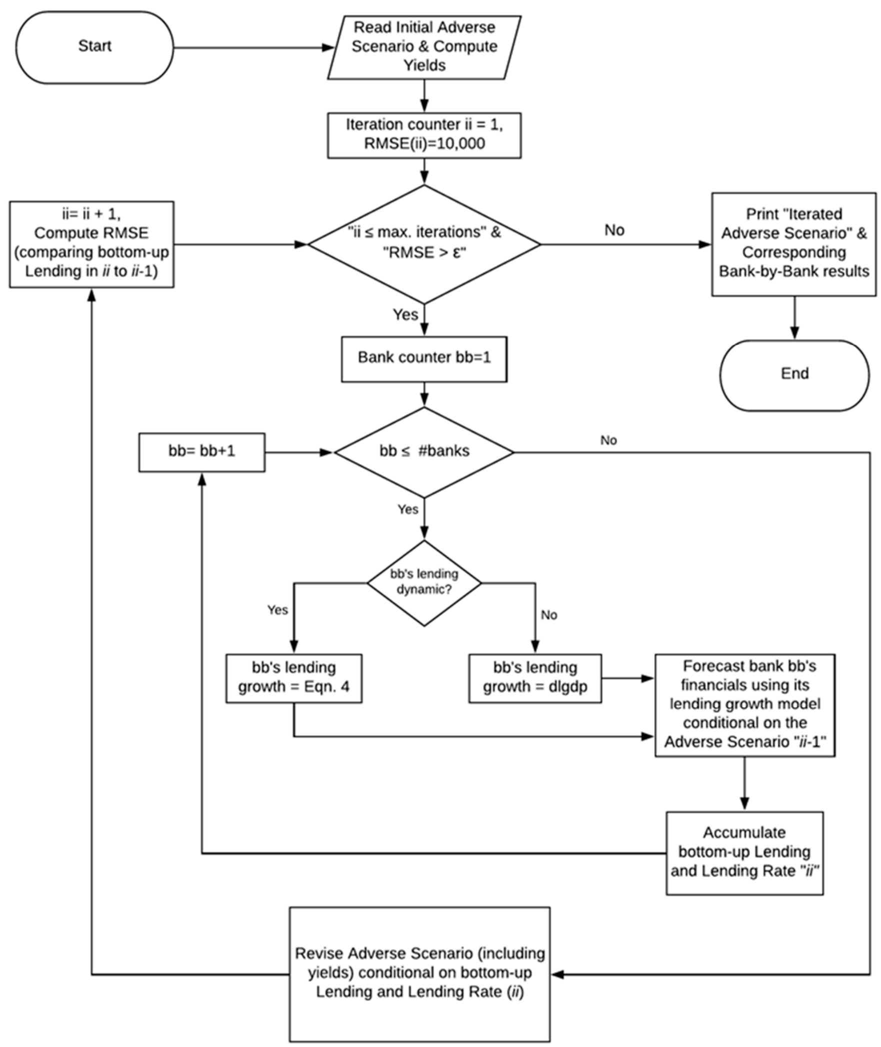
[27] The purpose of the "initial scenario" is to initialize the search for a solution and should not be confused with the solution of the model which, as noted above, solves simultaneously for bank stress tests results and the scenario (both final outputs of the stress simulation exercise).

- When convergence has not been achieved, differences between the previous and current iterations of the credit and lending interest rate paths are treated as "shocks," and impulse responses obtained from the estimated VARX model (Eq. 1) are used to revise the paths of all macroeconomic variables.
- The *ii* loop continues iterating until a fixed point (defined over credit and lending interest rates paths) is found.

Algorithm



APPENDIX III. DATA SOURCES

Macroeconomic data. Data sources include Bank Indonesia, Statistical Bureau Indonesia, IMF International Financial Statistics, CEIC, JP Morgan, Federal Reserve Bank of St. Louis, and Haver Analytics. The tables show definitions of the series and their corresponding sources.

Variable	Notation	Source	Unit and Details
Domestic variables			
Real GDP	$RGDP$	Bank Indonesia, CEIC	In billions of rupiah at 2000 prices; seasonally adjusted.
Nominal GDP	$P \cdot RGDP$	Bank Indonesia, CEIC	In billions of rupiah.
Inflation	INF	Bank Indonesia, Statistics Bureau Indonesia	Proportional q-o-q change in the value of the consumer price index.
Nominal interest rate	i^0	Bank Indonesia	Annual interest rate; the series is based on Statistics Bureau Indonesia one-month rate from 1990 to 2005 and Bank Indonesia rate from 2005.
Real effective exchange rate	$REER$	Haver Analytics, JP Morgan	JP Morgan Real Broad Effective Exchange Rate Index.
Nominal credit to the private sector	L	Bank Indonesia	In billions of rupiahs; total credit to the private sector based on bank reports.
External variables			
Trading partners' real GDP	$RGDP^*$	Haver Analytics, authors' calculations	Index, Base=2010Q1; weighted index of the real GDP of Indonesia's top export partners, U.S., Japan, China, Singapore and EU. Weights are time varying and calculated as the shares of Indonesia's exports to a given country over total exports.
US nominal interest rate	i^{US}	Haver Analytics, IMF International Finance Statistics	Annual interest rate.
Commodity price	P^{COMM}	Haver Analytics, IMF	World: Commodity Price Index: All Commodities (2010=100).

References

Bocola, Luigi. 2016. “The Pass-Through of Sovereign Risk.” *Journal of Political Economy* 124 (4): 879-926.

Brunnermeier, Markus K., Thomas M. Eisenbach, and Yuliy Sannikov. 2013. “Macroeconomics with Financial Frictions: A Survey.” In *Advances in Economics and Econometrics: Tenth World Congress* (Econometric Society Monographs), edited by D. Acemoglu, M. Arellano, and E. Dekel. Cambridge, U.K.; Cambridge University Press.

Brunnermeier, Markus K., Luis Garicano, Philip R. Lane, Marco Pagano, Ricardo Reis, Tan Santos, David Thesmar, Stijn Van Nieuwerburgh, and Dimitri Vayanos. 2016. “The Sovereign-Bank Diabolic Loop and ESBies.” *American Economic Review: Papers and Proceedings* 106 (5): 508-12.

Brunnermeier Markus K., and Yuliy Sannikov. 2014. “A Macroeconomic Model with a Financial Sector.” *American Economic Review* 104 (2): 379-421.

Budnik, Katarzyna, Mirco Belatti Mozannica, Ivan Dimitrov, Johannes Gross, Ib Hansen, Giovanni di Iasio, Michael Kleemann, and others. 2019. “Macroprudential Stress Test of the Euro Area Banking System.” *ECB Occasional Paper Series 226*, European Central Bank, Frankfurt.

Catalán, Mario, Alexander W. Hoffmaister, and Cicilia Anggadewi Harun. 2019. “Bank Capital and Lending: An Extended Framework and Evidence of Nonlinearity.” IMF Working Paper 17/252, International Monetary Fund, Washington, DC.

Cushman, David O., and Tao Zha. 1997. “Identifying Monetary Policy in a Small Open Economy Under Flexible Exchange Rates.” *Journal of Monetary Economics* 39 (3): 433-448.

Dávila, Eduardo, and Anton Korinek. 2018. “Pecuniary Externalities in Economies with Financial Frictions.” *The Review of Economic Studies* 85 (1): 352-395.

Dungey, Mardi, and Adrian Pagan. 2000. “A Structral VAR Model of the Australian Economy.” *The Economic Record* 76 (235): 321-342.

___________. 2009. “Extending a SVAR Model of the Australian Economy.” *The Economic Record* 85 (268): 1-20.

Enria, Andrea. 2019. “The Future of Stress Testing—Realism, Relevance and Resources.” Keynote speech at the 2019 European Systemic Risk Board Annual Conference, Frankfurt.

Fahri, Emannuel and Jean Tirole, 2016. "Deadly Embrace: Sovereign and Financial Balance Sheet Doom Loops," *Review of Economic Studies*, forthcoming.

Gerali, Andrea, Stefano Neri, Luca Sessa, and Federico M. Signoretti. 2010. "Credit and Banking in a DSGE Model of the Euro Area." *Journal of Money, Credit, and Banking* 42 (6): 107-141.

Haldane, Andrew. 2009. "Why Banks Failed the Stress Test." Speech at the Marcus-Evans Conference on Stress-Testing, London.

Hoffmaister Alexander W., and Jorge E. Roldós. 2001. "The Sources of Macroeconomic Fluctuations in Developing Countries: Brazil and Korea." *Journal of Macroeconomics* 23 (2): 213-239.

Krznar, Ivo, and Troy Matheson. 2017. "Towards Macroprudential Stress Testing: Incorporating Macro-Feedback Effects." IMF Working Paper 17/149, International Monetary Fund, Washington, DC.

Lorenzoni, Guido. 2008. "Inefficient Credit Booms." *Review of Economic Studies* 75 (3): 809-833.

Meh, Césaire A., and Kevin Moran. 2010. "The Role of Bank Capital in the Propagation of Shocks." *Journal of Economic Dynamics and Control* 34 (3): 555-576.

Pesaran, Hashem M. 2006. "Estimation and Inference in Large Heterogenous Panels with Multifactor Error Structure." *Econometrica* 74 (4): 967–1012.

Pesaran, Hashem M., and Ron Smith. 1995. "Estimating Long-run Relationships from Dynamic Heterogeneous Panels." *Journal of Econometrics* 68 (1): 79-113.

Sims, Christopher A. 1980. "Macroeconomics and Reality." *Econometrica* 48 (1): 1-48.

Sosa, Sebastian. 2008. "External Shocks and Business Cycle Fluctuations in Mexico; How Important Are U.S. Factors?" IMF Working Paper 08/100, International Monetary Fund, Washington, DC.