INTERNATIONAL MONETARY FUND

MONETARY AND CAPITAL MARKETS DEPARTMENT

The Global Bank Stress Test

Prepared by Xiaodan Ding, Marco Gross, Ivo Krznar, Dimitrios Laliotis, Fabian Lipinsky, Pavel Lukyantsau, and Thierry Tressel

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Executive Summary

Shocks to financial systems can lead to financial crises, which have large costs in terms of foregone growth and weakening of economywide balance sheets. Financial policymakers around the world aim at increasing the resilience of their financial systems, an important part of which is risk analysis.

Bank stress tests are conducted at a national level by central banks and supervisory authorities to assess the resilience of banks. In some cases, these analyses are conducted by supra-national authorities for members of a currency union. But generally, the focus is on risks to national banking systems, with less emphasis on global risks and resilience. Moreover, countries differ widely in the nature of their granular supervisory data and methodologies for stress testing and scenario design used in authorities' stress tests. This factor poses challenges for comparing scenarios and stress testing results across countries.

The IMF staff assess systemic risk as part of the IMF's mandate to monitor global financial stability, leveraging the conceptual framework of "growth-at-risk" approach developed by the IMF (see IMF 2017). These risks are analyzed at the multilateral level in the flagship series *Global Financial Stability Report* (GFSR) and at the country level in the context of Article IV surveillance and the Financial Sector Assessment Program (FSAP). Assessing the impact of global shocks—such as those arising from the pandemic—that have highly differentiated effects across countries and economic sectors, eliciting equally diverse policy responses, is a challenge. This has flagged the importance of developing a global bank stress testing approach that undertakes consistent risk analysis of the impact on countries of common global shocks, incorporating cross-country spillovers and synergizing with the more granular deep dives undertaken in the context of the IMF's bilateral work.

In this context, IMF staff developed the Global Bank Stress Test (GST) launched in the October 2020 GFSR to provide insights on the impact of the pandemic on banking systems around the world. Beyond the pandemic, the GST provides a flexible yet rigorous framework to assess the implications of common global shocks and their spillovers on the IMF membership and to inform policy discussions at both the bilateral and multilateral level. The GST is the first cross-country framework that provides an analysis of resilience of banks at the global level using consistent global scenarios and a common methodology. It also provides a benchmark for national authorities to compare the resilience of their banks to banks in other countries and captures the effects of cross-border spillover and implicit spill backs via both financial and real economy linkages, and the effects of such linkages under various stress scenarios.

This paper presents the framework underlying the GST and applies it to recent data and global scenarios to illustrate the usefulness of the framework in assessing the potential impact of global shocks on banks around the world. The results of this latest update of the GST continue to point to relatively lower levels of resilience of banks in emerging market economies (EMs) than in advanced economies (AEs). The simulation uses baseline and adverse scenarios for macro-financial variables during 2022–24 based on the October 2021 *World Economic Outlook* (WEO). The adverse scenario simulates the potential impact of a prolongation of the pandemic owing to new variants, vaccine efficacy, and the pace of vaccine rollout. The exercise finds that banks in AEs have raised bank capital (CET1) ratios by about 0.8 percentage points in 2020 and are generally resilient to continued pandemics shocks. However, stresses could be higher in EMs reflecting the fact that EM banks face larger downside macro-financial risks in an adverse scenario, have a higher sensitivity to shocks, and have built somewhat less capital during the peak of the pandemic in 2020. Considering the significant uncertainty about the evolution of the global outlook, the exercise also presents the results of a severe adverse scenario, going further into the tail of the distribution of global macro-financial outcomes. Larger effects on bank capital would materialize in such a tail event, with a similar pattern of EMs being

more exposed. These results paint an encouraging picture of resilience, but also a need for continued close monitoring, especially in EMs experiencing a more restrained macro-financial policy space in responding to further shocks.

Acronyms and Abbreviations

AEs . . . . Advanced Economies

BMA . . . . Bayesian Model Averaging

CET1 . . . . Capital Tier 1

EMs . . . . Emerging Markets

FSAP . . . . Financial Sector Assessment Program

FSGM . . . . Flexible System of Global Models

GDP . . . . Gross Domestic Product

GFC . . . . Global Financial Crisis

GFSR . . . . *Global Financial Stability Report*

GST . . . . Global Bank Stress Test

LGD . . . . Loss Given Default

NFCI . . . . Net Fee and Commission Income

NII . . . . Net Interest Income

NLL . . . . Net Loan Losses

NTI . . . . Net Trading Income

OCI . . . . Other Comprehensive Income

PD . . . . Probability of Default

P&L . . . . Profit and Loss

RWA . . . . Risk-Weighted Assets

WEO . . . . *World Economic Outlook*

1. Introduction

Shocks to financial systems can lead to financial crises that have large costs in terms of foregone growth and weakening of economywide balance sheets (see, for example, Stein 2021). As part of overall policy frameworks to assess and mitigate these risks, bank stress tests are conducted at a national or supranational level with a focus on the resilience of national banking systems. These exercises typically do not emphasize cross-country channels for transmission of global risks. Moreover, the comparison of scenarios and stress testing results across countries is challenging due to differences in the granularity of supervisory data, stress testing methodologies, and scenario design used in authorities' stress tests.

In this context, assessing the impact of global shocks—such as those arising from the COVID-19 pandemic—is a challenge. This difficulty highlights the importance of developing a global bank stress testing approach that undertakes consistent risk analyses at the international level. To address this need, IMF staff developed the Global Bank Stress Test (GST) launched in the October 2020 GFSR to provide insights into the impact of the pandemic on banking systems around the world. The GST is a framework that can be used to assess the impact of adverse global shock scenarios on bank capital in major advanced and emerging market economies on a regular basis. It represents the first cross-country, globally consistent, macro scenario-based stress testing exercise to assess the resilience of banks to global shocks based on publicly available data. In this context, staff have developed a user-friendly tool based on the GST methodology for the assessment of solvency risks in advanced and emerging market economies. The GST analysis is updated on a periodic basis to inform the IMF's multilateral surveillance (for example, through the GFSR)[1] and bilateral surveillance efforts to assess the evolution of banking sector resilience.

While global in nature, the GST provides several benefits for authorities' analysis of the stability of their own banking sectors. It provides a high-level global assessment of potential pressure points ahead that could impact domestic banking sectors' stability and banks' ability to provide credit to the real economy. It also provides a useful context for national authorities as they judge the resilience of their own banking systems, benchmark their banks against similar banks in other countries, and inform decisions regarding policies to support banking system capitalization. The analysis captures important aspects of the resilience of the global banking system that are not typically a part of authorities' stress testing exercises, such as an analysis of cross-border spillovers and (implicit) spillbacks. For example, spillovers are captured via financial and real linkages in the scenarios. Spillbacks are captured implicitly as they are part of the multilaterally consistent scenarios underpinning the analysis. The ease of use and flexibility to update the framework, given that it uses publicly available data, are also attractive features for its application as a complement to more in-depth analysis in FSAPs.

The use of publicly available data comes with certain constraints. Due to the more aggregated nature of publicly available data, the methodology of the GST is simpler than methodologies used in Financial Sector Assessment Programs (FSAPs) and authorities' stress tests. As such, the GST is not a substitute for more in-depth FSAPs or country authorities' stress testing exercises. Moreover, the GST at the current level of granularity does not fully capture the effects of borrower-specific support policies—of the type extensively deployed by many authorities during the pandemic—on banks' balance sheets. This is again because

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[1] For example, the October 2020 GFSR used the GST to assess the impact of the pandemic shock in 2020 on bank capital in major AEs and EMs over the next three years. The analysis showed that in a baseline scenario, consistent with the October 2020 World Economic Outlook (WEO), bank capital falls sharply but recovers quickly, while an adverse scenario suggested sustained damage to average capital ratios. In the adverse scenario, a weak tail of banks, corresponding to 8.3 percent of banking system assets, would fail to meet minimum regulatory requirements, and the capital shortfall relative to broad statutory regulatory thresholds would reach $220 billion. The exercise also suggested that if COVID-19-related mitigation policies were not implemented, the weak tail of banks would reach 14 percent of banking system assets, and the global capital shortfall would be $420 billion.

publicly available data have insufficient detail and sectoral breakdown to allow for the analysis of financial policies to support borrowers. The aggregate effects of such policy support should however be captured in the macro-financial scenarios used as input to the GST analysis.

The application of global scenarios to the GST discussed in the October 2020 GFSR—reflecting the WEO baseline and adverse scenarios at the time—flagged downside risks to bank capital that were generally manageable. This reflected the continued strong internal capital generation of especially advanced economies' banking systems, bolstered by supervisory measures to contain a spike in provisions for nonperforming loans and the suspensions of divided payouts in many jurisdictions, among other factors. However, emerging market systems have tended to face larger shocks to their capital in the GST analysis. This overall risk assessment is borne out also in the current update of the GST, illustrated in this paper, that draws on the October 2021 updated WEO baseline and adverse scenarios.

The paper is structured as follows. It first explains the analytical approach and methodology underpinning the GST framework. It then presents an application to illustrate the impact of new scenarios on bank capital, informed by the October 2021 WEO. Finally, it discusses how the GST framework can be extended to incorporate the direct effects of policies to support borrowers.

2. How Does the GST Work?

The GST provides a framework for conducting a stress test on bank capital in response to global shocks for 29 major banking systems (Table 1).[1] It uses a solvency stress testing methodology that is based on country-specific panel data and econometric and structural models to link the dynamics of the components of individual bank income and expense to the evolution of macro and financial variables. The GST projects banks' income statement components, risk weights, and the implied capital ratios over a three-year horizon. The methodology ensures that the main drivers of banks' financial statements are analyzed in a consistent manner across different countries—comparable data and modeling techniques are used across countries. Capital shortfall estimates are computed at the bank-level.

Supervisors typically pursue different stress testing approaches to achieve different objectives. As noted by Adrian, Morsink, and Schumacher (2020). "A microprudential, supervisory stress test is a forward-looking supervisory tool that assesses the adequacy of individual banks' capital (or liquidity) conditional on their portfolio risks. Key to the supervisory purpose is the ability of the bank 'to pass or not to pass the test' as well as the subsequent supervisory measures that may be needed to beef up cushions when the bank does not pass the test." Moreover, "A macroprudential stress test instead focuses on financial vulnerabilities that can trigger systemic risk… (such as high leverage, mispricing, concentration of risk, liquidity mismanagement, and others)," requiring macroprudential policy responses such as the introduction of counter-cyclical capital buffers amongst other tools. Stress tests may also be "bottom-up"—conducted by banks using scenarios given by the supervisors or as part of a systemwide exercise—or "top-down" and conducted by the supervisors based on their own granular supervisory data. In general, supervisory exercises rely on the use of very granular portfolio and credit history data at the individual bank level to test the impact of the application of macro-financial scenarios designed by the supervisor.

The GST methodology is different from supervisory bottom up or top-down approaches to stress testing. The use of public data imposes constraints on the methodology, scope, and the use and interpretation of the results. Public data have less granularity and coverage compared to supervisory data that are usually employed in FSAP stress testing exercises[2] or stress tests by the authorities. As such, the GST methodology is simpler and more aggregated, capturing high-level bank balance sheet dynamics. Hence, the results should be interpreted with caution, including when compared with exercises that are based on more granular supervisory data.

The GST covers the largest banks from 24 AEs and 5 EMs. Combined, the banking sector assets of these 29 economies account for 70 percent of global banking assets. In each economy, the GST covers as many banks as necessary to account for at least 80 percent of the individual banking system's total assets. Altogether, the sample consists of 53 banks in EMs and 204 banks in AEs.

The GST introduces several innovations to top-down stress testing at the global level:

- **Consistent stress testing methodology.** The GST methodology ensures that the main drivers of banks' financial statements are analyzed in a consistent manner across different countries.

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[1] The intention was to include all jurisdictions with largest banking sectors in the world. However, for few large EMs, the GST could not be applied due to methodological issues (see below the discussion of challenges).

[2] "While an important part of IMF stress testing involves assessing the health of individual banks, the final objective is not to determine whether individual banks are adequately capitalized based on a hurdle rate but to assess whether the identified vulnerabilities can compromise banking sector stability for the whole economy. Results by institution are not published; instead, they are discussed with the authorities and used to support the banking sector stability assessment and the recommendations that are at the core of the IMF FSAP reports," (Adrian and others 2020).

Table 1. Sample of the GST

Africa	Asia and Pacific	Europe	Western Hemisphere
South Africa	Australia	Austria	Brazil
	Hong Kong SAR	Belgium	Canada
	India	Denmark	Mexico
	Indonesia	Finland	United States
	Japan	France	
	Korea	Germany	
	Singapore	Greece	
		Ireland	
		Italy	
		Luxembourg	
		The Netherlands	
		Norway	
		Portugal	
		Spain	
		Sweden	
		Switzerland	
		United Kingdom	

Source: IMF staff.

▪ **Internally and globally consistent scenarios.** The baseline scenario for each economy reflects globally consistent forecasts of macro and financial variables for each country developed by IMF desk economists and published in the WEO. The adverse scenarios are designed using the IMF Flexible System of Global Models (Andrle and others 2016), a class of cross-country, general equilibrium models, which ensure internal consistency of the scenarios. Using country-level scenarios derived from the IMF's global general equilibrium modelling framework is particularly crucial when considering large global shocks. Each scenario is characterized by two macro variables (real GDP growth and the unemployment rate) and six financial variables (short-term interest rates, term spreads, two measures of risk premiums (VIX and corporate bond spreads), and country-specific stock returns), as well as global oil price growth.

▪ **Spillovers.** The GST captures the effects of cross-border spillovers and implicit spill backs via both financial and real economy linkages that are included in the multilaterally consistent global models used in scenario design. Moreover, cross-border spillovers are also captured via the impact of shortfalls in subsidiaries' capital at the parent level. Subsidiaries of foreign parent banks that are present in the 29 economies can be included or excluded from the exercise depending on the objective of the exercise. For the purposes of multilateral surveillance, subsidiaries of the parent banks should be excluded to avoid double-counting, if the parent is in a country which is included in the sample. This was the approach taken in the October 2020 GFSR. For the purposes of bilateral surveillance, all subsidiaries of parent banks should be included in the exercise.[3]

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[3] In both cases, subsidiaries of a parent that are in a country that is not included in the sample are included in the exercise.

- **A unique global bank data set.** Comparable data for bank income statements, balance sheets, and several risk metrics were sourced primarily from Fitch Connect and banks' financial reports. The historical bank data set has an annual frequency spanning a 25-year period from 1995 to 2020. Annex 2 explains the comprehensive approach taken to build a robust cross-country dataset for this analysis.

- **Accounting for model uncertainty.** To account for model uncertainty a novel Bayesian Model Averaging (BMA) methodology is employed (Gross and Poblacion 2019). The BMA entails estimating a large set of models for a given dependent variable (about 5,000 models for each dependent variable), consisting of all possible combinations of the explanatory variables and assigning weights to each model based on predictive power.

- **Inferring probabilities of default and loss given default from loan losses.** Due to the lack of granular data, probabilities of default (PDs) and losses given default (LGDs) are calculated from the projections of loan losses using a variant of the Frye-Jacobs (2012) methodology. PDs and LGDs are in turn used as an input to project individual banks' nonperforming loans and risk weights under the internal rating-based approach (using the Basel formulae, see BCBS 2019).

The use of public data in such a large cross-country sample raises many challenges. First, for a few large emerging markets, the estimation results suggested that many components of banks' published income statements are not sensitive to macro variables, and these countries were excluded from the GST.[4] Second, the structure of the publicly available data used for the GST precludes the analysis (and incorporation) of the impact of borrower-support policies on bank capital. For example, the data does not allow for a breakdown of loan losses by enterprises versus households, which would be required for the assessment of mitigation policies. While the macro scenarios used from the WEO reflect IMF staff analysis and judgment regarding the aggregate real effects of policy support, aggregate stress test analysis such as in the GST could understate the positive effect on bank capital of financial policies to support household and enterprise borrowers, thus requiring ancillary analysis of the effect of borrower support policies—see for example IMF (2020).

The stress testing methodology entails projecting the change in capital ratios resulting from the impact of macro-financial scenarios on profit and loss (P&L) components, other comprehensive income (OCI), and risk-weighted assets (RWAs). It consists of two parts:

- **Econometric models for the components of the P&L and OCI accounts** (Table 1 in Annex 1). All econometric models are cross-bank-country panel regression models—bank fixed effects models (FE)—that link the components of the P&L (except trading income) and changes in OCI to macro-financial variables. Each component of the P&L is projected separately based on estimated econometric (or structural) models over the stress testing horizon and then aggregated to net income based on the accounting identities. The components of the P&L include: (1) net loan losses supplemented with structural model elements for PDs and LGDs; (2) net interest income (NII); (3) net trading income (NTI); (4) net fee and commission income (NFCI); and (5) other income/expense, which "closes" the P&L and is equal to pre-tax net income minus the four main components.

- **A balance sheet projection module.** This module maps the projections of P&L components, RWAs, and OCI into a projection of CET1 capital ratios and capital shortfalls over the stress testing horizon. Bank-specific balance sheet information as of 2020 is used as a starting point for most of the banks. The module involves user-defined assumptions for dividend distribution and taxes.

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[4] Likely factors behind this lack of sensitivity include (1) the absence of economic downturns in the sample; (2) strong time trends in financial deepening; (3) data quality issues; and (4) past accounting, regulatory, and other practices.

The loan-loss model is coupled with a structural model element that decomposes loss rates into PDs and LGDs, using a variant of the Frye-Jacobs (2012) methodology. While the loan-loss model is based on P&L provision flows, PDs were needed to infer the dynamics of performing and nonperforming loan stocks. The migration of nonperforming loans back to performing status ("cures") is allowed implicitly but not explicitly modeled.

NTI is projected using a simple historical standard deviation-based approach as the in-sample predictive power of panel regression models of NTI ratios is generally low. For each bank, the NTI ratio was projected as the difference between the average NTI ratio over the last five years and a product of a scalar and the standard deviation of the NTI ratio over the last five years (to penalize for the historical variability of NTI). The scalar was set to a common value for all banks, reflecting the scenario-implied stress on positional risk and net trading income from agency business.[5]

Tax rates and dividends over the stress test horizon are set to zero if projected net income before taxes is negative. Otherwise, tax rates are assumed to be equal to individual banks' effective tax rates in the last year of the sample with a cap of 30 percent. Dividend payout ratios are set to be 50 percent of net income before tax if the ratio is positive, and zero otherwise. No deferred tax asset accumulation is considered.

Credit risk-weighted assets are allowed to change as a function of the scenarios. A breakdown of total credit exposures into exposures under standardized (STA) and internal rating based (IRB) regulatory approaches are approximated for each bank based on publicly available information from banks' annual reports or information from past FSAPs. For the STA component, the risk-weighted densities are assumed to remain constant over the stress test horizon. Densities corresponding to IRB exposures are adjusted using the Basel formulae. Through-the-cycle PDs that serve as input to the risk weight formulas are estimated using the change of the scenario-dependent point-in-time PDs and involve a "smoothness" parameter[6] to account for the through-the-cycle nature of the PDs. Downturn LGDs are held constant over the stress testing horizon. Other risk-weighted assets (market, operational, and residual) are assumed to remain constant.[7]

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[5] In a scenario/year during which market volumes and agency business for banks might be severely constrained (for example, resurgence of COVID lockdowns) a higher scalar was used to reflect more conservative market conditions for NTI. In the general case, scalar calibration might be country specific to better reflect the impact of the scenario on the NTI mix for the country. To keep the approach neutral and facilitate cross-country comparisons and given the low materiality of NTI for the overall capital impact, a common scalar path was used for all countries in the results presented.

[6] The smoothness parameter is set at 15 percent and is multiplied by average changes in annual point-in-time PDs relative to the starting point of the through-the-cycle PDs.
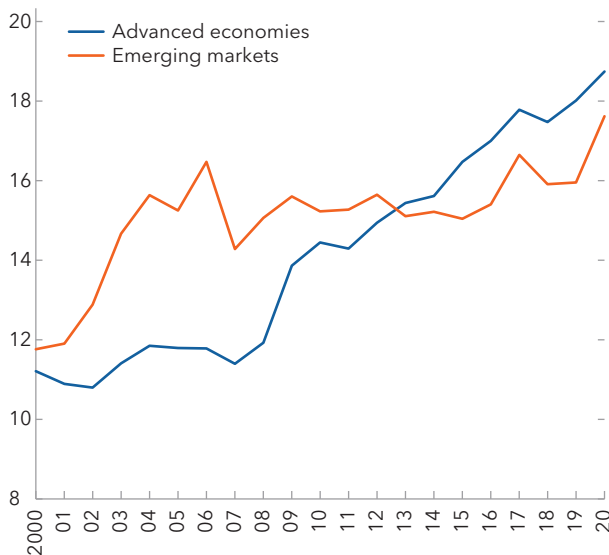
[7] These assumptions underestimate the impact of the adverse scenarios on bank capital: under a stress scenario, downturn LGDs and other risk-weighted assets would be expected to increase.

3. Global Bank Stress Test–2021/22 Update

Global banks entered the COVID crisis with higher capital ratios than before the global financial crisis (Figure 1). Banks in advanced economies increased their capital ratios substantially since the eve of global financial crisis (GFC) with the median increasing by more than 540 basis points. The increase was a result of regulatory reforms, stable profitability, lower dividend payouts, higher equity issuance, and increased issuance of hybrid and debt capital securities. Capital ratios in emerging markets were relatively stable (at high levels) until 2015 and have increased since then to nearly match the level of capital ratios of banks in advanced economies by the end of 2020.

Figure 1. Capital Ratio Evolution, EMs and AEs

1. Total Regulatory Capital Ratio, Median, All Banks
(Percent)

2. Total Regulatory Capital Ratios, Distribution Across all Banks, 2007 versus 2020
(Percent)

Source: Fitch Connect.
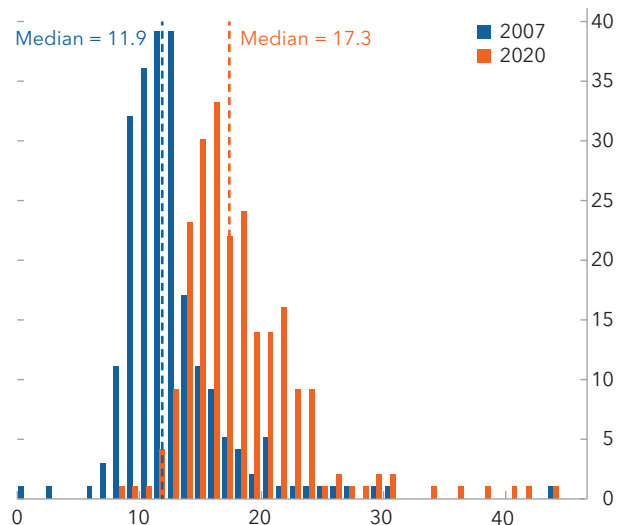
Bank stability risks have remained contained so far during the COVID-19 pandemic, reflecting extensive policy support and the ongoing rebound of the global economy. Banks around the world, on average, are exiting the 2020 COVID-19 shock with stronger capital positions due to unprecedented policy measures to mitigate the impact of the pandemic. Governments introduced substantial fiscal support to households and corporates (see the October 2020 *Fiscal Monitor*) to prevent large-scale borrower failures, monetary policy rates were cut worldwide to ease funding costs, and many central banks implemented large asset purchase programs to support markets and to maintain the flow of credit to the real economy (see the April 2020 GFSR). On top of these measures, policymakers introduced targeted measures that directly addressed banks' financial needs and balance sheet resilience. For instance, certain capital buffers, such as countercyclical capital buffers that are designed to be used during downturns, were released to sustain the flow of credit to households and firms. Transitional arrangements to smooth the impact of expected credit loss accounting on regulatory capital have also been introduced. Finally, banks were also required in many jurisdictions (by regulation or strong administrative guidance) to suspend dividend distributions. Collectively, these direct and indirect measures helped the banking system weather the pandemic despite

its sizable negative impact on the global economy, pushing the median total capital ratio to 17.3 percent globally at end-2020, 80 basis points higher than at the end of 2019. However, while most regulators used the flexibility embedded in the accounting and prudential frameworks to mitigate excessive procyclicality, some authorities froze the status of asset classifications and provisioning requirements for loans that were performing before the outbreak of the pandemic or changed the definition of nonperforming loans, which raises concerns as financial statements and prudential ratios no longer adequately reflect the true values of banks' assets.

Nonetheless, concerns remain regarding the economic outlook reflecting continued uncertainties on the trajectory of the pandemic and new emerging risks that could impact the strength of the recovery. From a COVID-19 perspective, vaccine-resistant strains are potential headwinds for economic activity, as are operational risks, such as vaccine production and distribution delays. The prospect of renewed outbreaks and restrictions to slow transmission remain risks to welfare and economic activity. A reassessment of market fundamentals such as in response to adverse COVID-19 developments could trigger a sharp repricing of financial assets. Risky asset prices could fall sharply, causing volatility and triggering significant losses at major nonbank financial institutions. Higher risk premiums would generate financing difficulties for leveraged firms and households. Amid high and rising debt levels, vulnerable borrowers could face rollover risks, an issue that would be particularly acute for some emerging markets and low-income countries. Tighter financial conditions would hamper growth prospects. This could lead to further repricing of financial assets in a potentially dangerous feedback loop. Although policy actions have so far prevented the severe health and economic shock from morphing into a systemic financial crisis, risks remain for substantial and persistent damage to supply potential. Several of these channels are relevant also for new emerging risks related to the prospect of unexpected tightening in global financial conditions (see January 2022 WEO Update).

The GST was updated for the period 2022–24 to assess these risks. The exercise was anchored, for illustrative purposes, on the October 2021 WEO baseline forecast and informed by the adverse scenarios developed for the April 2021 WEO (the latter designed using FSGM to ensure global consistency of the scenarios). In particular, the GST adverse scenario is a linearly scaled extension of the WEO downside scenario that illustrates the consequences of a 2½ standard deviation shock to global growth rates, relative to the baseline, in 2022–24. The size of the shock for the adverse scenario is informed by the practice typically used in stability analysis, including the FSAP program, to construct severe but plausible adverse scenario (see Box 1 on the design of adverse scenarios in FSAPs). The cutoff date for bank data is end-2020 as end-2021 public data are not available yet. Reflecting the extraordinary uncertainty resulting from the historic pandemic shock and its continuing ripple effects, the GST explores a second severe adverse scenario that goes further into the tail of the distribution of growth outcomes for each country.

Emerging risks to the inflation outlook and supply chain disruptions point to challenges that the next iteration of the GST could consider. Nonetheless, while the narrative and certain features of the scenario and their impact may change, the range of scenarios considered in the current GST update straddle severe outcomes that provide reasonable approximations on resilience. Overall, the scenarios illustrate the application of the GST and its value in surveillance of risks to banking systems around the world.

The baseline scenario features a continued multispeed recovery in 2022 across all regions and across income groups, linked to differences in the pace of vaccine rollout, the extent of economic policy support, and structural factors such as reliance on tourism. After a contraction of almost 5 percent in 2020 and a rebound of 5½ percent in 2021, output in the group of countries included in the current GST baseline sample was projected to grow at about 4⅔ percent in 2022 and 2.3 percent in 2023. Growth is expected to moderate to about 2 percent over the medium term reflecting projected damage to supply potential and forces that predate the pandemic, including aging-related slower labor force growth in advanced economies and some emerging market economies. Emerging market economies and low-income developing countries have been hit harder by the pandemic shock and are expected to suffer more significant medium-term losses.

Box 1. Designing Adverse Scenario in FSAPs

FSAP scenario design includes three steps: outlining risk transmission channels, choosing the severity of the shock, and mapping into full-fledged macro-financial scenarios. The risk transmission channels of adverse scenarios are guided by the country risk assessment matrix (RAM) underpinning the IMF's bilateral surveillance and that is informed by the IMF Global Risk Assessment Matrix (G-RAM) to support multilateral consistency. Severity is measured by the deviation of the GDP path compared to the baseline and should be "severe but plausible," typically aiming at once in 20-year events. Real GDP is the anchor variable of the scenario because a recession typically defines the worst macro-financial environment for most financial institutions. Then, a full set of other macro variables consistent with the GDP shock is simulated using existing IMF dynamic stochastic general equilibrium models (such as FSGM or the Global Financial Model (GFM) (see Vitek (2018)), S-VAR type empirical models, or models used by the country authorities.

The usual approaches to calibrating the severity of the adverse scenario include using the at least two-standard-deviation as a rule of thumb or conditional shocks using growth at risk (GaR) taking into account the evolution of the output gap or the level of GDP (Adrian and others, 2020). IMF staff have used a rule of thumb where shocks to GDP growth should represent a deviation from the IMF baseline projection over the first two to three years of the scenario of at least two historical standard deviations from the mean. The two standard deviation shock to cumulative growth in the first two years is based on the unconditional historical distribution of GDP growth. This rule of thumb is used in combination with GaR as a minimum severity related to cyclical vulnerabilities.

Using standard severity approaches could result in overly benign (severe) scenarios when the economy is at the top (bottom) of economic and financial cycles. Therefore, some FSAPs have applied smaller/larger shocks depending on the cyclical state, targeted the size of the output gap or set the decline of the level of GDP to those observed during benchmark crisis episodes.[1] For example, the size of the pandemic shock implied that, in many countries, even the baseline scenario was more improbable than one percentile GaR estimates based on historical data. As such, applying an additional two-standard-deviation shock to an already weak baseline could have been seen as less plausible. In a period of strong, above trend growth, as in post-pandemic years, using the standard rules might produce scenarios judged as overly benign. Overall, the pandemic is an ahistoric event where applying the usual rules of thumb and principles is a challenge. Therefore, if the baseline forecast for GDP growth is significantly above the long-term average, larger shocks (for example, minimum three standard deviation shocks) are considered to ensure that the adverse scenario represents a stress event.

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[1] Some FSAPs that took place during the significant GDP contractions of the COVID-19 crisis used the output gap approach. More recent FSAPs aim at 2–3 percentile GaR estimates.

Considering the increased uncertainty about the path of the pandemic, the adverse scenario considers the potential adverse impact owing to new variants, the efficacy of vaccines, and the pace of vaccine rollout. These factors would slow economic activity and increase risk aversion, which in turn would lead to tighter financial conditions for vulnerable businesses, further undermining growth. Unconventional monetary policy measures are assumed to prevent significant increases in sovereign rates. The lack of conventional monetary policy space and shrinking fiscal space limit policymakers' ability to respond further, and no additional discretionary fiscal measures or policies to ameliorate the financial position of borrowers and banks are assumed. The weaker rebound in activity leads to more pronounced scarring than assumed in the baseline, despite a gradual return in mobility to pre-pandemic levels.

Figure 2. Global Stress Test Macroeconomic Scenarios (29 Countries)

1. GDP Scenarios
(Level, 2021=100)
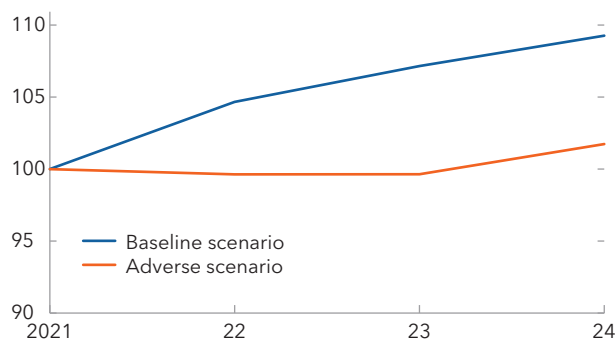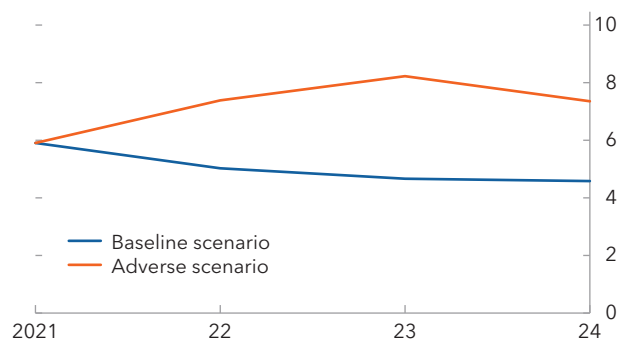
2. Unemployment Rate Scenarios
(Percent)

3. Stock Price Scenarios
(Level, 2021=100)
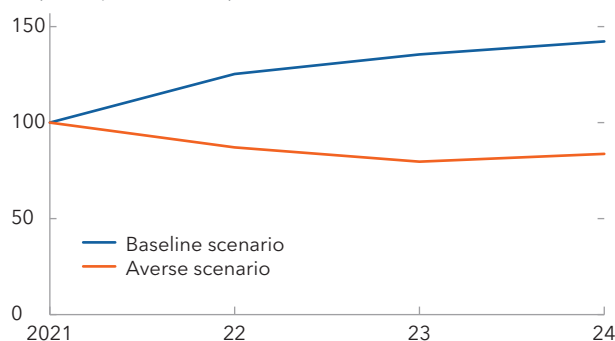
4. Corporate Credit Spread Scenarios
(Percentage points)
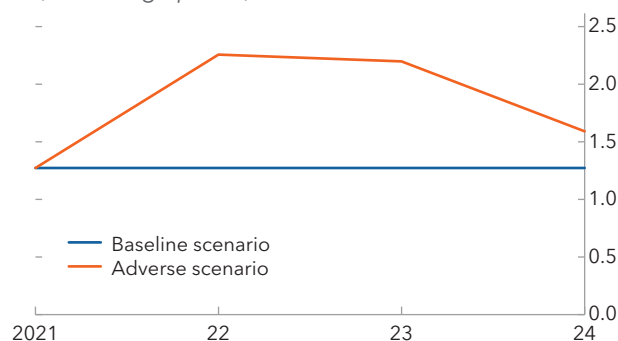
5. Term Premium
(Percent)
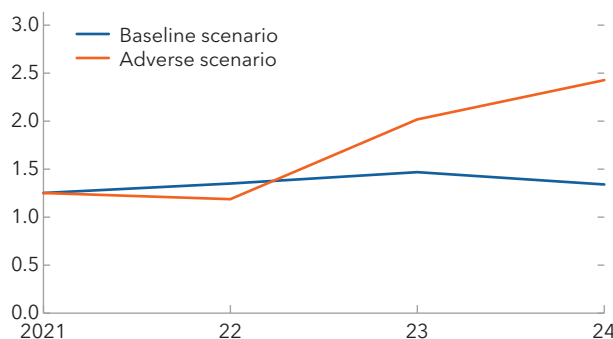
Sources: IMF, October 2021 *World Economic Outlook*; Bloomberg; IMF staff calculations.

In the adverse scenario, global GDP is about 5 percentage points and 2½ percentage points lower than in the baseline in 2022 and 2023, respectively (Figure 2). A sharper tightening in financial conditions for vulnerable businesses in emerging markets and developing economies results in a larger shock for EMs (Annex 3). In particular, the level of GDP in AEs is about 6.5 percentage points lower than in the baseline by 2024 in the adverse scenario, compared to a 9.4 percentage point in EMs. The larger GDP shock in EMs compared to AEs is also reflected in more severe shocks to unemployment, credit spreads, and stocks prices.

The exercise suggests that banks, on aggregate, remain resilient to prolonged pandemic shocks. In the baseline scenario, banks, on average, would see a strong upward trend in their CET1 ratio, reaching 17.2 percent in 2024, 3.2 percentage points above the end-2021 level. In the adverse scenario, the average CET1 ratio would fall moderately in the first year—a drop of 1.4 percentage points below the 2021 level and 2.7 percentage points below the baseline scenario.
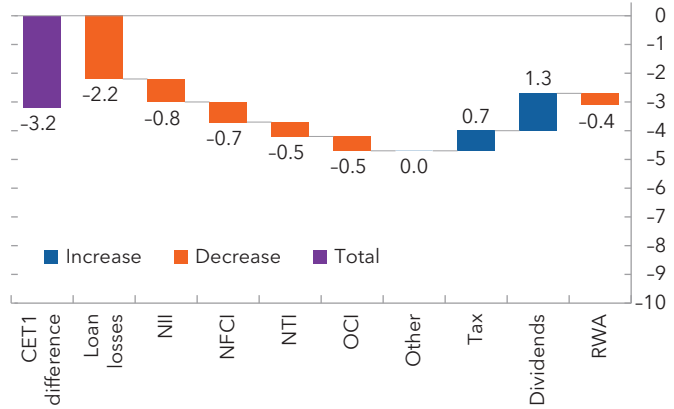
Figure 3. GST Results–Baseline and Adverse Scenarios (29 Countries)

1. CET1 Ratio
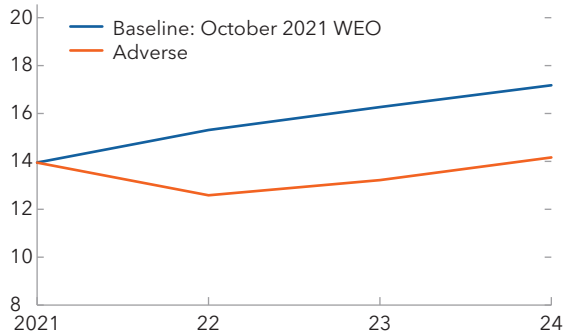*(Aggregate, percent)*
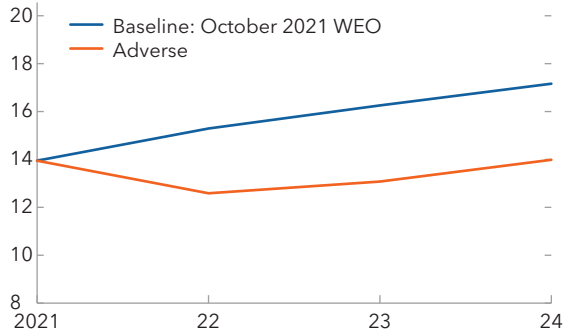
2. CET1 Ratio Difference in Baseline and Adverse Scenario
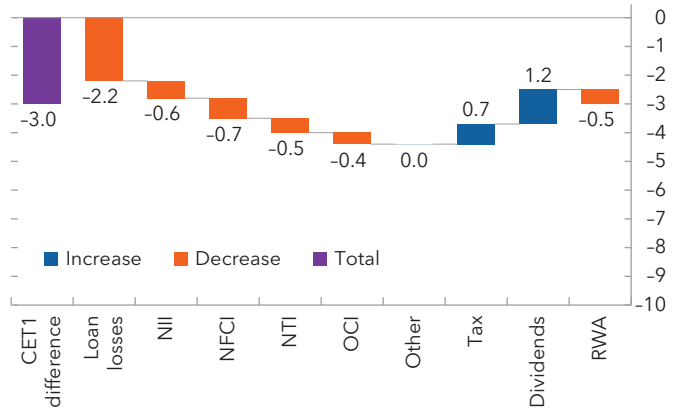*(All countries, percentage points, 2024)*

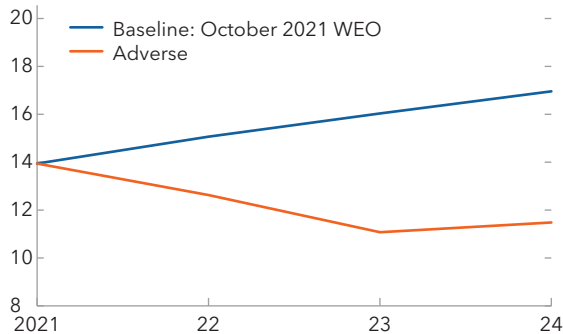**3. CET1 Ratio–Advanced Economies**
(Aggregate, percent)

4. CET1 Ratio Difference in Baseline and Adverse Scenario
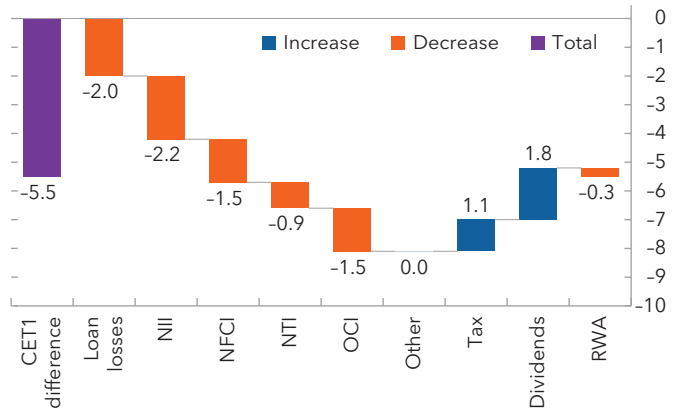*(Advanced economies, percentage points, 2024)*

5. CET1 Ratio–Emerging Markets
(Aggregate, percent)

6. CET1 Ratio Difference in Baseline and Adverse Scenario
(Emerging markets, percentage points, 2024)

Sources: Fitch Connect; IMF, October 2021 *World Economic Outlook*; and IMF staff estimates.
Note: CET1 = common equity tier 1; NFCI = net fees and commissions income; NII = net interest income; NTI= net trading income; OCI= other compressive income; RWA= risk-weighted assets.

The resulting decline in the CET1 ratio over the stress testing horizon stems mainly from an increase in loan loss provisions (Figure 3). In the baseline scenario, higher loan loss provision expenses contribute to a 2 percentage-point decline in the global CET1 ratio, 2.2 percentage points less than in the adverse scenario.

This is directly related to the different trajectories of GDP growth rates (and other variables)[1] in the two scenarios, where the rebound in economic activity projected in the baseline scenario results in lower provisioning expenses. For all banks, the contribution of other risk factors is smaller, ranging from 0.4 percentage points (in terms of the difference in CET1 ratios between the baseline and the adverse scenario in 2024) for risk-weighted assets to 0.8 percentage points for net interest income.

The GST points to relatively lower levels of resilience of banks in EMs than in AEs whose banks have increased CET1 ratios by about 0.8 percentage points in 2020. While there is some notable country-specific heterogeneity, the exercise suggests that AE banks would see a modest deterioration of CET1 capital ratios and net income in the first year before recovering in the outer years. The decline in CET1 ratios in the adverse scenario is much larger in emerging economies, reaching 2.5 percentage points below the starting point and 5.5 percentage points below the baseline in 2024.

The larger impact on banks in emerging economies reflects the fact that banks in EMs face larger downside macro-financial risks in a plausible downside scenario (Annex 3), have a higher estimated sensitivity of loan losses (the largest driver of the typical P&L) to growth shocks (Figure 4), and have built somewhat less capital over the past two years.

Figure 4. Sensitivities of Net Loan Losses to Main Drivers, AEs versus EMs
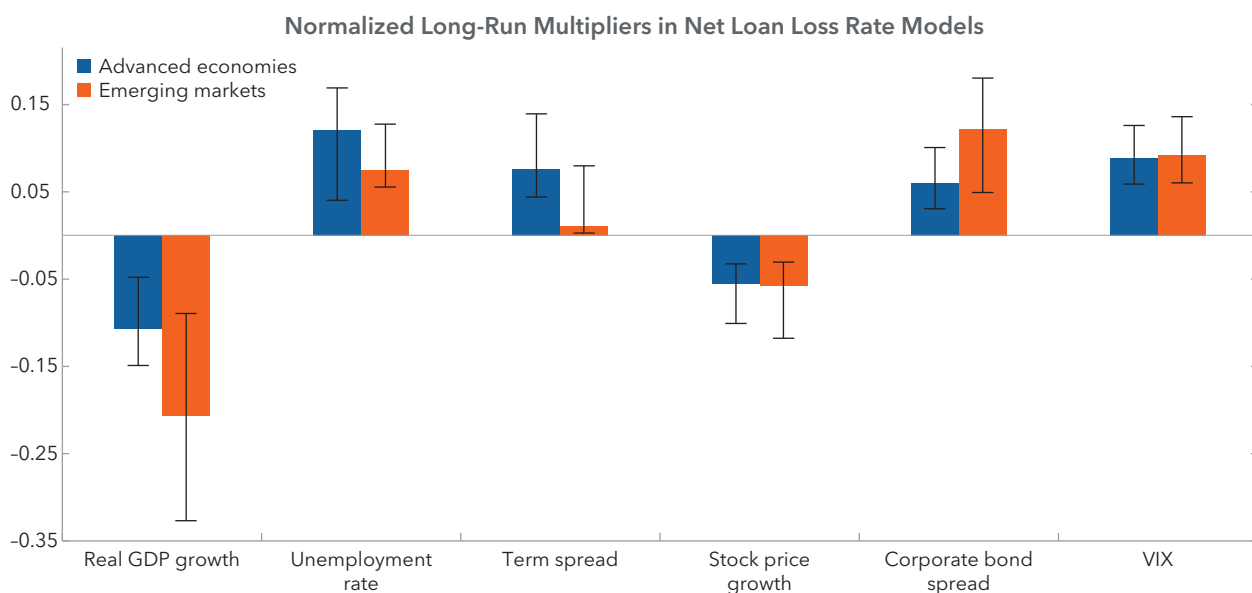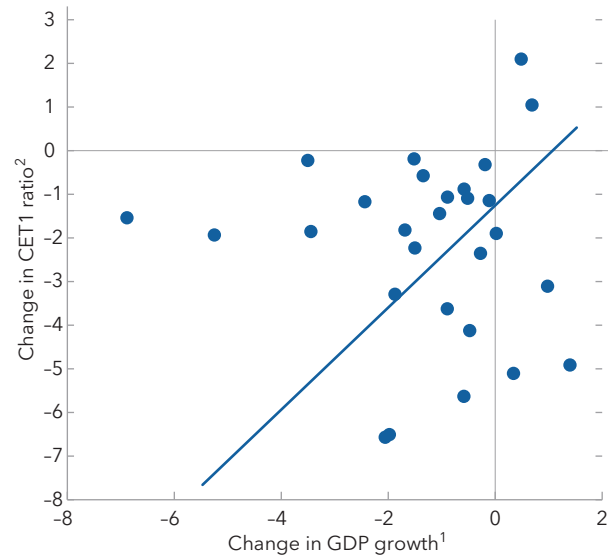

Source: IMF staff estimates.
Note: The bars show the median normalized long-run multipliers (LRMs) across AEs and EMs. The bars extend to the 25th and 75th percentiles. The country-specific long-run multipliers (LRMs) were normalized; that is, the initial country-specific LRMs were multiplied with the ratio of the standard deviations of the independent variables (main macro and financial variables in the figure) over the standard deviation of the dependent variable (banks' net loan loss rates). The interpretation of the LRMs equal to X (X is the value displayed in the figure) is: a 1 standard deviation change in the independent variable results in an X standard deviation change of the net loan loss rate.

The trajectory of aggregate capital ratios masks heterogeneity across economies and banks. Changes in CET1 ratios, measured as the difference between country specific CET1 ratios in 2021 and the trough of their banks' capital trajectory, reach up to 7 percentage points in some cases. This cross-country variation

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[1] For example, monetary accommodation in the adverse scenario provides an offset. It increases the term spread due to lower policy rates. Larger term spreads have a generally positive effect on net interest income and this effect is larger, on average, than the negative effect on net interest income due to lower short-term rates and weaker economic activity.

can be explained in large part by the size of GDP shocks in the adverse scenario (Figure 5).[2] Capital shortfalls, calculated for each bank relative to a 4½ percent minimum capital level, appear contained in most countries—across economies they range from zero to 0.6 percent of GDP in the adverse scenario. Economies that face capital shortfalls are those that, on average, face larger capital shocks and/or have lower initial capital ratios. Nonetheless, in the adverse scenario, there remains a non-negligible share of banks by assets in several countries, especially in emerging markets, which could face solvency pressures (Figure 6). The share of banks by assets experiencing shortfalls differs quite markedly between regions, with a higher share of stress observed in emerging markets (14 percent of total bank assets) in 2024. This points to the potential importance of considering targeted policies to support bank capital such as maintaining restrictions on distributing bank capital and preparation of capital restoration and contingency plans for weak banks going forward.

Figure 5. GDP Shock and Change in CET1 Ratio
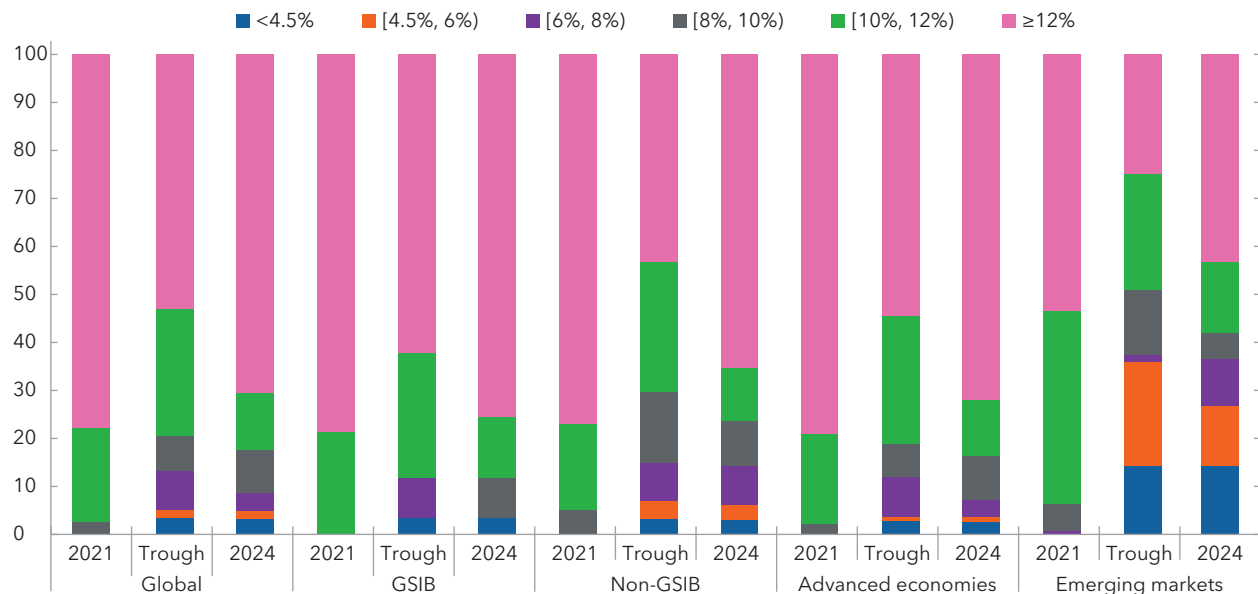*(Adverse scenario, percentage points)*

Source: IMF staff estimates.
[1]Defined as the minimum of the cumulative real GDP growth over the period 2022–24.
[2]Defined as the change of the CET1 ratio in year of the minimum CET1 ratio and the CET1 ratio in 2021.

Figure 6. Distribution of Bank Assets by Capital Ratio under Adverse Scenario
(Percent of total assets)

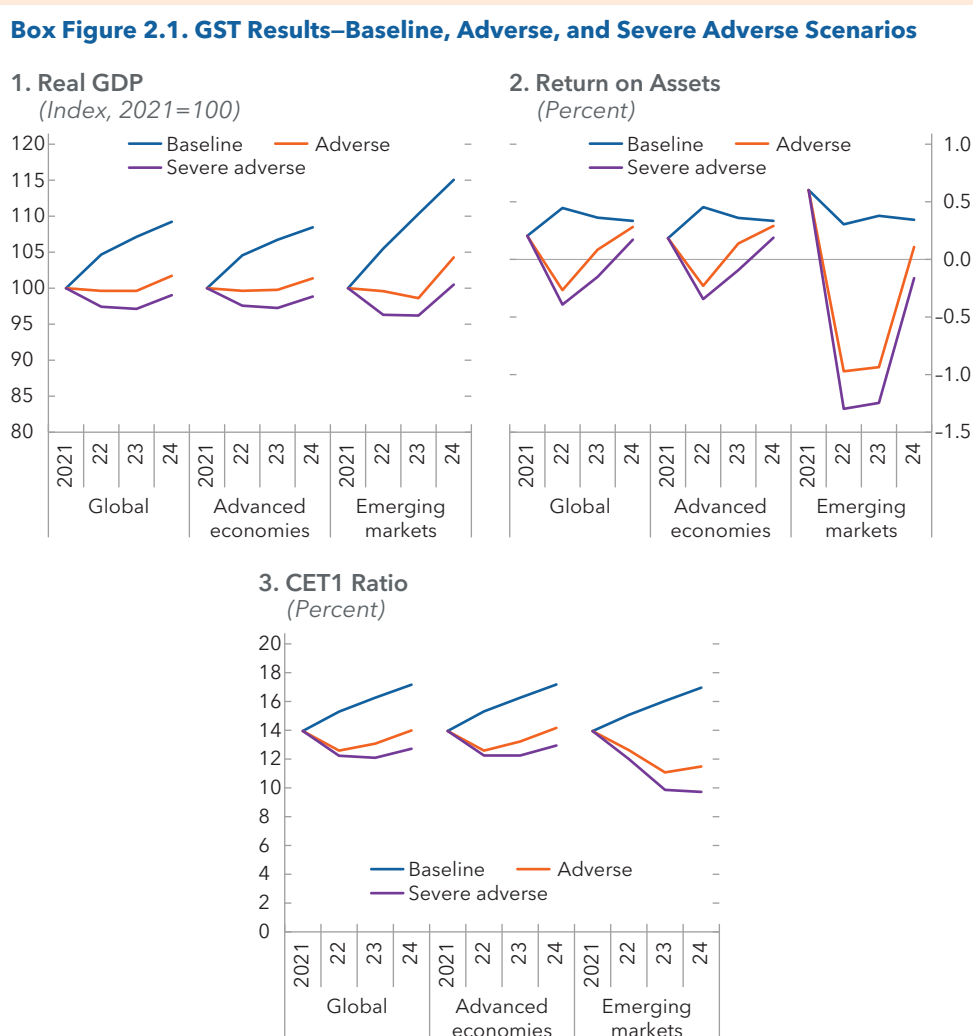Sources: Fitch Connect; IMF, October 2021 *World Economic Outlook*; and IMF staff estimates.
Note: GSIB = global systemically important bank.

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[2] Other factors, beyond banks' sensitivities to GDP growth, affect the change in capital. For example, the estimated sensitivities of income statement items with respect to macro and financial variables vary across banking systems and shares of IRB exposures in total portfolio differ notably across economies—for those economies with higher IRB shares, risk weights increase and contribute to falling capital ratios, while for many banking systems with large shares of standardized portfolios, risk weights are constant.

Reflecting the unprecedented uncertainty in the wake of the ahistoric pandemic shock we also consider a severe adverse scenario (Box 2) that points to continued downside risks to the global banking system in such a tail event and illustrates the same message of exposure to downside shocks, especially in emerging markets.

Box 2. Severe Adverse Scenario

The severe adverse scenario (Annex 3) is simulated as a linear extension of the scenario derived from the multilateral global model but using separate econometric estimates of the relationships between GDP growth and other macro and financial variables used in the GST. The initial GDP shock, for each country, is calibrated by assuming GDP growth in 2022 is equal to half of the GDP growth in 2020. This shock corresponds to a four standard deviation shock from the baseline—which builds in rapid year-over-year growth rates as output gaps close following the extremely sharp fall in 2020— but is equivalent to a 2½ standard deviations shock from average GDP growth spanning the years preceding the pandemic.

Box Figure 2.1. GST Results—Baseline, Adverse, and Severe Adverse Scenarios

1. Real GDP
(Index, 2021=100)

2. Return on Assets
(Percent)

3. CET1 Ratio
(Percent)

Source: Fitch Connect; October 2021 *World Economic Outlook*; IMF staff estimates.
Note: Results for 29 economies.

4. Accounting for Mitigating Policies

As noted previously, the structure of publicly available data precludes the analysis of the direct impact of policies to support borrowers on bank capital in the GST. For example, the data do not allow for a breakdown of loan losses by corporations and households, which would be required for an assessment of mitigation policies. The aggregate analysis could therefore understate the positive effect on bank capital of financial policies to support household and corporate borrowers.[3]

Accounting for policy support measures deployed during the COVID-19 pandemic requires additional modeling techniques and granular data, particularly regarding the borrower segmentation on the asset side of banks' balance sheets. To model the effects of support policies such as debt payment moratoria and guarantees, which were critical during the pandemic, sectoral data would be needed that differentiates between exposures to households and corporates.

IMF staff have developed methodologies to assess the impact of mitigating policies. Chapter 4 of the October 2020 GFSR (IMF 2020)[4] considers an extension to the GST that allows decomposing the aggregate loan loss provision scenario forecasts into their contributions from corporate and retail loan portfolios. The model extension entails the use of direct step regression specifications (that is, a local projection method) to capture the contribution of corporate and retail exposure shares, along with their respective macro-financial drivers, to loan losses of the banks' portfolio aggregates. Based on that extension, the contribution of sovereign guarantees pertaining to corporate loans was quantified.

Staff have also developed two micro data-based modeling approaches to analyze the implications of mitigating policies on the health of nonfinancial corporates and households (Boxes 3 and 4).[5] These models can be "plugged into" the GST model suite to account for those policies that affect PDs and LGDs through payment moratoria (either policy induced or as a result of banks' own response) and government guarantees. Moratoria exert their impact primarily through PDs, while guarantees primarily affect LGDs. However, guarantees may also have secondary positive effects on PDs, since lower LGDs likely imply lower lending rates, which reduces the debt service burden of firms.

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[3] The differences between the actual and projected capital position for 2020 in the previous round of the GST simulation (see Chapter 4, October 2020 GFSR) can be explained by the differences in the actual and projected macroeconomic variables and offsetting effects of the mitigating policies.

[4] See also Annex 4.1 of the October 2020 *Global Financial Stability Report*, sections D and E.

[5] A micro–macro simulation model to assess the impact of macro scenarios and policy measures in response to the pandemic on performance of nonfinancial firms and banks was developed by IMF staff for the Canadian economy. See "Canada 2021: Selected Issues," pp 26–40.

Box 3. Corporate Stress Testing: Assessing Mititgating Policy for Corporate Portfolios

Tressel and Ding (2021) developed a new methodology for stress-testing publicly listed nonfinancial corporates in 24 AEs and EMs to assess the impact of the COVID-19 pandemic. The new tool allows performing both multifactor sensitivity analysis and dynamic multiyear scenario-based stress tests of individual firms. The analysis presents an assessment based on three main metrics: (1) *liquidity*, assessed by the interest coverage ratio and the cash balance; (2) *viability*, assessed by the interest coverage ratio and the price-to-book ratio; and (3) *solvency*, assessed by the book value of equity. Firm-level outcomes are aggregated at the country level and linked to bank loan and bond markets' PDs to assess potential systemic risk in the corporate sector and spillovers to the financial system.

The multifactor sensitivity analysis allows to assess the one-off impact of various shocks at the firm level. It encompasses a variety of shocks at the firm level such as (1) *real shocks and behavioral choices affecting* sales and/or production costs; (2) *financial shocks* affecting borrowing costs, roll-over risks, and borrowing capacity; (3) *policy shocks* such as monetary policies, fiscal policies (for example, guarantee programs, wage subsidies, grants, tax measures, etc.), and regulatory policies (moratoria on debt payment).

The dynamic scenario-based stress test provides a novel approach to generate scenario-dependent and consistent projections of the firm-level indicators of financial health over multiyear periods. The macroeconomic scenario provides the flexibility of introducing sectoral shocks into the projections of the firm-level indicators. The set of projected firm-level financial health indicators can be relied on to perform a triage of firms and a viability assessment. The general equilibrium impact of macroeconomic policies is reflected in the path of macroeconomic variables (for example, financial conditions, real GDP path). Thus, the general equilibrium effects of policies can be assessed by comparing the projections of financial health indicators under different counterfactual macroeconomic scenarios with and without policies. However, the direct impacts of micro policies at the firm level (for example, such as a grant, wage subsidy, or debt moratoria) are not quantified in the scenario-based stress tests.

Other recent work has assessed the impact of the pandemic on nonfinancial firms and the role of policies. For example, IMF (2020) quantifies the potential impact of the pandemic on the liquidity and solvency of European large corporates and small and medium-sized enterprises and examines the extent to which various direct and indirect policy measures could have dampened these risks in 2020. IMF (2021a) presents an assessment of nonfinancial firms' health as they exit the pandemic. The assessment combines liquidity, solvency, and viability indicators projected based on market indicators to perform a triage of firms and assess the appropriate design of future policy support. IMF (2021b) projects industry-level probabilities of default of Canadian firms linked to industry-level indicators of corporate health and link them to macroeconomic scenarios. This allows performing different scenario policy counterfactuals of interest rates and their general equilibrium impact on default risk. IMF (2021c) performs a multifactor sensitivity analysis similar to the approach of Tressel and Ding (2021) to assess the impact of the pandemic on Nigerian nonfinancial firms.
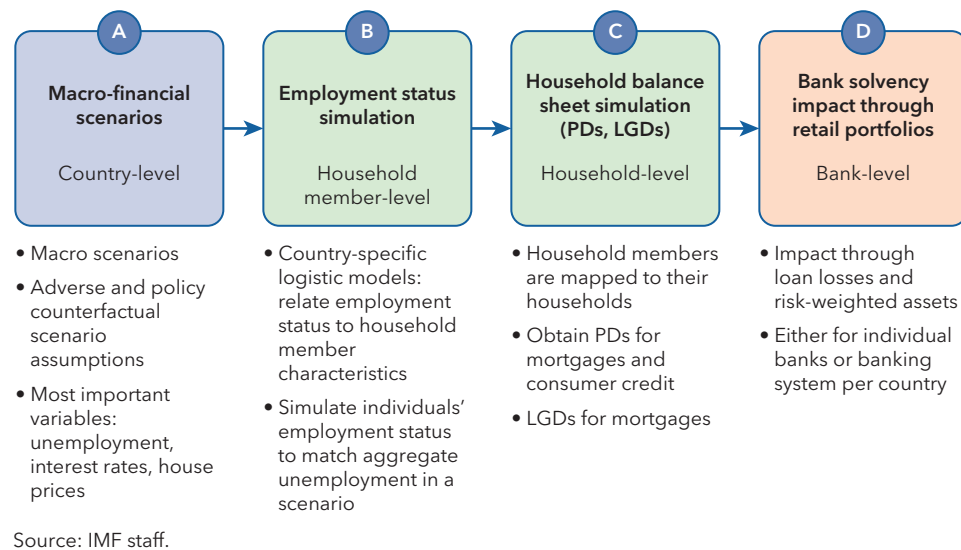
Box 4. Household Debt: Assessing Mitigating Policies Using a Micro–Macro Simulation Model

A framework that can be used to model household sector risk parameters (PDs and LGDs) is presented in Gross and others (2021) and Gross and Población (2017). The structural micro–macro simulation model, called the Integrated Dynamic Household Balance Sheet (IDHBS) model, allows obtaining macro scenario- and policy-counterfactual estimates of PDs and LGDs. Since time series data for household credit risk metrics are usually not publicly available, a structural micro simulation-based approach is used. Even if time series data were available, the use of time series models would not allow for conducting a rich policy counterfactual analysis as with a structural model rooted in microdata.[1]

Box Figure 4.1 summarizes the household model's four layers. It simulates the P&L and balance sheets of households based on large-scale micro databases.[2] Individuals' employment status is simulated conditional on a scenario-based unemployment rate path. Interest rate changes influence the debt service burden for households that have variable rate loans. Their employment status determines their wage income (or unemployment benefit), their ability to service debt, and thus their PDs. House prices drive the value of collateral and hence their LGDs. Step D in Box Figure 4.1 could be linked to the GST model, where loan losses and risk weights are aligned with the outcome of the micro-macro simulation model.

Gross and others (forthcoming) conduct policy counterfactual analyses with a focus on debt moratoria. The estimated mortgage PDs, LGDs, and loss rates suggest that household sector-oriented policies can have notable mitigating effects. The implied counterfactual impact of household debt moratoria on banks is significant for many countries, shielding the banks from incurring material capital losses.

Box Figure 4.1. Household Simulation Model Structure

A	B	C	D
Macro-financial scenarios	**Employment status simulation**	**Household balance sheet simulation (PDs, LGDs)**	**Bank solvency impact through retail portfolios**
Country-level	Household member-level	Household-level	Bank-level

- Macro scenarios
- Adverse and policy counterfactual scenario assumptions
- Most important variables: unemployment, interest rates, house prices

- Country-specific logistic models: relate employment status to household member characteristics
- Simulate individuals' employment status to match aggregate unemployment in a scenario

- Household members are mapped to their households
- Obtain PDs for mortgages and consumer credit
- LGDs for mortgages

- Impact through loan losses and risk-weighted assets
- Either for individual banks or banking system per country

Source: IMF staff.

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[1] The model was employed in the past for conducting counterfactual analyses in relation to borrower-based macroprudential policies. It is used at the European Central Bank (ECB) and by various national central banks in Europe to inform the ex ante impact of borrower-based measures such as loan-to-value and debt service to income (DSTI) caps. The model is useful for assessing policies also in other areas: monetary policy (for example, interest rate-based policy), fiscal policy (for example, regarding the design of unemployment benefits), and policies and banks' own behavioral responses in the pandemic.

[2] Such household databases for European countries are compiled centrally in the ECB's Household Finance and Consumption Survey, or the Panel Study of Income Dynamics for the United States. See Gross and others (2021) for details.

5. Conclusion

The objective of the GST is to simultaneously assess the potential impact of large global shock scenarios on individual bank capital across a range of advanced and emerging market economies on a periodic basis. The analysis provides a cross-country point-in-time snapshot of bank resilience using a consistent global scenario and a common methodology. It captures important aspects of the resilience of the global banking system that are not the focus of stress tests undertaken by most national authorities, such as an analysis of cross-border spillovers and (implicit) spill backs. Moreover, the global perspective could help individual supervisors to benchmark banks in local jurisdictions against similar banks in other countries.

The GST will be periodically updated to inform IMF surveillance regarding the evolution of stress in global banking systems. At the multilateral level, it can provide early indications of risks, including by offering a mechanism to analyze cross-border spillovers of shocks and policy actions via the banking sector channel. It also offers a tool to enhance macro-financial analysis at the individual country level, with a quantification of comparative risks that could support a discussion with the authorities about possible supervisory policies.

The results of the updated GST continue to point to relatively lower levels of resilience of banks in EMs than in AEs. However, despite large drops in capital ratios for some countries in the adverse scenario, capital short-falls continue to remain contained. This is mainly because most banking systems around the world faced the COVID-19 crisis with capital ratios that had grown substantially since the global financial crisis, affirming the efficacy of the post-GFC regulatory reforms and the effectiveness of mitigating measures during the pandemic. Banks are, on average, in a much stronger position to absorb the impact of large shocks than they were on the eve of the global financial crisis.

Nonetheless, a sizable share of banks by assets could come under pressure, especially in emerging markets, which in turn could have negative implications for financial stability and the real economy. Therefore, continued vigilance by the authorities is warranted. For countries where banks have drawn down capital buffers, the stress test results can help inform discussions on the timing and pace at which capital buffers can be rebuilt. Preparing contingency plans that detail how the authorities would respond to possible future pressures will be critical to support effective policy responses in the event the adverse scenarios were to materialize. Supervisors should re-assess banks' forward-looking capital plans and take measures to preserve and support plans to rebuild capital for the most vulnerable entities gradually to ensure that confidence is maintained and financial stability preserved. It would also be useful to keep under review, as feasible, public support to the household and corporate sector (for example, via government loan guarantees, unemployment schemes) that could also indirectly reduce the impact of the pandemic on bank balance sheets.

Annex 1. The GST Methodolgy

A bank-fixed effects model is the basis for the econometric analysis of the GST. The dependent variables, as defined in Annex Table 1.1, were regressed on macro and financial variables (X) using a fixed effects panel structure:

$$y_t = a_i + b_{ig}X_{i,t,g} + \varepsilon_{it}$$

The subscripts i, t, and g denote banks, time, and groups to which banks might have been assigned (see below). The vector X was allowed to contain contemporaneous and lagged macro-financial predictor variables.

A Bayesian Model Averaging Methodology (BMA) is employed to account for model uncertainty, in a panel model setting (Gross and Población 2019). It entails estimating a large set of models for a given dependent variable, which consists of all possible combinations of a predefined set of potential predictor variables. The right-hand side variables include real GDP growth, unemployment rates (and year-over-year changes), stock price growth, short-term interest rates and term spreads, corporate bond spreads, and the VIX; and first lags of all these variables—16 variables in total. The individual models for a given left-hand side variables are combined into a final model by computing predictive performance-weighted averages of the individual models based on Bayesian Information Criteria (BIC). The initial number of models in the "model space" for each dependent variable is

$$I = \sum_{l=1}^{L} \frac{K!}{l!\,(K-1)!}$$

where K is the total number of independent variables and L is the maximum number of independent variables which was set to five. For K=16, I equal 6,884 models. The resulting number of models was reduced by imposing a condition that no model was allowed to contain both unemployment rates and their changes at the same time and that each equation should contain at least one of the macro variables (real GDP growth, unemployment rates, their changes, or one of the lags of these three). This reduced the number of models to 4,722.

Sign constraints on long-run multipliers ensure that the long-run effects of changes in macro-financial variables on the banks' P&L and other drivers are consistent with economic theory (Annex Table 1.2). Models that did not meet at least one sign constraint were removed from the pool of candidate models. This ensured that the final, weighted average models (the so-called posterior models) resulted in meaningful conditional forecasts.

Net loan loss rates were decomposed into expected default rates and loss given default. The decomposition was required to compute the projected performing exposure stocks and the related ratios (Annex Table 1.1) and to derive NII and compute other P&L and balance sheet items. The principle underlying the methodology from Frye and Jacobs (2012) is used to do the decomposition. The methodology comprises three steps.

Step 1: Compute a bank-specific LGD risk index, denoted k:

$$k_i = \frac{\Phi^{-1}[PD_i^{TTC}] - \Phi^{-1}[PD_i^{TTC} \times LGD_i^{TTC}]}{\sqrt{1 - \rho}}$$

The through-the-cycle (TTC) LGD (LGD_i^{TCC} was proxied for each bank i by its historical long-term average coverage ratio (defined as accounting provision stocks over NPL stocks). The long-term average net loss rates (NLR) were divided by that TTC LGD proxy to obtain the TTC PD proxy (PDI_i^{TCC} in the equation). The asset correlation was set to 10 percent. Annex Figure 1.1 shows the distribution of the resulting TTC PD and LGDs for all banks. The LGD index k is assumed to be constant over the scenario horizon.

Annex Table 1.1. Methodology: Econometric Model Components

Model Component		Definition
P&L flows	Net Interest Margin (NIM)	NIM = NII(t) / (av(TEA(t)+PR(t)–NPL(t), TEA(t-1)+PR(t–1)–NPL(t–1)))
		TEA = total earning assets net of loan loss provisions stocks (PR). NII = net interest income. NPL = non-performing loans.
	Net Loan Loss Ratio (NLR)	NLR = NL(t) / (TEA(t-1)+PR(t–1)–NPL(t–1))
		NL = Net Loan Loss flow.
	Net Trading Income Ratio (NTIR)	NTIR(t) = av(NTIR) – a(t) stdev(NTIR)
		NTIR(t) = NTI(t) / TA(t), the average and standard deviation taken over the last five years and the a(t) multiplier reflecting scenario-implied stress on positional risk and bank business.
	Net Fee and Commission Income Ratio (NFCIR)	NFCIR(t) = NFCI(t) / av(TEA(t)+PR(t), TEA(t-1)+PR(t–1))
	Other Income/Expense (RESR)	RES = NI after tax + tax + NL – NII – NTI – NFCI
		RESR = RES / av(TEA(t)+PR(t), TEA(t-1)+PR(t–1))
	Delta OCI Ratio (DOCIR)	DOCIR = (OCI(t)–OCI(t-1)) / av(AFS(t), AFS(t-1))
		AFS = available for sale securities

Source: IMF staff.

Annex Table 1.2. Constraints Imposed on Signs of Long-Run Multipliers (LRMs) of Macro-Financial Predictor Variables

	Real GDP growth	Unemployment rate	Short-term interest rate	Term spread	Stock price growth	Corporate bond spread	VIX
Net loan loss rates	−1	1	5	1	−1	1	1
Net interest margin	1	−1	5	0	5	−1	5
Net fee and commission income ratio	1	−1	0	0	1	−1	0
Other income/expense ratio	1	−1	5	−1	1	−1	−1
Change in OCI	1	−1	0	0	1	−1	−1

Source: IMF staff.

Note: +1 = inclusion allowed, with positive LRM sign constraint. −1 = negative LRM sign constraint. 0 = inclusion allowed no sign constraint. 5 = exclusion. LRMs = long-run multipliers; OCI = other comprehensive income.

Annex Figure 1.1. TTC PD and LGD Proxies for All Banks (Locational Data, 261 Entities)

1. TTC PDs

2. TTC LGDs (Coverage ratios)
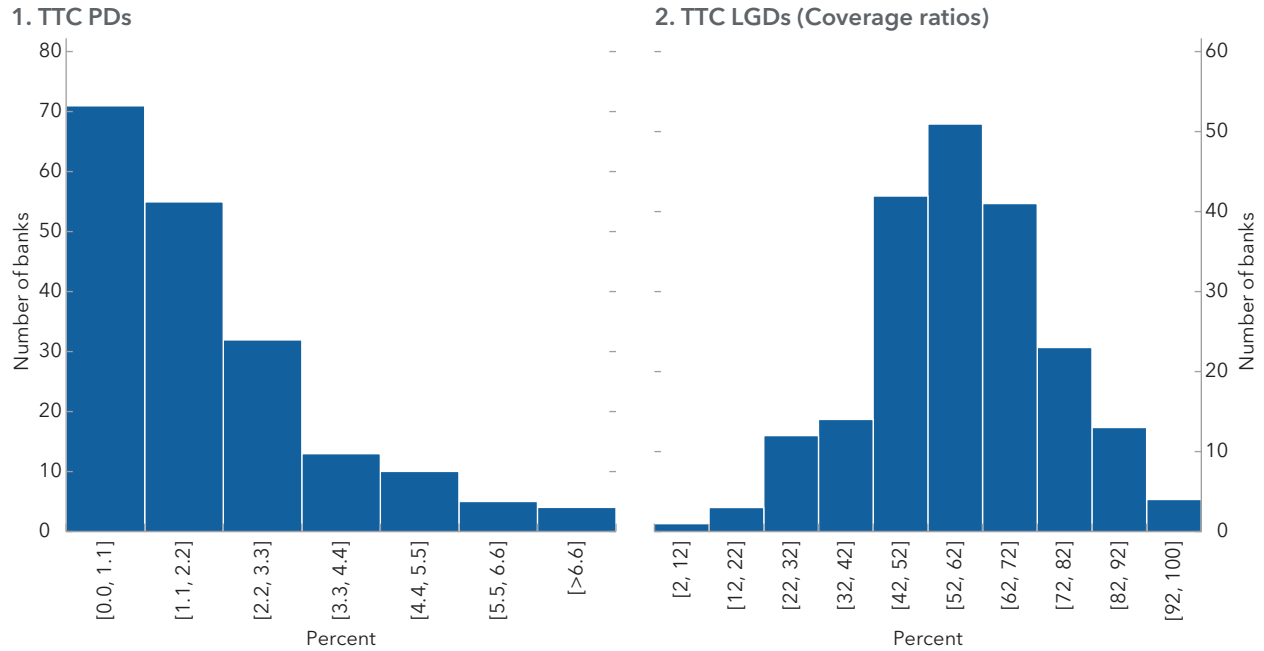
Source: IMF staff estimates.
Note: LGD = loss given default; PD = probability of default; TTC = through the cycle.

Step 2: Compute point-in-time (PiT) PD using k and the PiT NLR projections. The PiT PDs in period horizon h for bank i is given by:

$$PD_{ih}^{PiT} = \Phi[\Phi^{-1}[NLR_{ih}^{PiT}] + k_i]$$

Step 3: Compute the PiT LGDs.

$$LGD_{ih}^{PiT} = {NLR_{ih}^{PiT}}\big/{PD_{ih}^{PiT}}$$

Annex 2. Data Used in the GST

Bank data were scrutinized to ensure maximum coverage, completeness, and accuracy (Annex Figure 2.1). This is done on a period basis to ensure that maximum coverage is attained and that a multitude of validation checks are performed. The process involves four steps:

- **First step.** Data obtained from Fitch Ratings contain bank-level time series of balance sheets and regulatory indicators, which were reported at the highest level of consolidation under multiple accounting standards. Initially, a computationally intensive filtering process identifies entries within the Fitch file that includes data for all banks in the world with historical data that are relevant for the GST exercise. The filtering process selects reported entries for entities and full accounting years within scope and accounting standards. This reduces the dimension of data from 1.6 million records to approximately 11,000 entries.

Annex Figure 2.1. Process Flow for Data Preparation
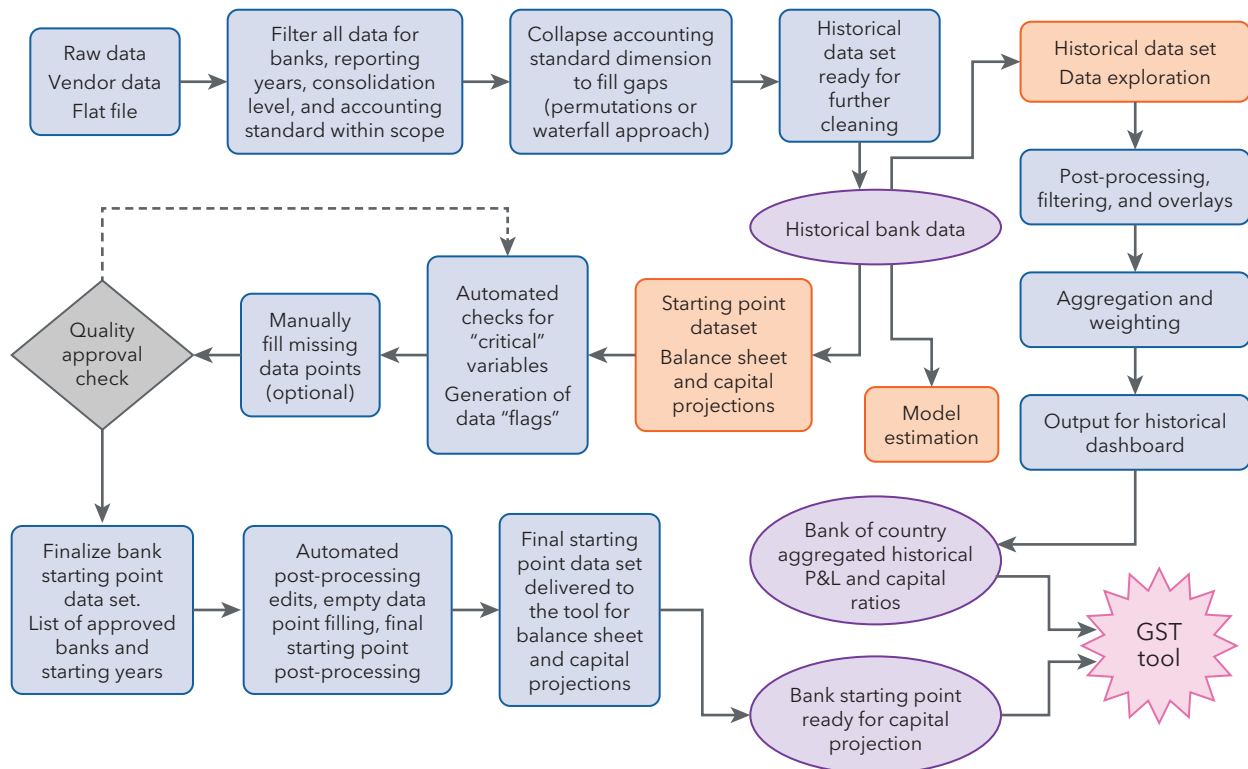
Source: IMF staff.

- **Second step.** The pre-processing algorithm maximizes data coverage by looping through all available accounting standards for each bank and accounting year. Using a hierarchical waterfall approach, missing data points in a higher priority standard are proxied with values obtained from alternative reported standards. Next, the data set is routed to two separate post-processing steps for further cleaning and validation: one flow in charge of the historical data set analysis and the other for starting points preparation and validation for income statement and capital projection purposes.

- **Third step.** End-2020 financial year reports were used as the starting points for the capital projection. The GST exercise identified a subset of bank balance sheet variables that are critical for capital projections and checked their availability in 2020 which was used as the starting point. Alternative sources were used to manually complement missing required starting data points and data going back to 2017 were also allowed to substitute the starting points when real 2020 data were missing or incomplete. The data filling process was repeated until maximum coverage was reached. In addition, historical data sets are fed into a process flow that generates historical ratios of income statement components and aggregates of such ratios involving different weighting schemes at the bank and country level.

- **Final step.** The final data sets covering both time dimensions (historical and latest/starting point) are saved in the active database which is the backbone of the GST.

The rich bank data set suggests a difference in business models between AEs and EMs (Annex Figure 2.2). Emerging markets tend to have higher credit losses due to a more financially vulnerable customer base. Concentrated banking sectors and higher net interest rate spreads are likely behind higher interest margins. As a result, profitability and capital ratios for EMs have been historically higher. However, following the global financial crisis banks in advanced economies issued more capital. Capital ratios grew in both AEs and EMs even during the 2020 pandemic mostly due to higher trading income and net interest margins. The pandemic shock has had a relatively small impact on loan losses due to policy interventions.

Annex Figure 2.2. Profit and Loss (P&L) and Capital Ratios–A Regional Comparison
(Median, percent, unless otherwise noted)

1. Net Loan Loss Ratio
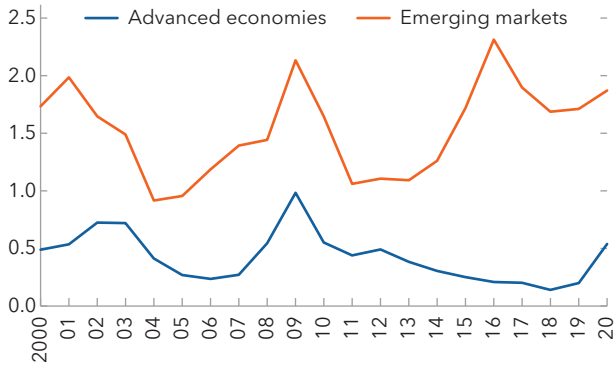
2. Net Interest Margin
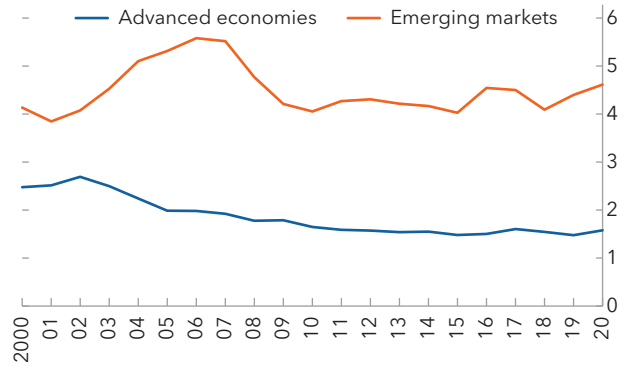
3. Net Trading Income Ratio
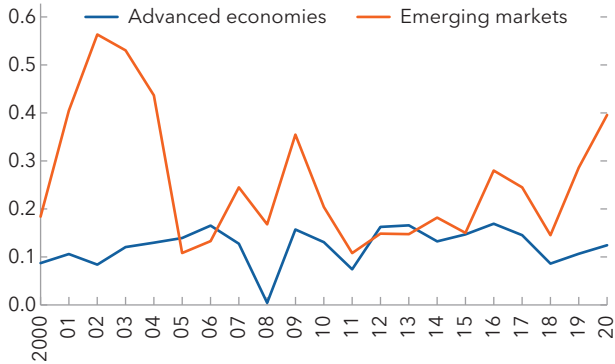
4. Net Fees and Commission Ratio
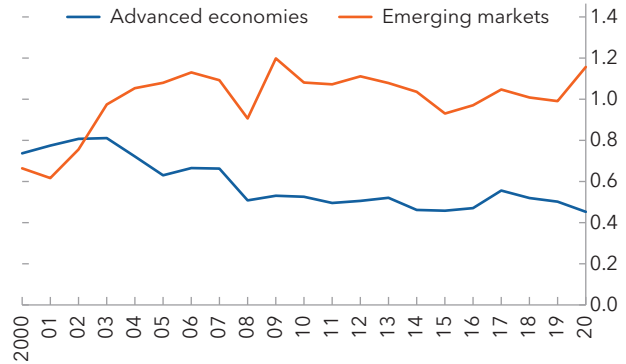
5. Return on Assets
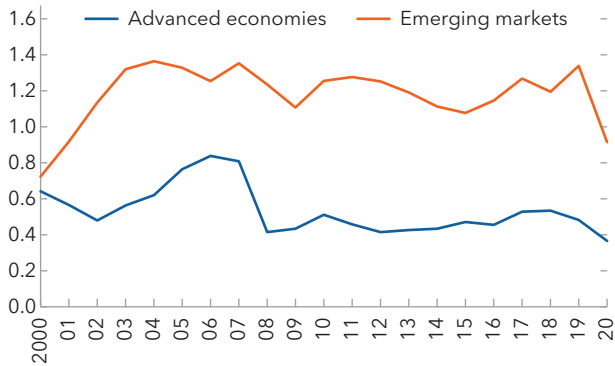
6. Total Regulatory Capital Ratio
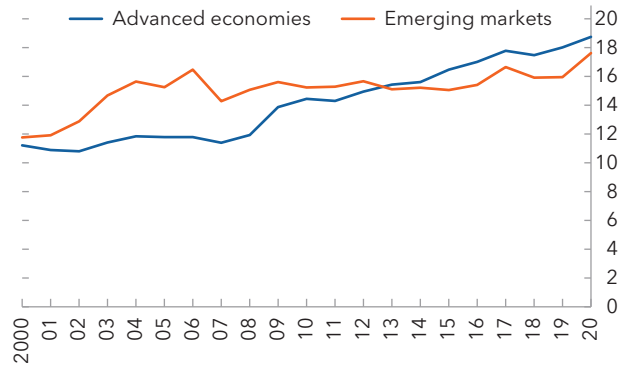
Sources: Fitch Connect; and IMF staff estimates.
Note: P&L = profit and loss.

Annex 3. GST Scenarios

Annex Figure 3.1. Global Bank Stress Test (GST) Macroeconomic Scenarios, Advanced Economies

1. GDP Scenarios
(Level, 2021=100)
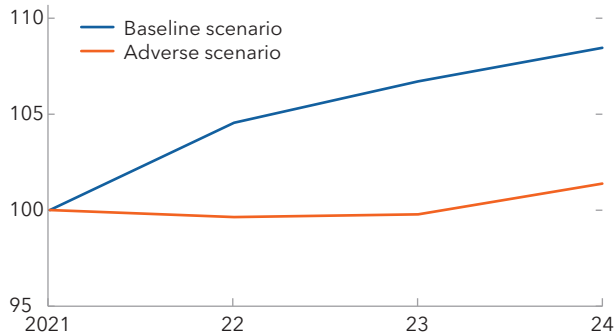
2. Unemployment Rate Scenarios
(Percent)
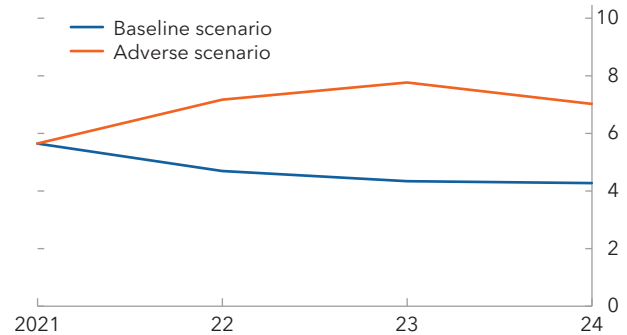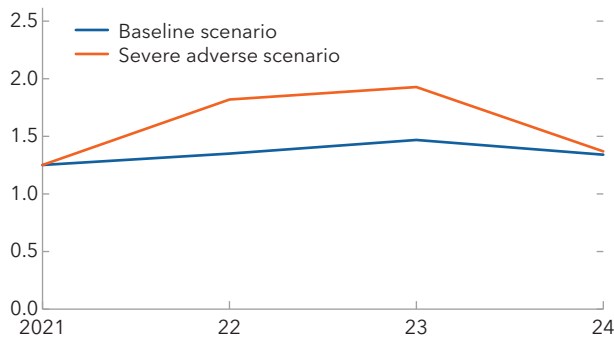
3. Stock Price Scenarios
(Level, 2021=100)
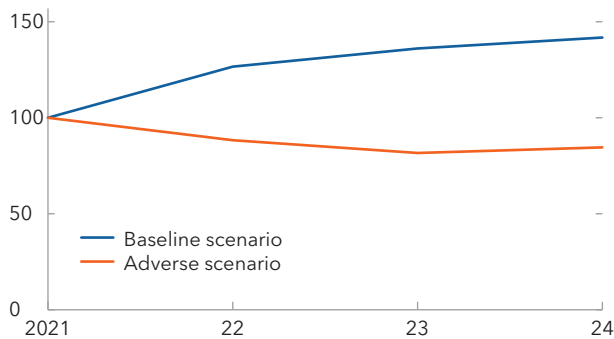
4. Corporate Credit Spread Scenarios
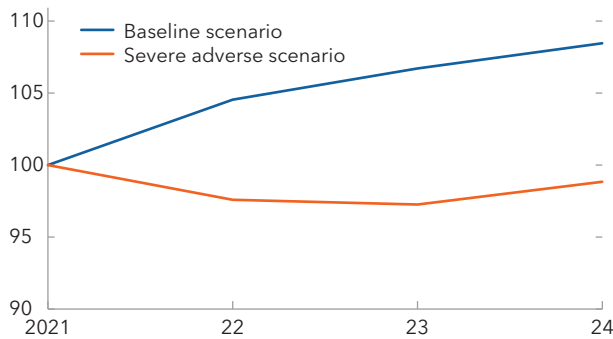*(Percentage points)*
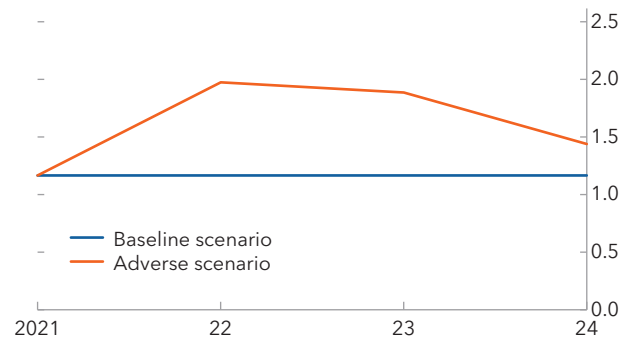
5. Term Premium
(Percent)
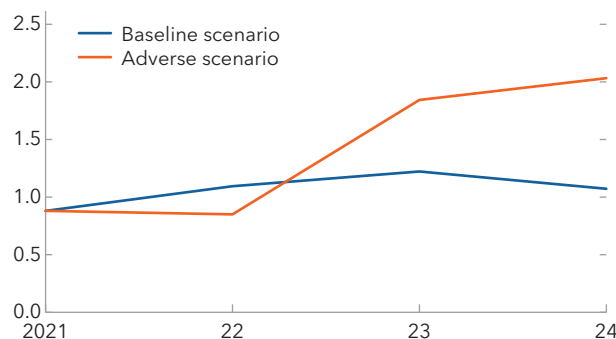
Sources: IMF, October 2021 *World Economic Outlook*; Bloomberg; IMF staff estimates.

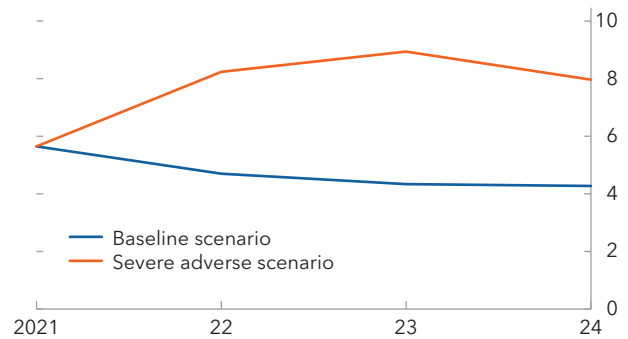**Annex Figure 3.2. Global Bank Stress Test (GST) Macroeconomic Scenarios, Emerging Markets**
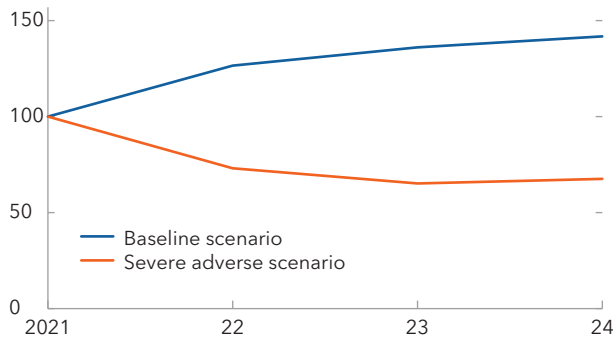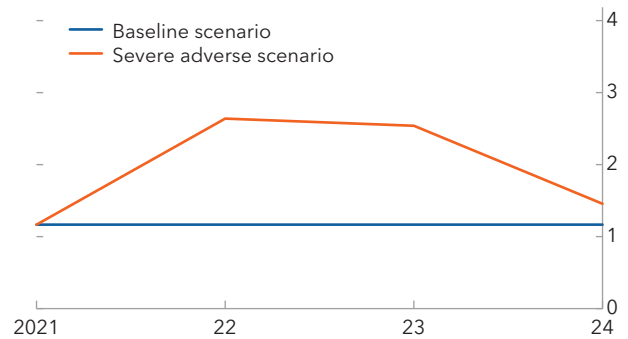
1. GDP Scenarios
(Level, 2021=100)
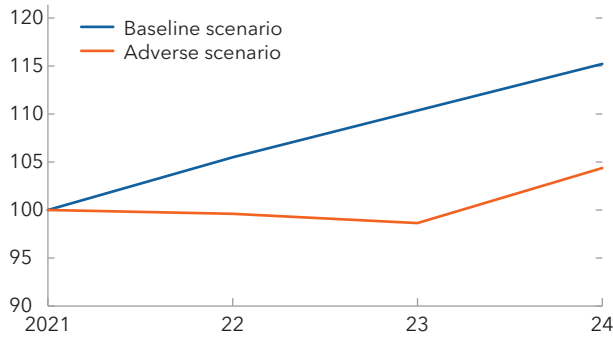
2. Unemployment Rate Scenarios
(Percent)
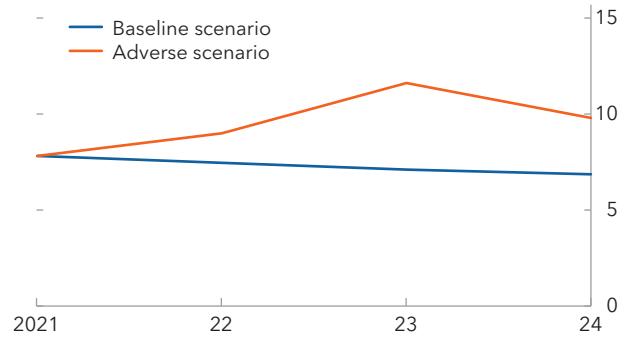
3. Stock Price Scenarios
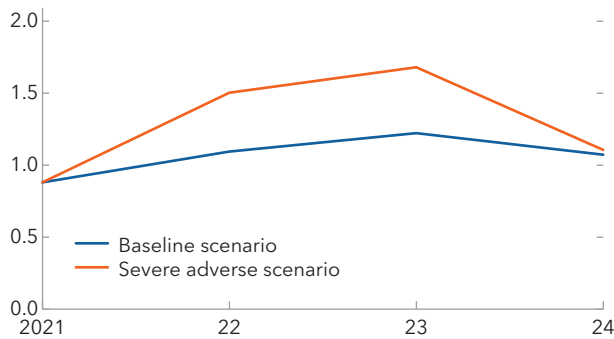*(Level, 2021=100)*
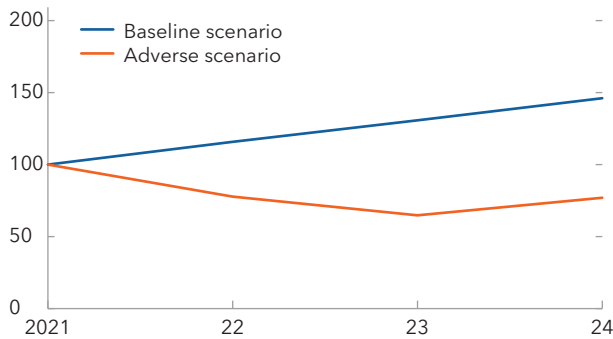
4. Corporate Credit Spread Scenarios
(Percentage points)
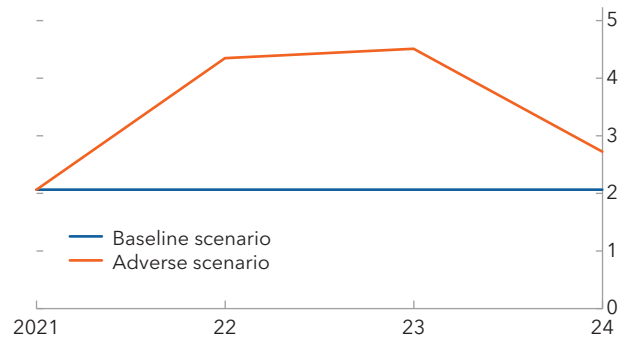
5. Term Premium
(Percent)
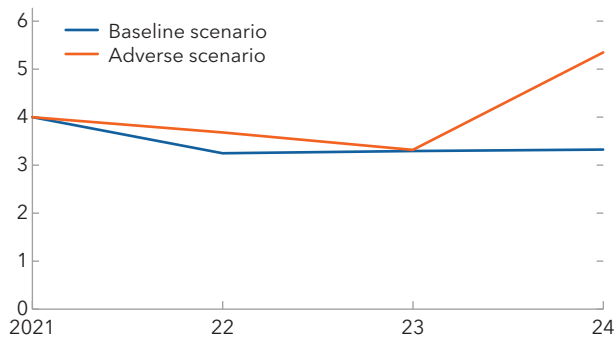
Sources: IMF, October 2021 *World Economic Outlook*; Bloomberg; IMF staff estimates.

Annex Figure 3.3. Global Bank Stress Test (GST) Macroeconomic Scenarios, Global

1. GDP Scenarios
(Level, 2021=100)
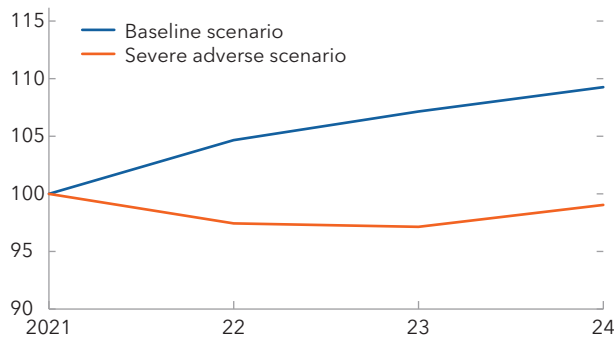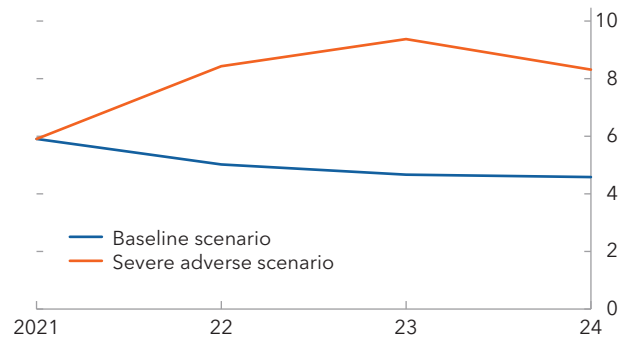
2. Unemployment Rate Scenarios
(Percent)

3. Stock Price Scenarios
(Level, 2021=100)
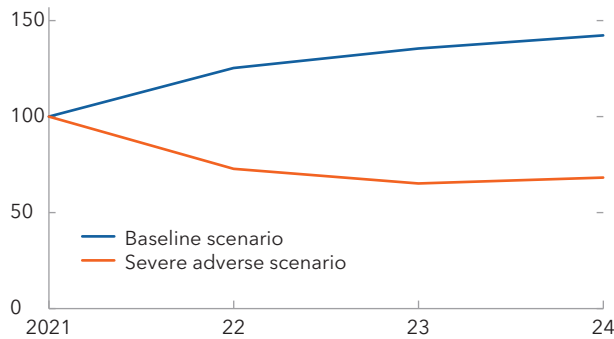
4. Corporate Credit Spread Scenarios
(Percentage points)
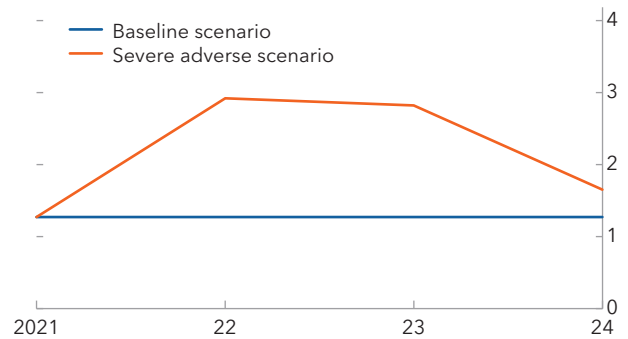
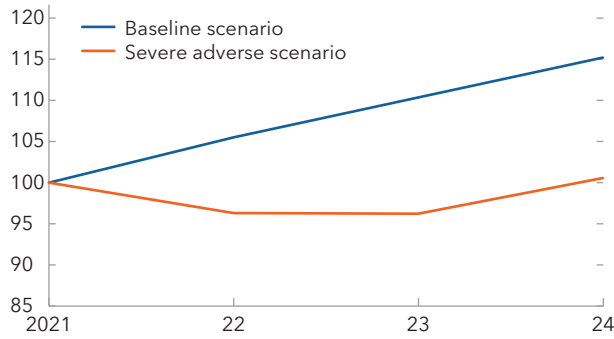**5. Term Premium**
(Percent)

Sources: IMF, October 2021 *World Economic Outlook*; Bloomberg; IMF staff estimates.

Annex Figure 3.4. Global Bank Stress Test (GST) Macroeconomic Scenarios, Advanced Economies

1. GDP Scenarios
(Level, 2021=100)

2. Unemployment Rate Scenarios
(Percent)

3. Stock Price Scenarios
(Level, 2021=100)

4. Corporate Credit Spread Scenarios
(Percentage points)

5. Term Premium
(Percent)

Sources: IMF, October 2021 *World Economic Outlook*; Bloomberg; IMF staff estimates.

Annex Figure 3.5. Global Bank Stress Test (GST) Macroeconomic Scenarios, Emerging Markets
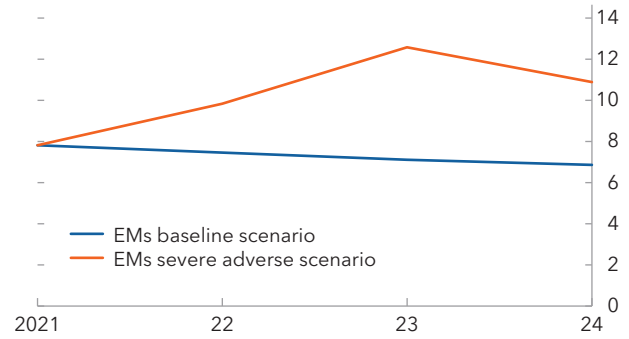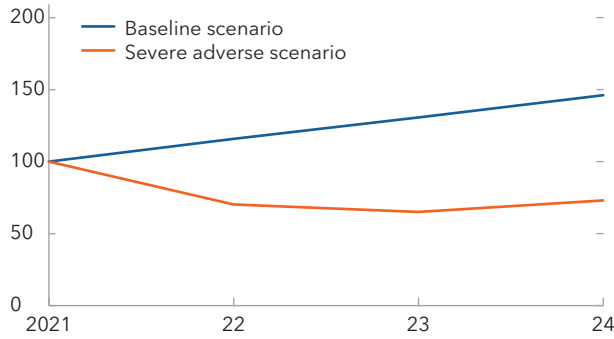
1. GDP Scenarios
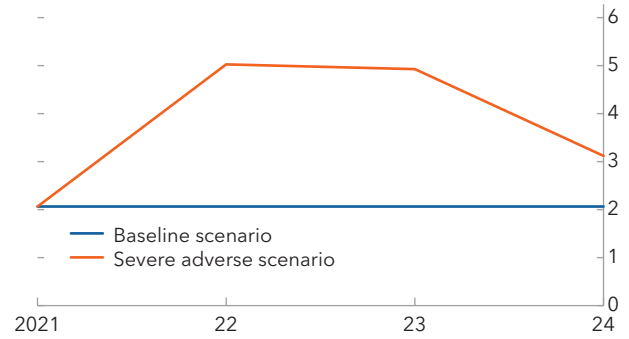*(Level, 2021=100)*

2. Unemployment Rate Scenarios
(Percent)

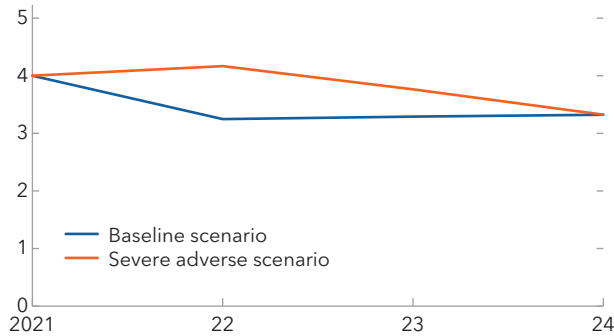**3. EMs Stock Price Scenarios**
(Level, 2021=100)

4. Corporate Credit Spread Scenarios
(Percentage points)

5. EMs Term Premium
(Percent)

Sources: IMF, October 2021 *World Economic Outlook*; Bloomberg; IMF staff estimates.

References

Adrian, Tobias, J. Morsink, and L. B. Schumacher. 2020. "Stress Testing at the IMF." IMF Departmental Paper No. 20/04, International Monetary Fund, Washington, DC.

Andrle, M., and others. 2015. "The Flexible System of Global Models – FSGM." IMF Working Paper 15/64, International Monetary Fund, Washington, DC.

Basel Committee on Banking Supervision (BCBS). 2019. "CRE31 – IRB Approach: Risk Weight Functions." Basel.

Baudino, P, R. Goetschmann, J. Henry, K. Taniguchi, and W. Zhu. 2018. "Stress-Testing Banks—A Comparative Analysis." FSI Insights on Policy Implementation No. 12, Bank for International Settlements, Basel.

Frye, J., and M. Jacobs. 2012. "Credit Loss and Systematic Loss Given Default." *The Journal of Credit Risk* 8 (1): 1–32.

Gross, M., and J. Población. 2017. "Assessing the Efficacy of Borrower-Based Macroprudential Policy Using an Integrated Micro-Macro Model for European Households." *Economic Modelling* 61: 510–28.

Gross, M., and J. Población. 2019. "Implications of Model Uncertainty for Bank Stress Testing." *Journal of Financial Services Research* 55: 31–58.

Gross, M., T. Tressel, X. Ding, and E. Tereanu. Forthcoming. "What Drives Mortgage Default Risk in Europe and the US?" IMF Working Paper, International Monetary Fund, Washington, DC.

International Monetary Fund (IMF). 2017a. "Is Growth at Risk?" *Global Financial Stability Report*, Washington, DC, October.

International Monetary Fund (IMF). 2020a. "Markets in the Time of COVID-19." *Global Financial Stability Report*, Washington, DC, April.

International Monetary Fund (IMF). 2020a. *Regional Economic Outlook: Europe*, Chapter 3, Washington DC, October.

International Monetary Fund (IMF). 2020b. *World Economic Outlook*. Washington, DC, October.

International Monetary Fund (IMF). 2020b. *Global Financial Stability Report*. Chapter 4, Washington, DC, October.

International Monetary Fund (IMF). 2020b. *Fiscal Monitor*. Washington, DC, October.

International Monetary Fund (IMF). 2021a. *Global Financial Stability Report*. Washington, DC, April.

International Monetary Fund (IMF). 2021b. "Canada: Corporate Sector Risk Analysis, COVID-19 Policy Counterfactuals, and Link to Bank Balance Sheets." IMF Country Report No. 21/55, Selected Issues, Washington, DC.

International Monetary Fund (IMF). 2021c. "Nigeria: 2021 Article IV Consultation," IMF Country Report No. 22/33, Washington, DC.

Jobst, A., and A. Weber. 2016. "Profitability and Balance Sheet Repair of Italian Banks." IMF Working Paper 16/175, International Monetary Fund, Washington, DC.

Stein, J. 2021. "Can Policy Tame the Credit Cycle?" *IMF Economic Review* 69 (1): 5–22.

Vitek, F, 2018. "The Global Macrofinancial Model." IMF Working Paper No. 18/81, International Monetary Fund, Washington, DC.
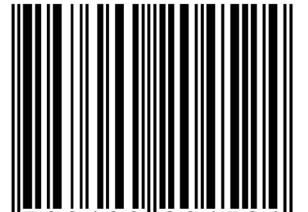
PUBLICATIONS

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