TECHNICAL ASSISTANCE REPORT

INDIA

Review and Evaluation of the Reserve Bank of India's Stress Test Model Framework

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Prepared By

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Glossary

ARDL	Autoregressive distributed lag model
FX	Foreign exchange
HQLA	High quality liquid assets
IRB	Internal Ratings Based approach
LCR	Liquidity coverage ratio
LGD	Loss given default
MtM	Mark-to-market
NBFIs	Non-bank financial institutions
NII	Net interest income
NPLs	Nonperforming loans
NSFR	Net Stable Funding Ratio
OCI	Other comprehensive income
OOE	Other operating expense
OOI	Other operating income
PD	Probability of default
P&L	Profit and loss
RBI	Reserve Bank of India
RE	Real estate
RoA	Return on Assets
RWA	Risk weighted assets

Preface

The Technical Assistance (TA) mission was organized in April 2023 at the request of the Reserve Bank of India (RBI) for the IMF to review and evaluate its stress test model suite. The mission team was composed of Mr. Marco Gross (TA mission lead) and Ms. Wei Sun, both from the Monetary and Capital Markets (MCM) Department of the IMF.

The mission team's primary counterparts from the RBI included Ms. Kaya Tripathi (Head of Financial Stability Unit), Mr. Sneharthi Gayen (Director, Financial Stability Unit), Ms. Sangeetha Mathews (Assistant Adviser in the Financial Stability Unit), Mr. Kush Sharma (Assistant Adviser in the Financial Stability Unit), and Mr. Prem Mohan (Manager in the Financial Stability Unit). The team further included Mr. Ayyappan Nair (General Manager, Financial Stability Unit), Mr. Rakesh Kumar (Director, Financial Stability Unit), Mr. Avdhesh Kumar Shukla (Director, Research and Modelling Group, Department of Supervision), and Dr. Vijay Singh Shekhawat (Chief General Manager, Department of Supervision). Valuable discussions took place with RBI's Executive Director Dr. O. P. Mall.

The IMF TA mission members wish to thank the RBI for their friendly hospitality and great cooperation during the mission.

Executive Summary

The mission's purpose was for the IMF to provide a thorough review of the Reserve Bank of India (RBI)'s analytical capacity and model suite for solvency risk analysis, liquidity risk analysis, and balance sheet connectedness of banks (alongside non-bank financial institutions) in India. The RBI furnished the IMF team with all the accessible documentation in the form of records, presentations, and through detailed discussions over a series of meetings that extended to ten days. Toward the later phase of the mission, the IMF team provided RBI staff with an overview of what it considers to be best practice—at the Fund and by drawing on practices in other countries—in the areas mentioned above.

The RBI's stress test model suite was found to be well developed in various respects. RBI's model suite and analysis were found to be particularly robust in the following areas: (1) the *content and structure of all primary databases*, including through supervisory reporting, that are required for systemic risk analysis; it is commendable that all required data can "flow freely" between the departments that require access to it; (2) the *systemic risk analysis* that encompasses a wide range of risks and institutions, including credit, market, interest rate, liquidity, and counterparty risks for derivatives; beyond banks, assessments are included for insurers, mutual funds, and central counterparties (e.g., in the most recent Financial Stability Report); and (3) the *structural network-contagion module* that builds on a long time series of sizeable bilateral exposure data matrices, dating back to 2010, which covers banks and non-bank financial institution types, including pension funds, insurance firms, housing finance companies, and non-bank financial companies. The model incorporates a total of 225 banks and NBFIs.

The main recommendations pertain to credit risk, market risk (including interest rate risk), and macro-financial scenario design. The high-level recommendations are summarized in Table 1. More detailed recommendations are laid out throughout this report. The last recommendation in Table 1 relates to the workforce at RBI's financial stability unit, which should benefit from augmentation.

The mission team suggested that most recommendations ideally be addressed within a two-year window, i.e., by 2025. Addressing them before the beginning of 2025 will be beneficial because a new accounting regime (akin to International Accounting Standards (IFRS) 9 in other jurisdictions in 2018) will be instated in India in 2025 and will imply newly arising tasks and analytical development needs.

The mission team also provided the RBI with a primer on climate risk analysis. The RBI had enquired whether such a session could be included in the mission. In response, a three-hour session was included in the program to provide the RBI with an understanding of how to go about climate risk analysis, including data, analytical tools, and models. The IMF team conducted some India-specific research ahead of the related meetings to provide context to the discussion.

Table 1. Main Recommendations

Recommendation	Priority	Time frame
Revise the credit risk model component of the scenario-based bank solvency risk model to ensure its consistent integration with the modeling of default flows, loss given default, NPL formation, and loan loss provisioning.	High	Medium term
Integrate a market risk component, in particular concerning interest rate risk related to bank security holdings, into the scenario-based solvency stress test model suite.	High	Short term
Refine the interest rate risk module (via net interest income, NII) to better capture the underlying drivers of bank interest expense and income, alongside the spillover effects from default risk for bank interest income.	High	Medium term
Refine macro-financial scenario building by utilizing semi-structural macro-financial models such as structural vector autoregressive models (SVARs); consider a scenario horizon of 2-3 years.	Medium	Medium term
Consider expanding the workforce of the RBI's financial stability unit to ease the current workload of its staff, enabling them to better address the primary recommendations laid out in this report.	High	Short term

Note: Short- and medium-term time frames refer to a horizon of 1 year and 1-2 years, respectively, during which the suggested action is recommended to be addressed.

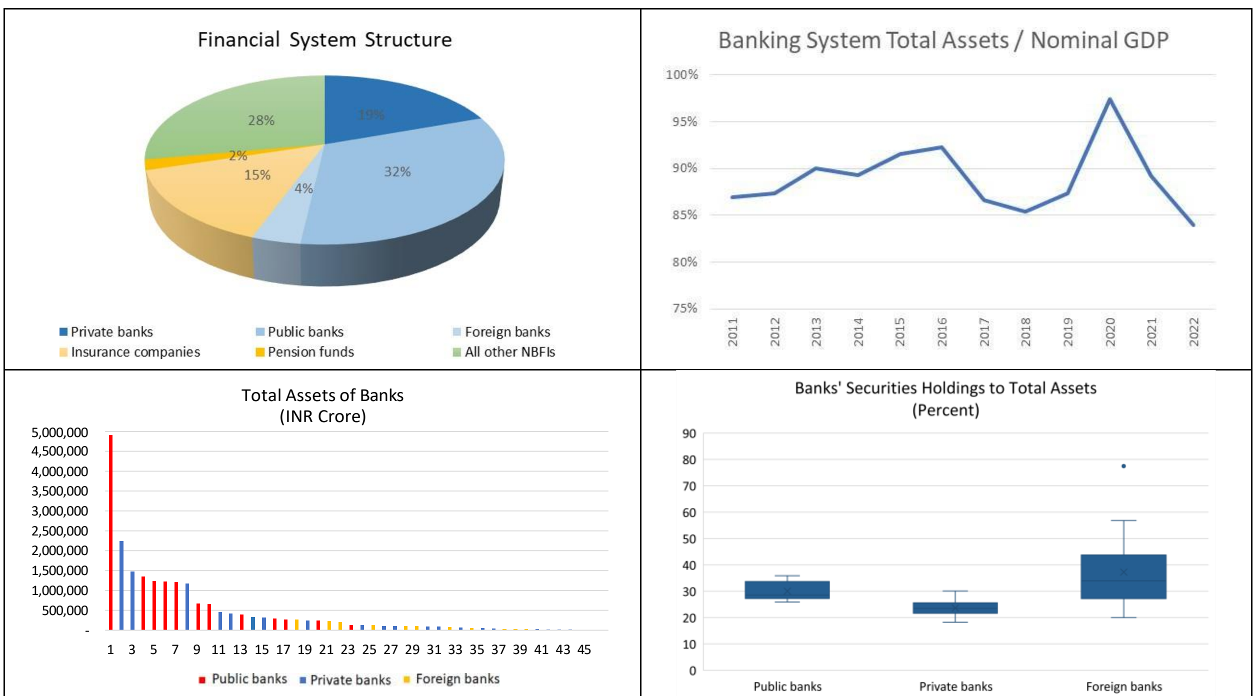
I. Background

India's financial system contains a sizeable share of banks, but also a non-negligible portion of non-bank financial institutions (NBFIs). Public, private, and foreign commercial banks represent 55 percent of financial system assets (as of end-2022, Figure 1). The banking system is composed of public banks (59 percent), private banks (35 percent), and foreign banks (6 percent). The largest 16 of 46 banks cover 85 percent of banking system assets. Insurance firms constitute the largest non-bank financial segment, at 15 percent of total assets. NBFIs other than insurers and pension funds, such as mutual funds, housing finance firms, and others, contribute 28 percent to financial system assets.[1] The ratio of banking system assets to annual nominal GDP averaged 81 percent over the last decade; it dropped in 2021 and 2022 due to strong nominal GDP growth of 18 and 16 percent, respectively.

The Indian banking system has experienced a recovery in terms of capitalization since the pandemic. Its aggregate capital ratio ranked in the middle of peers at about 16 percent in late 2022 (Annex Figure 1). Its profitability (return on assets, RoA) was weak until 2019 but has strengthened since 2020 (Annex Figure 2), standing at 1.4 percent in 2022. Its interest income and expenses are both low (negative and positive a characteristic, respectively). Its net interest income is relatively weak in comparison to its peers.

In a cross-country comparison, the Indian banking system is characterized by a high share of securities in total assets. It exceeded 26 percent in late 2022 at the system level (Annex Figure 3). Private banks tend to have lower ratios than public banks (Figure 1, lower right side). The high share of securities highlights the importance of including a well-developed market risk module in a bank stress test model suite for India.

Figure 1. India: Banking and Financial System Structure



Note: NBFIs = Non-bank financial institutions. INR = India rupee. Crore denotes 10,000,000 (or 100 lakh in the Indian numbering system). The chart in the lower left corner displays the total assets of 46 banks, which represent nearly 100 percent of the Indian banking system. The data for the financial system structure, total assets of banks, and security holdings, all correspond to end-2022.

Sources: RBI supervisory reporting and IMF staff calculations.

[1] RBI's December 2022 Financial Stability Report included several customized analyses related to NBFIs, such as mutual funds, alternative investment funds, and central counterparties.

II. Model Review and Evaluation

A. BANK SOLVENCY RISK ANALYSIS

The RBI conducts solvency risk analysis for 46 commercial banks.[2] This sample represents 98 percent of India's commercial banking sector assets. The analysis considers a range of risk factors and assesses the capital positions of public, private, and foreign banks. Data from supervisory returns are the main source for undertaking this analysis. It is supplemented by bank-specific data submissions for specific topics that the RBI's financial stability unit conducts with the banks.

Two complementary approaches underpin the bank solvency analysis. The first approach is a scenario-based stress testing analysis that involves translating macro-financial scenarios into bank capital ratio trajectories with a one-year scenario horizon. Numerous model components are developed at the bank cluster level (time series models). The projections resulting from such models are then distributed to the bank level. The second approach considers various sensitivity analyses that supplement the scenario-based stress test, such as those related to interest rate risk in the banking and trading book.

Credit Risk

The RBI models credit risk in three ways: using NPL ratios, credit loss provision flows, and industry-level probabilities of default (PDs). These three elements serve different purposes in RBI's current framework. First, the NPL ratios are obtained for feeding the econometric net interest income (NII) models (this aspect will be discussed in the NII section). They are not currently used to imply default flows and do not structurally influence bank capital ratio dynamics. Second, the econometric models for provision flows (accounted for through the P&L) serve to imply loan losses and influence the capital ratio numerator. Third, the sectoral PD models serve as input to the IRB-RWA module. This will be discussed in a separate sub-section.

Two model approaches are in place for the NPL model component. These include an autoregressive distributed lag model (ARDL) structure and a vector autoregressive (VAR) model structure. They capture the relationship of NPL stocks (modeled as ratios to gross loans) and real GDP growth, interest rate (spread) fluctuations, and a variety of corporate sector vulnerability variables. The ARDL models are used to translate the macro-financial scenarios through the equations' right hand-side variables. The VAR models are used in conjunction with an impulse response method to imply the scenario conditional response of the NPL ratios. Simple averages are taken from the two models' projections for each bank.

The credit loss provision flow models are used to project loan losses that flow through the P&L. These regression models have the NPL ratios as explanatory variables on their right hand-side, alongside other macro-financial drivers.

Remarks regarding the current credit risk module:

- The NPL ratio models are not used to structurally imply the performing exposure stock that generates interest income, i.e., there is no link to the interest income module.
- The NPL and provision flow models do not consider portfolio breakdowns.
- The three credit risk-related model components—for NPLs, provision flows, and sectoral PDs—do not interact in any structural manner.

[2] The RBI refers to them as so-called "scheduled commercial banks." That terminology stems from them being subject to the second schedule of the central bank charter.

- The way the VAR models are used entails some methodological deficiency: impulse responses for each driver are simulated separately first, and the responses of NPL ratios are obtained as averages of those paths subsequently. The better alternative would be to use only the equation for the NPL variable and omit all others, thus obviating the need of the VAR system, and compute scenario conditional forecasts. In turn, this reveals that ARDLs are, in principle, superior as they also allow for time contemporaneous relations.

Table 2. Recommendations: Credit Risk

#	Recommendation	Comments / Rationale
1	Implement a stock-flow consistent credit risk module. Option 1: Model default flows econometrically and imply NPL stocks structurally. Option 2: Model NPL stocks econometrically and imply default flows structurally. A portfolio segmentation is recommended, splitting at least into: nonfinancial corporate, household mortgages, and all non-mortgage household retail credit.	Option 1 is preferred, because it is easier to relate point-in-time default flow metrics to current macro-financial conditions. Both options require additional assumptions, particularly regarding gross credit growth and NPL write-off rates. Write-off rates can be informed by historical observed write-offs at bank-portfolio level. A portfolio disaggregation allows capturing portfolio-specific dependencies on macro-financial conditions.
2	Use primarily (panel) ARDL model structures as opposed to VARs.	The ARDL model structure is sufficient to capture the impact of macro-financial drivers. Of the VAR, only the equation with the target variable of interest is needed (while such VAR-extracted equation would not include time contemporaneous terms). Endogenous macro-financial feedback would already be captured at the scenario design stage. Bank-panel model structures are recommended.
3	Attempt to obtain and include unemployment rates and wage growth in the credit risk models for the retail segment.[3] For all segments, ensure proper capture of interest rate drivers for default risk.	These factors are structurally important for capturing the drivers of borrowers' repayment capacity, and interest rates particularly in economies with notable variable rate shares, such as in India. Including wage growth alongside price inflation allows for capturing real wage growth effects, which are particularly important to account for when considering supply shock scenarios.
4	Decommission the separate provision flow models; introduce LGD models and use them for implying provision flows in conjunction with the default flows (resulting from point 1 above).	The LGD component is required if the credit risk module is to become internally consistent. A distinction can be considered for real estate-collateralized portfolios and all other portfolios.

[3] RBI staff noted that obtaining long and reliable time series statistics for unemployment rates and wages poses some challenges in India. The incorporation of a related recommendation here for modeling purposes is warranted nonetheless, to thereby provide additional incentives for improving the collection of such statistics in the future.

Box 1 summarizes some formulas related to the stock-flow consistent relationships referred to under point 1 in Table 2. Box 2 lays out some LGD model options, thereby relating to point 4 in Table 2.

Box 1. Credit Risk Basics—Stock-Flow Relationships[1]

Gross loan stocks (L) are the sum of performing (PL) and nonperforming exposure stocks (NPL):

$$L_t = PL_t + NPL_t \ . \tag{1}$$

NPL stocks are implied by write-off flows (a function of write-off rates, WRO_t), cure rates ($CURER_t$), and default rates (PD_t):

$$NPL_{t+1} = NPL_t(1 - WRO_{t+1} - CURER_{t+1}) + PD_{t+1}(L_t - NPL_t) \ . \tag{2}$$

Performing loans are implied by principal repayment flows, default rates, new business flows, and cures:

$$PL_{t+1} = PL_t\,(1 - M_{t+1} - PD_{t+1}) + NB_{t+1} + CURE_{t+1} \ . \tag{3}$$

Equation (2) can be solved for default flow rates:

$$PD_{t+1} = \frac{NPL_{t+1} - NPL_t(1 - WRO_{t+1} - CURER_{t+1})}{L_t - NPL_t} \ . \tag{4}$$

This equation can be used not only to derive PD paths from NPL paths conditional on forward-looking scenarios, but also for deriving default rate metrics historically. Econometric models can be set up for either PDs or NPL stocks (or ratios). The respective other metric can be implied using eq. (2) or (4).

The credit loss calculations are then conducted in three steps. All formulas in the following apply at the bank-portfolio level; the notation omits this for brevity.

Step 1: Project gross exposures and performing and nonperforming portions thereof.

Gross exposures are aligned with gross credit growth (g_{t+1}) from a scenario, e.g., as output from a macro-financial model:

$$E_{t+1} = E_t(1 + g_{t+1}) \ . \tag{5}$$

Keeping g at zero means a static balance sheet; allowing it to be positive or negative implies a dynamic balance sheet. Nonperforming exposures are projected based on the NPL ratio paths ($NPLR_{t+1}$) from the econometric models:

$$NPL_{t+1} = NPLR_{t+1} \times E_{t+1} \ . \tag{6}$$

The performing exposures are obtained as a residual:

$$PL_{t+1} = E_{t+1} - NPL_{t+1} \ . \tag{7}$$

1/ For details, see "Expected Credit Loss Modeling from a Top-Down Stress Testing Perspective," by M. Gross, D. Laliotis, M. Leika, and P. Lukyantsau (IMF Working Paper 2020/111).

Box 1. Credit Risk Basics—Stock-Flow Relationships (concluded)

Step 2. Project provision stocks.

The provision stocks for performing exposures involve the provision coverage ratio for the performing exposure bucket (PCR^{PL}), which can be bank-specific due to different shares in the underlying regulatory asset quality classes 1 and 2:

$$PS_{t+1}^{PL} = PCR^{PL} \times PL_{t+1} \ . \tag{8}$$

The nonperforming provision stock involves the provision coverage ratios for NPLs net of collateral (PCR^{NPL}), and for that reason the LGD path, aligned with house prices in a scenario as outlined earlier for real estate portfolios, appears in the equation:[/2]

$$PS_{t+1}^{NPL} = PCR^{NPL} \times LGD_{t+1} \times NPL_{t+1} \ . \tag{9}$$

The regulatory provision coverage ratio for nonperforming exposures (PCR^{NPL}) is bank-specific, due to different shares held in the underlying asset quality classes 3-5.[/2]

Step 3. Compute provision flows (capital impact).

The provision flow for performing exposures (LL_{t+1}^{PL}) equals the change in its provision stock:

$$LL_{t+1}^{PL} = PS_{t+1}^{PL} - PS_{t}^{PL} \ . \tag{10}$$

The capital impact for nonperforming exposures equals the change in the provision stock plus a term that controls for write-offs:

$$LL_{t+1}^{NPL} = PS_{t+1}^{NPL} - PS_{t}^{NPL} + WRO_{t+1} \times LGD_{t} \times PCR^{NPL} \times NPL_{t} \ . \tag{11}$$

The combined net loan loss provision flow is the sum of the flows for performing and nonperforming exposures:

$$LL_{t+1} = LL_{t+1}^{PL} + LL_{t+1}^{NPL} \ . \tag{12}$$

This periodic flow represents the change in capital from period to period, as accounted for through the bank P&L statements.

[2/] In other words, the product of the NPLs and the LGD is intended to capture the exposure net of collateral. The specifics of the Indian regulation in this regard may need to be more accurately incorporated into this equation.

[3/] For simplicity, PCR^{PL} and PCR^{NPL} are assumed to be constant over time for each bank. Otherwise, it would be necessary to model the migration of exposures across all quality buckets within performing exposures (i.e., stages 1 and 2) and within non-performing exposures (i.e., stages 3-5), which would be more data demanding.

Box 2. LGD Modeling Options[1]

A simple LGD model variant for real estate-collateralized portfolios entails the revaluation of housing collateral in line with house price paths considered in macro-financial scenarios. The equation used to project the LGDs of real estate-collateralized portfolios is:

$$LGD_{t+1} = 1 + (LGD_t - 1)\frac{HP_{t+1}}{HP_t}, \tag{13}$$

where HP denotes a house price index, that can pertain to either residential or commercial property, depending on the portfolio type, i.e., a household mortgage and commercial property lending portfolio.

The RBI could compile exposure-weighted current loan-to-value ratios for the real estate portfolios, enabling the use of a more nuanced LGD model variant in the future. Such a variant would account for the uncertain (stochastic) nature of the collateral value lapsing between the time of default/collateral seizure and its sale in the future (see Section 3 in Gross et al. 2020).

For portfolios that are not collateralized by real estate, an alternative model option can be considered that calculates LGDs from PD trajectories. The method was put forth in Frye and Jacobs (2012)[2] and considers a Vašíček-type equation. It builds on two primary formulas:

$$\mathrm{LGD_{t0+h}} = \frac{\Phi(\Phi^{-1}(\mathrm{PD_{t0+h}})-\mathrm{k})}{\mathrm{PD_{t0+h}}}, \tag{14}$$

which is the LGD formula as such, together with one for parameter k:

$$\mathrm{k} = \frac{\Phi^{-1}(PD^*_{t0})-\Phi^{-1}(PD^*_{t0}\times LGD^*_{t0})}{\sqrt{1-\rho}}. \tag{15}$$

The method as sketched here (eqs. 14 and 15) was used in the IMF's Global Bank Stress Test (see further references also therein). The PD and LGD terms with an asterisk in eq. (15) are long-term average PDs and LGDs. The $LGD*$ term in the equation can be numerically determined for the overall model, i.e., eqs. (14) and (15) combined, to imply an observed "T0" point-in-time LGD. After that, the equations can be used for forecasting the LGD conditional on a PD path.

LGD starting point data can be obtained by using information about actual recoveries from banks. In their absence, provision coverage data can be employed to obtain proxies for LGDs; this would involve accounting-type provisions specifically for NPLs.

1/ See Gross et al. (2020) for all information contained in this box; and including more details.

2/ See "Credit Loss and Systematic Loss Given Default," by J. Frye and M. Jacobs (*The Journal of Credit Risk*, Spring 2012).

Interest Rate Risk (via NII)

The RBI models interest rate risk (via NII) using econometric time series models. The same empirical strategy with ARDL and VAR models is employed. NII-to-total-asset ratios serve as the dependent variable. Lending rates (spreads to policy rates), GDP growth, and NPL ratios are included as explanatory variables.

The RBI supplements this regression approach with a sensitivity analysis of the interest rate risk on the banking book. It uses a gap analysis to quantify the earnings-at-risk when being subjected to rising interest rate scenarios. It also employs a modified duration approach to assess the change in market value of equity to bank net worth.

Remarks regarding the current NII module:

- The spillover of default risk to interest income is captured solely through the econometric models and indirectly through the inclusion of NPL ratios as an explanatory variable in the NII model.
- The same comment regarding the parallel use of ARDL and VAR models (and the impulse response method) as for the credit risk module applies here.

Table 3. Recommendations: Interest Rate Risk (via NII)

#	Recommendation	Comments / Rationale
5	Split NII into interest income and expense and model them separately, e.g., using (panel) error correction models (P-ECMs).	Splitting the components up will enhance model precision and allow a deeper analysis of the underlying drivers of NII.
6	Define interest income as a ratio to *performing* banking book exposures (plus trading book exposures that generate interest). Bank P-ECMs can be used. They would include the relevant drivers, e.g., cost of funding, market rates, policy rates, and variables that capture borrower risk.[4]	The use of such models alongside the definition of the left hand-side variable will allow a structural link between the credit risk and interest rate risk module: The credit risk module will establish the performing exposure base, while the interest income rate can be applied to the performing exposure base, thereby better capturing the important dependence of interest income on default risk.
7	For interest expense, consider including solvency feedback to cost of funding, if such feedback is relevant empirically, likely so for banks with non-negligible wholesale funding shares.	Banks with weak capital position tend to pay a higher cost for wholesale funds.

Market Risk

Banks in India hold significant amounts of securities on their balance sheets (Figure 1). Most of these securities are issued by India's sovereign and state governments. Public and private banks tend to hold them to maturity, while foreign banks mainly treat them as tradable. Net trading income (e.g., valuation gains/losses for government securities) can be a sizable income source. In the quarter ending March 2022, it represented 23 percent of the pre-tax income for public banks.

The RBI incorporates market risk in its scenario-based stress testing analysis only econometrically and in conjunction with other P&L items. It is indirectly modeled as part of "other operation income" (OOI, see next section) in an econometric fashion.

A separate sensitivity analysis assesses the impact of interest rate fluctuations on bank capital through trading book revaluation. In this analysis, the RBI applies a universal shock of 250 basis points to the entire yield curve. It then uses the modified duration approach to calculate the valuation losses for securities under the held-to-maturity, available-for-sale, and held-for-trading accounts.

[4] The credit risk models (for either default flows or NPL stocks) will imply bank-portfolio level projections. The nonperforming exposure stocks can then be aggregated from portfolio to bank level. These bank-level aggregates are the input to the bank-level interest income and NII calculations.

Table 4. Recommendations: Market Risk

#	Recommendation	Comments / Rationale
8	Include a mark-to-market (MtM) valuation module in the scenario-based stress test. The impacts should be through both P&L and other comprehensive income (OCI). Reflect the investment fluctuation reserve in the module.[5]	The RBI has the data and relevant model components in place for their sensitivity analysis. It may therefore be able to incorporate it readily and easily into the macro stress test framework. Under the International Financial Reporting Standard (IFRS) accounting framework, which India plans to transition to in 2025, the valuation change of held-for-trading securities should be reflected in bank P&L statements. The valuation change of the available-for-sale securities goes through OCI.
9	Treat equity and FX risks separately if they are quantitatively significant for a notable number of banks.	The current stress testing exercise does not incorporate this explicitly. Equity and FX exposures can be separately measured.

Box 3 summarizes the principles underlying a basic MtM valuation scheme for fixed income instruments.

Box 3. Modified Duration and Mark-to-Market (MtM) Revaluation Calculations for Bond Exposures

An MtM revaluation for bank bond exposures requires three inputs: (1) the bond exposure, (2) the Macaulay duration, and (3) an assumed interest rate shock. The principles laid out below apply to individual instruments or portfolios of bonds, to bonds in different portfolio segments (e.g., sovereign, nonfinancial corporate, financial corporate), and likewise to bonds that are considered either assets or liabilities of a bank.

The Macaulay duration is not simply a residual duration of a bond until maturity but a variant thereof that takes account of the bond's expected income stream until maturity:

$$D = \sum_{t=1}^{T} \frac{\frac{x_t}{(1+r+s)^t}}{V} t \, , \qquad (16)$$

where x_t is the periodic income flows from today until maturity, r is a base interest rate of the combined current yield, s is its credit spread component, t the time steps until maturity T, and V the market value. The latter is defined as:

$$V = \sum_{t=1}^{T} \frac{x_t}{(1+r+s)^t} \, . \qquad (17)$$

When applying the valuation to *portfolios* of bonds, then the duration *D* should be an exposure-weighted average of the instrument-level durations. The bond revaluation formula is:

$$\Delta V_{t+1} = -V_t \frac{D}{(1+r_t+s_t)} (\Delta r_{t+1} + \Delta s_{t+1}) \, . \qquad (18)$$

[5] The OCI concept would be applicable for Indian banks only with the implementation of IFRS in 2025. Based on local accounting rules, a proportion of the valuation gains go to an investment fluctuation reserve. This reserve will compensate valuation losses when they occur and are intended to render bank income less pro-cyclical.

Box 3. Modified Duration and Mark-to-Market (MtM) Revaluation Calculations for Bond Exposures (concluded)

The base rate shift (Δr_{t+1}) and the credit spread shift (Δs_{t+1}) can also be combined into one interest rate shift if they are not intended to be differentiated.

The presence of the base rate shift (Δr_{t+1}) in eq. (18) makes the formula specific to fixed rate bonds. For variable rate bonds, the base rate delta term should be dropped since base rate shifts have no impact on the value of variable rate bonds as per their design. When banks hold both variable and fixed rate bonds, the formula can be applied separately to each portion and the impacts be summed up afterwards. Since variable rate bonds require a base rate shift to not be considered, carving out the credit spread component of the overall bond yield shock would be necessary.

Other P&L Components

The RBI projects all remaining bank income and expense items in an Other Operating Income (OOI) and Other Operating Expense (OOE) category. The OOI category consists of fees and commissions, net trading income, FX valuation effects, and some other residual components. An ARDL model relates the OOI-to-total asset ratio to a current account balance-to-GDP ratios and export-to-GDP ratios. The OOE category consists mostly of staff expense. Its regression model relates OOI-to-total asset ratios to consumer and wholesale price inflation.

Table 5. Recommendations: Other Operating Income and Expense

#	Recommendation	Comments / Rationale
10	Embed a top-down derivatives stress test into the macro stress test.	The RBI has already conducted a bottom-up stress test on derivative positions. It may incorporate a top-down stress test element for derivatives in the macro stress testing framework.
11	Set up separate models for net fee and commission income (NFCI) and exclude this component from OOI.	Fees and commissions appear to be a significant part of the OOI. This revenue source usually responds to interest rates in a manner that is to an extent opposite of other P&L components (banks tend to raise fees when interest rates fall), which warrants a separate econometric model.
12	Should market risk and FX effects be modeled separately (see recommendations #8 and #9 in Table 4), then exclude trading income and FX valuation effects from the respective OOI and OOE categories.	To avoid inconsistency.

Dynamic Balance Sheet Modeling

The RBI solvency stress test considers dynamic balance sheets. For the baseline scenario, it obtains credit growth for the banking sector from its Survey of Professional Forecasters with a one-year horizon. Based on recent historical patterns, aggregate growth is distributed across the three bank clusters (private, governmental, foreign), subject to the constraint that bank cluster-weighted aggregate credit growth matches aggregate target growth. For the adverse scenarios, the bank cluster-specific credit growth rates are calibrated by considering one-to-two standard deviation gaps from the baseline.

Table 6. Recommendations: Dynamic Balance Sheets

#	Recommendation	Comments / Rationale
13	Include credit in a macro-financial model that is used to design macro-financial scenarios.	Including credit in such a model allows two-way endogenous feedback between credit and real economic dynamics to be captured.

RWA Modeling

The credit risk-RWA calculations that the RBI embeds in its credit risk module reflect the rationale of the Foundation Internal Rating-Based (F-IRB) approach. Sectoral point-in-time probabilities of default (PDs), prescribed loss given default (LGD) parameters, and balance sheet growth are used as inputs for projecting them under the scenarios. For the PDs, the RBI employs the aforementioned PD models (based on annualized "slippage ratios," i.e., default rates) for 18 portfolio segments. For the LGDs, it uses prescribed values at 60, 65, and 70 percent for the baseline, mild adverse, and severe adverse scenarios, respectively. IMF technical assistance on stress testing conducted in 2015 recommended the use of this approach. At present, all banks in India still follow the standardized approach.

The market risk-RWA calculations entail an adjustment for valuation losses. Currently, for the RBI's sensitivity analyses, the valuation change resulting from the market risk module is deducted from the RWA balance in an unweighted manner.

Table 7. Recommendations: Risk Weighted Assets

#	Recommendation	Comments / Rationale
14	Smoothen the default rate inputs to the IRB risk weight formulas.	Thereby obtain and use through-the-cycle rather than point-in-time PDs as input to the risk weight formulas. Basel regulations recommend that banks employ smoothing measures to avoid undue procyclicality. Moreover, Indian banks still use the STA approach, which does not entail any risk weight variation. To obtain smooth, through-the-cycle default rates, long-term averages, e.g., 5-10 year moving averages, of point-in-time default rates at the bank-portfolio level can be considered.
15	Use historical downturn LGDs as input to the regulatory risk weight formulas.	As per Basel guidance concerning risk weight formulas. Statistical upper tail estimates of historical LGD data at the bank-portfolio level can be used to inform the downturn LGDs.
16	Subtract a market risk-weighted valuation change from the RWA.	Currently, the MtM valuation changes are deducted from the RWA in an unweighted manner. It risks overstating capital ratios, i.e., underestimating market risk when expressed through the risk-weighted capital ratio metric.

B. BANK LIQUIDITY RISK ANALYSIS

The RBI assesses bank liquidity risk based on the ratio of liquid assets to total assets. Liquid assets are defined as the sum of "statutory liquidity" (largely composed of Indian government securities), together with the currency reserves in excess of the required 4.5 percent minimum. A haircut of 10 percent, i.e., a factor of 0.9, is applied to the resulting sum of the two components, which forms the numerator of the liquid asset ratio.

A stress version of the liquid asset ratio entails haircuts for the assets and stress assumptions for credit line drawdowns and deposit run-offs. Run-off rates for uninsured deposits are assumed at 10, 12, and 15 percent, for three scenarios of increasing severity. Credit lines are assumed to be drawn by 75 percent in all scenarios. The critical threshold for the "stress version" of the liquidity asset ratio is 0 percent. The ratio and its underlying calculations do not entail an explicitly defined time horizon for the drawdowns of credit lines and outflows of deposits. At present, the RBI's analysis based on the liquid asset ratio does not consider any currency breakdowns.

The RBI is transitioning to a liquidity coverage ratio (LCR)-based stress testing analysis. It has set up the infrastructure and banks have already started reporting the required data. The haircuts applied to HQLA, along with cash in- and outflow assumptions, follow the Basel prescriptions.

The RBI plans to introduce the net stable funding ratio (NSFR). NSFR guidelines came into effect in October 2021. The RBI analyzes bank-reported NFSRs in its internal reports. It is yet to set up the infrastructure to undertake NSFR-based stress test analyses. It may plan to report the related results in its financial stability report in the future.

Table 8. Recommendations: Liquidity Stress Testing

#	Recommendation	Comments / Rationale
17	Operationalize the LCR-type stress tests.	The LCR-type stress test incorporates a greater variety of funding and market liquidity factors. It will be a valuable complement to RBI's current stressed-liquid asset ratio-based analysis.
18	Establish a link to the market risk module in the solvency stress test. Consider mark-to-market valuation of HQLA to interest rates specified in a macro-financial scenario.	The liquidity stress test based on the liquid asset ratio and the prospective LCR-type stress test operate with ad hoc haircuts for the HQLA components. Bond exposures can instead be revalued in line with the assumed interest rate scenario trajectories as specified in a macro-financial scenario (using, e.g., the modified duration approach, see section II.A on market risk). As a result, the scenario-dependent haircuts will become specific to each bank, reflecting differential bond holdings, for example, in terms of duration.
19	Conduct reverse LCR-type stress tests against various drivers, such as run-off rates and interest rates, through a revaluation of HQLA.	Such reverse liquidity stress testing is instrumental in ranking banks based on certain parameters, to analyze their liquidity risk profile. Parameters used in reverse stress testing can include run-off rates for different deposit types (retail, wholesale), credit line drawdowns, interest rates to revalue bond holdings as part of the HQLA (see point 18 above), and others.
20	Analyze historical deposit inflow and outflow data for Indian banks to inform the run-off rate assumptions for the relevant liquidity metrics.	The run-off parameters are currently taken as given. Analyzing India-specific historical data can help assess the adequacy of such parameter settings and ensure they are set in a conservative manner.

		When direct measures of inflows and outflows are not available, proxies such as changes in deposit stocks can be used to obtain net flows.
21	Conduct NSFR-type stress testing.	The NSFR stress test is useful for judging the funding stability of individual banks, as a complement to the LCR-type stress test.

C. MACRO-FINANCIAL SCENARIO DESIGN

The RBI's macro-financial scenario comprises various variables and currently considers a 1-year horizon. For the definition of a baseline scenario, variables such as GDP and consumer price inflation forecasts are provided by RBI's Monetary Policy Department (quarterly, with a 1-year horizon). The Survey of Professional Forecasters informs several indicators, such as the wholesale price index, current account balance-to-GDP ratio, export-to-GDP ratio, fiscal deficit-to-GDP ratio, oil prices, sectoral gross value added, and credit growth, all at a 1-year horizon. Other variables, including weighted average lending rates, term spreads, corporate bond spreads, a corporate interest coverage ratio, net profit-to-sales ratio, operating profit-to-sales ratio, and house price-to-income ratio are all generated from ARDL-type models.

The RBI usually designs two adverse scenarios based on a multiple-of-standard-deviations approach. The adverse scenarios entail the use of 0.25-1 standard deviation (STD) gaps for the mild adverse scenario variant, and 1.25-2 STD gaps for the severe adverse scenario. The four grid points of the STD multiples in these ranges are applied to the four quarter of the 1-year horizon. They are applied to the baseline scenario.

Table 9. Recommendations: Scenario Design

#	Recommendation	Comments / Rationale
22	Consider a 2-year, potentially even 3-year scenario horizon.	A 1-year horizon implies the risk of not reaching the trough (maximal impact) that macro-financial stress scenarios may imply for bank solvency, due to lagged relationships of macroeconomic variables and the to-an-extent-lagged response of risk materialization (credit, interest rate risk).
23	Consider using (S)VAR models for scenario design. This approach will allow for defining and reflecting concrete scenario narratives.	This approach allows for obtaining internally consistent, dynamic scenarios that can be used to simulate concrete narratives (e.g., demand shocks vs. supply shocks), using, for example, sign restriction methodologies. When applying the standard deviation multiples approach, it is recommended to apply them to the historical mean rather than to the baseline to ensure capturing "state dependency" properly, especially when designing cyclical rather than structural shock scenarios.
24	Aim to include unemployment rates, wage growth, and house prices, or their proxies, in the scenario design package.	Such variables constitute important economic drivers for various risk factors facing banks. They should be incorporated once reliable statistics for them are available.

D. SOLVENCY AND LIQUIDITY RISK ANALYSIS FOR NBFIS

The RBI compiles the stress test results for various kinds of smaller bank clusters and NBFIs that are provided by different regulators. This includes a solvency analysis for primary urban cooperative banks (which constitute less than 3 percent of the banking sector assets). Solvency risk analyses for insurers and liquidity risk analyses for mutual funds are conducted by the relevant regulators. A bespoke stress test for clearing corporations determines the minimum required corpus (MRC) of the core settlement guarantee fund. The exercise is carried out by segment on a monthly basis. For example, the MRC for cash and equity derivatives segment is determined by the credit exposure arising from a presumed simultaneous default of the top-two clearing members. The RBI compiles all such results from the respective regulators and reports them in the Financial Stability Review.

Table 10. Recommendations: NBFI Stress Testing

#	Recommendation	Comments / Rationale
25	Apply the commonly defined macro-financial scenarios to other NBFIs, to the extent possible.	This represents one component of integrating a stress test for banks and NBFIs (in addition to possible integration through cross-exposures, as captured through network-contagion analysis). Interest rate scenario trajectories are an example of a metric that matters also for NBFIs, especially when revaluing insurer and pension fund security holdings.

E. NETWORK AND CONTAGION ANALYSIS

RBI's network and contagion analysis is based on a comprehensive data set currently comprising 225 financial institutions. These include commercial and cooperative banks, small finance banks, housing finance companies, pension funds, insurance firms, asset management companies, and other NBFIs. The network data captures the lending-borrowing relationships among all firms by instrument based on granular bank-reported data since 2011. Asset management companies, insurance firms, pension funds, and public commercial banks are net lenders to the financial system, while NBFIs and others are net borrowers. A connectivity ratio is computed, which measures the number of links between the nodes relative to all possible links in complete network. Another cluster coefficient measures how interconnected each node is. A high cluster coefficient for the network is interpreted as high local interconnectedness prevailing in the system.

The RBI's contagion analysis helps assess the impact of individual entity failure within a network of all banks and NBFIs. The failure of an entity that is assumed to default has solvency and liquidity implications at the same time. From a solvency perspective, its creditors face credit losses. If these, in turn, are not able to compensate such losses with capital buffers above a 7 percent Tier 1 capital ratio threshold, they fail, default on their debt obligations, and further propagate the shocks to their creditors. From a liquidity perspective, the trigger entity will withdraw all callable exposures from its borrowers. These borrowers will do the same to maintain their liquidity ratios. If insufficient, they will call all other exposures or fail, and generate further shocks. Contagion continues until the default cascade comes to an end. Currently, the RBI focuses its default simulations primarily on banks.

The results from solvency and liquidity stress tests can be used to inform the "trigger assumptions" of the contagion analysis. The RBI can consider using the results from the solvency and liquidity stress test to inform which entities to let default at the onset of the default cascade simulations. It may also at some point more structurally integrate the default cascade simulations in the multi-year solvency stress test. Such a recommendation has not been included among the main recommendations (Table 10), however, because other recommendations would be assigned higher priority first.

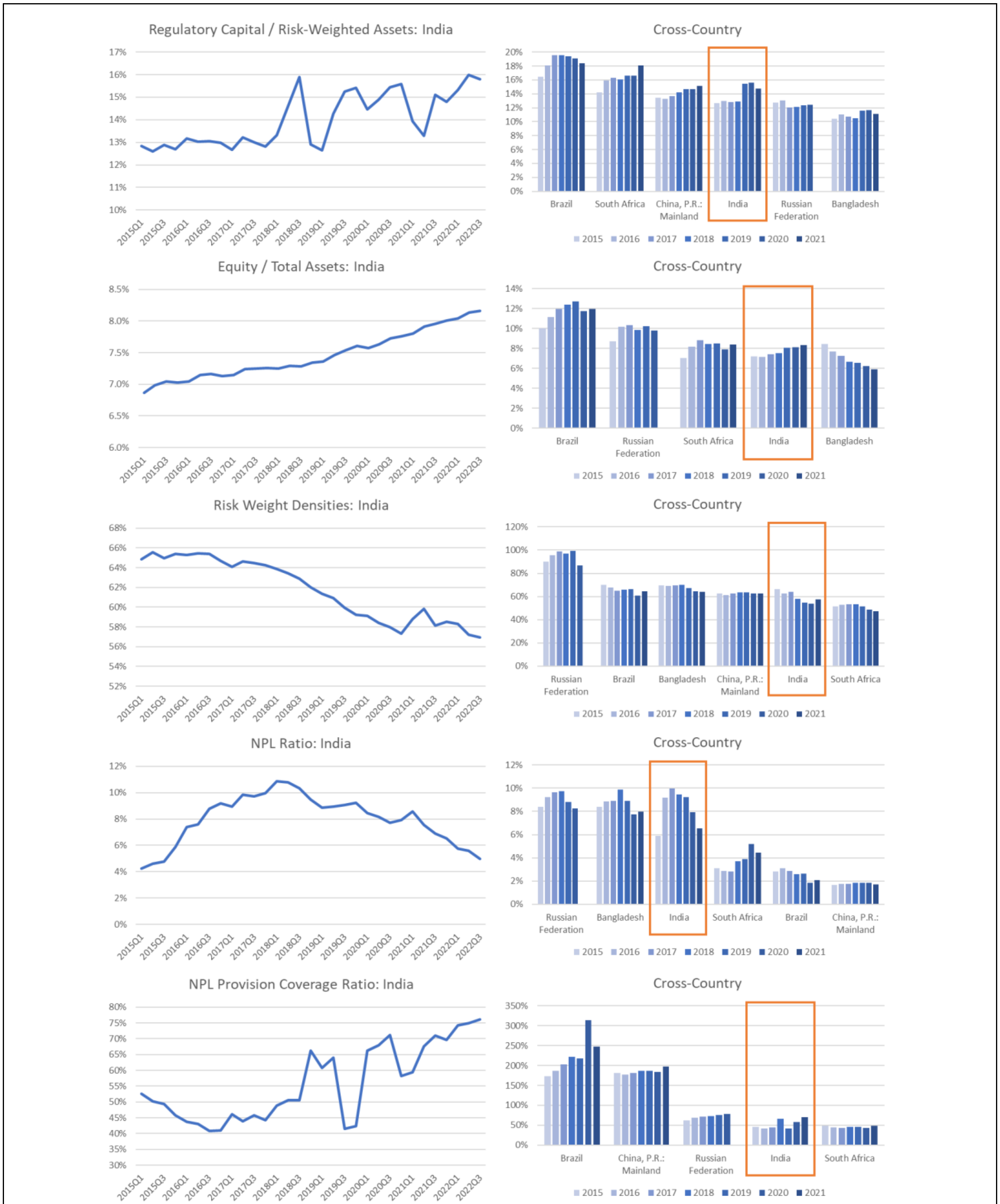
Table 11. Recommendations: Network and Contagion Analysis

#	Recommendation	Rationale
26	Consider employing some additional basic network metrics.	Numerous well-established and conventional network metrics exist, which can help further nuance the RBI's analysis. The RBI may consider introducing, for example, degree centrality, closeness, betweenness, and eigenvector centrality; which it can add to its existing software for network and contagion analysis.
27	Include *all* financial institution types, beyond just banks and NBFIs, in the contagion simulations, even if banks remain the focus of the analysis.	The inclusion of all institutions allows capturing all funding dependencies with a broader scope. This treatment is closer to reality and mitigates the risk of under- or overestimating risk transmission. The criteria for failure of non-banks can be set flexibly.[6]
28	Compute impact and vulnerability metrics. Identify entities that are impactful and vulnerable at the same time.	The identification of entities that are impactful (i.e., those causing sizeable capital losses throughout the system upon their default) and vulnerable (i.e., their own capital loss susceptibility conditional on other entities' failures) at the same time can help enrich the analysis and possibly inform macroprudential policy measures (e.g., surcharges for systemic importance, and others). The impact and vulnerability metrics can also be analyzed for all combinations of sub-clusters of all financial institutions. RBI's existing software for the conduct of network-contagion analysis would need to be modified to allow for the addition of vulnerability metrics in particular.

[6] A liquidity contagion loss analysis may not be feasible yet as long as liquid asset data for mutual funds, insurers, and other non-bank FIs is not available yet. The criteria for the failure of non-bank financial institutions will require further, more detailed deliberations that go beyond the scope of this report. A dedicated TA can be considered for this in the future.

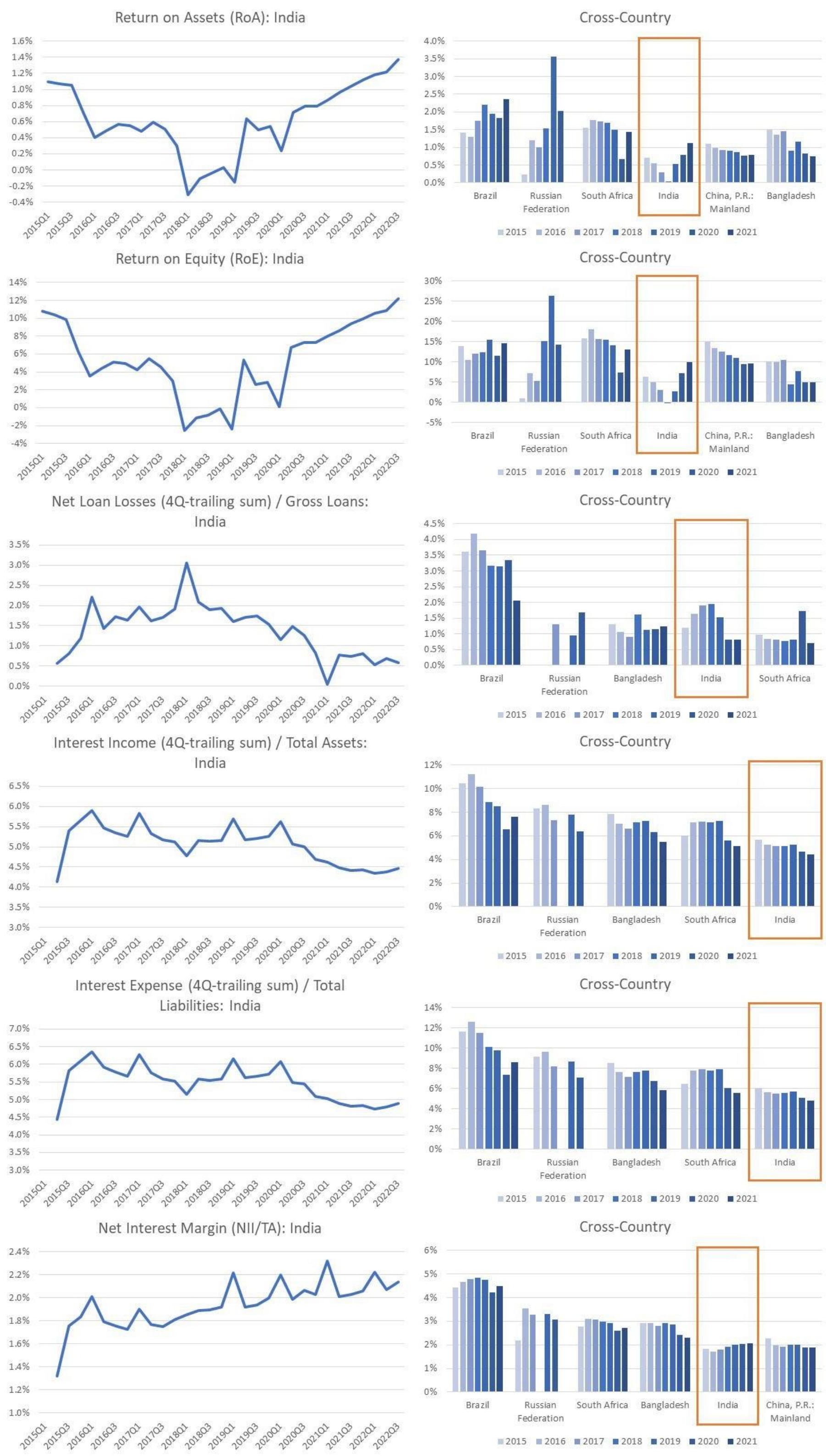
Annex: Banking System Data and Indicators

Annex Figure 1. India: Banking System Solvency and Asset Quality Metrics



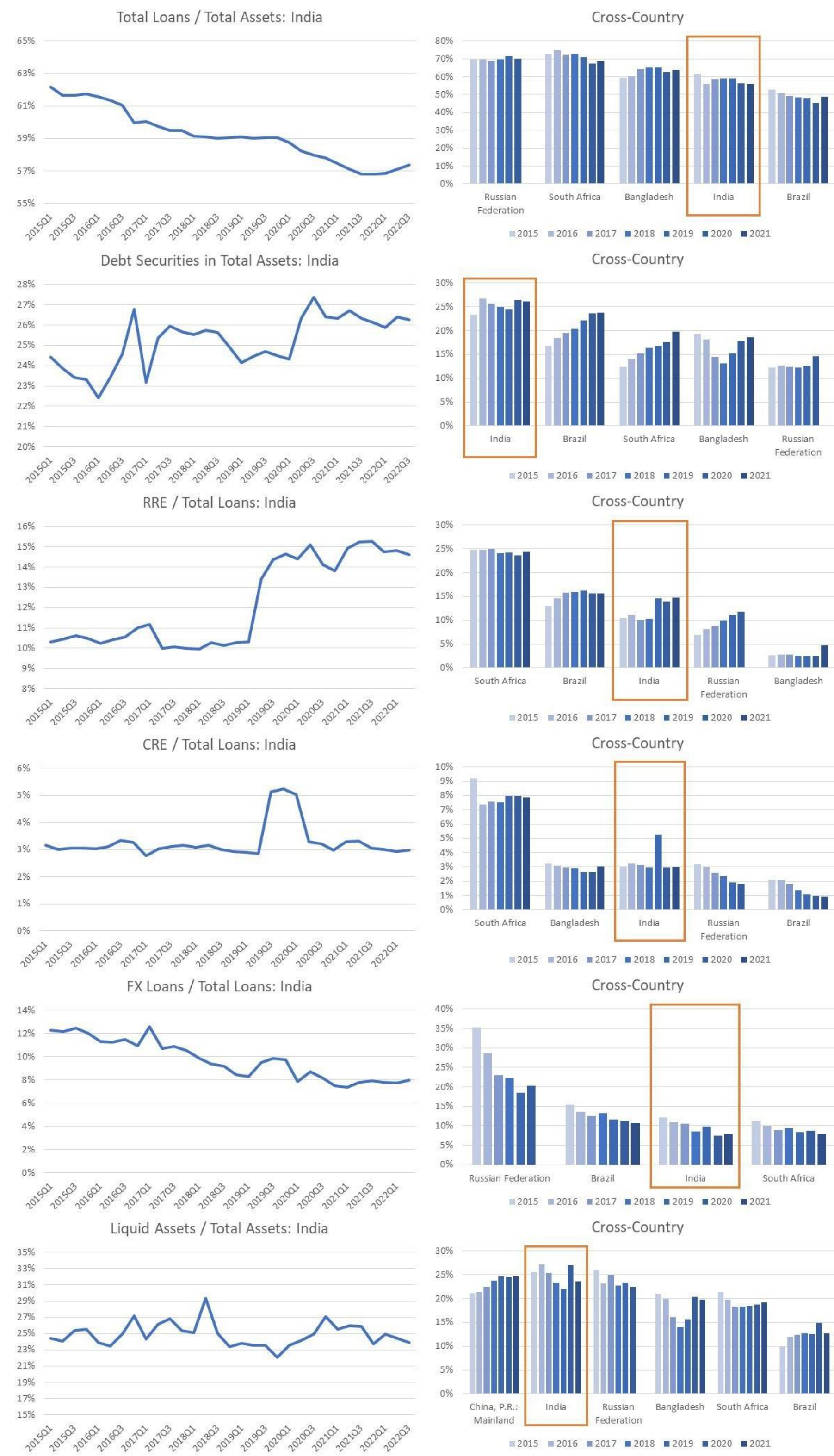
Source: IMF Financial Soundness Indicators database and IMF staff calculations.
Note: NPL = nonperforming loans.

Annex Figure 2. India: Banking System P&L and Profitability Metrics



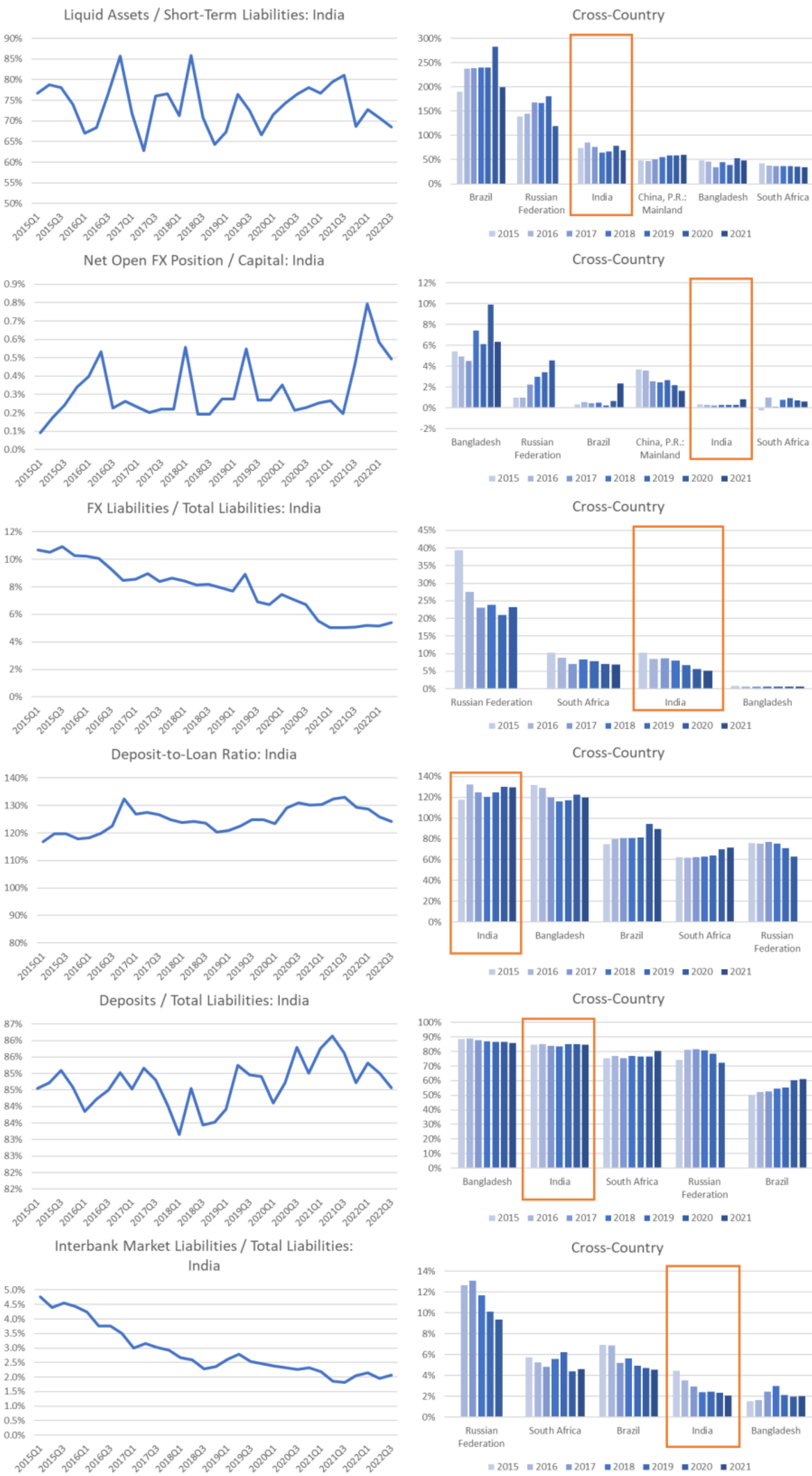
Source: IMF Financial Soundness Indicators database and IMF staff calculations.

Annex Figure 3. India: Banking System Balance Sheet Structure



Source: IMF Financial Soundness Indicators data and IMF staff calculations.
Note: RRE = residential real estate; CRE = commercial real estate.

Annex Figure 3. India: Banking System Balance Sheet Structure (concluded)



Source: IMF Financial Soundness Indicators data and IMF staff calculations.