ONLINE ANNEX 4.1. TECHNICAL NOTE[1]

This Annex describes the models methodology that is used as a basis for the analysis presented in Chapter 4 of the GFSR, which provides a quantitative assessment of the impact of COVID-19 on bank capital, including loan loss provisioning as one of its major drivers. Section A of this Online Annex presents an overview of the Global Solvency Stress Test (GST) methodology, its scope, data, and limitations. Section B provides details on the econometric estimation component of the methodology, which is used to relate banks' income and expense drivers to macro-financial conditions. Section C focuses on the decomposition of net loan loss rates (NLR) into probability of default (PD) and loss given default (LGD). Section D presents an empirical satellite model component which is part of the GST model suite, whose aim is to further decompose the aggregate loan loss provision forecasts into those stemming for corporate and retail loans. Section E presents a quantification of the impact of Government guarantees.

A. Global Solvency Stress Test for Banks in Advanced Economies and Emerging Markets

The objective of the GST is to assess the impact of the pandemic shock on bank capital in 29 advanced economies and emerging markets. Banks' resilience is assessed against three scenarios: the latest 2020 World Economic Outlook (WEO) baseline scenario (as of October 2020) and two adverse scenarios. The exercise is based on publicly available data and consequently on simpler stress testing methodologies than those usually employed by IMF staff in FSAPs.

Scope

The GST covers the largest banks in advanced economies and emerging markets (Online Annex Table 4.1.1). The country sample comprises 29 jurisdictions (Online Annex Table 4.1.1); the banking sector assets of which account for 73 percent of global banking system assets. The objective was to include as many banks as necessary to cover at least 80 percent of their respective banking system's total assets. The combined sample contains 347 banks.

Online Annex Table 4.1.1. Scope 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	
	Singapore	Germany	
	Republic of Korea	Greece	
		Ireland	
		Italy	
		Luxembourg	
		Netherlands	
		Norway	
		Portugal	
		Spain	
		Sweden	
		Switzerland	
		United Kingdom	

[1] This is an Annex to Chapter 4 of the October 2020 *Global Financial Stability Report*. The authors of the Annex include John Caparusso, Marco Gross, Nicola Pierri, and Tomohiro Tsuruga.

Data and Caveats

The GST is based on publicly available data. Data for bank income and expense flow data, balance sheet stock data, and several risk metrics were sourced from Fitch, Bloomberg, S&P Global, and banks' financial reports. Consolidated data at annual frequency covering the 1995–2019 period for 347 banks formed the basis for the model and the analysis.

The use of publicly available data imposes constraints on the methodology and therefore on the use and interpretation of the results. FSAP stress tests usually rely on supervisory data, which implies that detailed and advanced stress testing methodologies can be employed. For the present exercise, however, supervisory data was not available. Public data are of lower granularity, coverage, and quality compared to supervisory data. Therefore, the results should be interpreted with caution, including when comparing the results with exercises that are based on more granular, supervisory data.

Scenarios

Banks' resilience was assessed against three scenarios (the 2020 WEO baseline and two adverse scenarios) over the period 2020–2022. The latest 2020 WEO baseline scenario reflects the expected impact of COVID-19 pandemic and is characterized by a severe recession in 2020, followed by a rapid recovery in 2021. The adverse scenario is based on the October adverse WEO projections characterized by a more severe recession than in the baseline and assumes a second COVID-19 outbreak in early 2021. A second, more severe adverse scenario assumes a protracted COVID-19 pandemic resulting in a two-year recession. The January 2020 WEO baseline is included as a reference scenario, which did not reflect the effects of the COVID-19 pandemic yet. In the June baseline scenario, weighted-average real GDP drops by 8 percent year on year in 2020 for the country sample considered under the GST.

The scenarios include seven macro-financial variables. They included real GDP, the unemployment rate, short-term interest rates, term spreads, stock price growth, corporate bond spreads, and the VIX. For the baseline scenario, all variables except the last three were projected by IMF desk economists as a part of the WEO scenarios. Paths for the missing three variables in the baseline scenario were projected by using additional empirical bridge equations that link them to the variables included in the WEO (e.g., GDP growth, unemployment rates, etc.).

The severity of the adverse scenarios primarily reflects the assumed duration of the measures to contain the spread of the virus (the lockdown shock). The disruptions to domestic economic activity in all countries in 2021—resulting from measures taken to contain a second outbreak—were assumed to be roughly one-half the size of what is reflected already in the baseline for 2020. The severe adverse scenario takes the same WEO adverse scenario for 2020-21 but assumes no growth in 2022. This is an additional ad-hoc stress scenario to further assess the resilience of banks to a prolonged economic downturn. All scenarios are reflective of monetary and fiscal policy measures in response to COVID-19.

Stress Testing Methodology

A methodology which caters to publicly available data has been developed. The methodology aims at projecting banks' capital ratios as a function of scenario-conditional trajectories for their profit and loss (P&L) components, other comprehensive income (OCI), and risk weighted assets. It consists of two parts:

- Econometric models for the main components of P&L and OCI (Online Annex Table 4.1.2). These econometric models are cross-bank-country panel regression models that are used to derive scenario-conditional forecasts of the main components of the banks' P&L (except trading income, details follow below), and changes in OCI. The components of the P&L include: (i) net loan losses (NLL) (later supplemented with models of probability of default (PD) and loss given default (LGD), details follow in Section C), (ii) net interest margins (NIM), (iii) net trading income (NTI), (iv) net fee and commission income (NFCI), and (v) a residual income/expense component that "closes" the P&L (equal to the pre-tax net income minus the four main components which are modeled explicitly). A static balance sheet assumption was employed, meaning that gross loan stocks were assumed to stay constant and only the composition of performing and nonperforming assets therein was allowed to vary. Financial assets other than loans were assumed to not be actively traded. However, their market values were allowed to vary as a function of the scenarios reflected through the impact on trading income/change in OCI model. Risk weights were held constant for standardized exposures and made a (smooth) function of changes in risk parameters (PDs in particular) and hence a function of the underlying scenarios for IRB exposures.
- A balance sheet projection module. The module maps the projections of P&L components, RWAs and OCI into banks' balance sheets, including the impact on Common Equity Tier 1 (CET1) capital. The module involves assumptions for dividend distributions and effective tax rates.

All banking system-specific models (Online Annex Table 4.1.2) were estimated using bank-fixed effects panel structures. A Bayesian Model Averaging (BMA) methodology specific to panel model structures was employed to thereby account explicitly for model uncertainty.[2] In addition, sign constraints on the long-run multipliers of the macro-financial predictor variables were involved. The BMA entails the estimation of a large set of models for any given dependent variable, consisting of all possible combinations of the right-hand side variables.

For internationally active banks (GSIBs in particular), exposure weights were involved to create exposure weighted right-hand side variables. This is instrumental for capturing such banks' susceptibility to macro-financial conditions in all countries where they are active. From a

[2] See Gross and Población (2017), "Implications of model uncertainty for bank stress testing," Journal of Financial Services Research, Vol. 55, pp. 31-58; and Desbordes et al. (2018), "One size does not fit all… panel data: Bayesian model averaging and data poolability", Economic Modelling, November 2018, vol.75, p.364-376.

methodological viewpoint, it is an efficient means to capture such cross-border dependencies without increasing the number of model coefficients.[3]

Beyond the inclusion of the aforementioned macro-financial predictor variables which were allowed to enter in time contemporaneous and lagged form, no lags of the dependent variables were considered in order to maximize the predictive content that could be extracted from the macro-financial variables.

The balance sheet model was designed to take account of the fact that rising nonperforming loans imply less interest income. Nonperforming loan stocks do not generate any interest income by assumption. To capture this, the NII flows were defined as a ratio to total interest earning assets net of nonperforming loan stocks. Thus, even if a net interest margin was constant, a rising NPL ratio would imply a fall in the absolute NII.

Online Annex Table 4.1.2. Methodology: Econometric Model Components

Model Component		Definition for the Model / Comments
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 = Nonperforming 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.

The loan loss model was coupled with an additional model that decomposes loss rates into PDs and LGDs. While the loan loss model is based on P&L provision flows, PDs were needed to infer the dynamics of the performing and nonperforming loan stocks (details follow in Section C). Cures (migration of nonperforming back to performing loans) were allowed but not explicitly modeled. Projections of the loan loss provision flows were also cross-checked against

[3] The cross-border exposures have been sourced from banks' annual reports, and other data sources such as Bloomberg (which largely mirror information from bank reports in this respect). The weights reflect both loan and trading book exposures combined. They were sourced for the years 2018/19 and assumed to be constant in history.

the provision forecasts for a subset of European banks and alternative models that were estimated based on the EBA/ECB/SSM 2018 stress testing results.

The NTI ratio was projected as a difference between the bank-specific average NTI ratio over the last five years and a product of a scalar and the bank-specific standard deviation of the NTI ratio over the last five years (to account for 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.

Tax rates and dividends over the stress testing horizon were set to zero if projected net income before taxes is negative. Otherwise they were assumed to be equal to individual banks' effective tax rates and dividend payout ratios in 2019. No deferred tax asset accumulation is considered.

Credit risk weighted assets were allowed to change with the scenarios. First, a breakdown of total credit exposures into exposures under STA and IRB regulatory approach were approximated for each bank based on publicly available data. For the STA component, the densities of risk weighted assets were assumed to remain constant over the stress horizon. The risk weight densities corresponding to IRB credit exposures were projected using the Basel formulas. Through-the-cycle PDs were adjusted using the change of scenario-dependent point-in-time PDs and a "smoothness" parameter to account for the fact that risk weights are ideally fed with smoother through-the-cycle variants of the relevant risk parameters; as per Basel guidance and reflecting bank practice in many jurisdictions. Downturn LGDs were held constant over the stress testing horizon. Other risk weighted assets (market, operational and residual) were assumed to remain constant.

B. Panel Econometric Models for P&L and Other Components

A bank-fixed effects (FE) model structure was the basis for the econometric analysis. The dependent variables, as defined in Online Annex Table 4.1.3, were regressed on macro and financial variables (X) using an FE panel structure:

$$y_t = a_i + \mathbf{b}_{ig}\mathbf{X}_{i,t,g} + \varepsilon_{it}$$

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) was employed to account for model uncertainty. 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 left-hand side variables are shown in Online Annex Table 4.1.3. The right-hand side variables included real GDP growth, unemployment rates (and year-on-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

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

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 equaled 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 ensured that the long-run effects of changes in macro-financial variables on the banks' P&L and other drivers are consistent with economic theory and rationale (Online Annex Table 4.1.3). 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.

Online Annex Table 4.1.3. Sign restrictions on Long-Run Multipliers

	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

Notes: 1: positive sign constraint, -1: negative sign constraint, 0: no constraint, 5: forced exclusion.

Rationale behind sign restrictions

Real GDP growth and unemployment rates: lower growth (higher unemployment) increases loan loss rates and compresses other income (such as fees and commission income).

Short-term interest rates: The reason for not imposing sign restrictions on level (short-term) interest rates is because interest rates have an ambiguous effect on the P&L. For example, for NFCI, and dOCI, the effect of interest rate changes depends on the structure of banks' trading portfolios, the extent to which they are hedged, etc. The empirical estimates indeed suggest different signs of the LRMs on short-term rates in the NTI, NFCI, and dOCI models.

Term spread: Terms spreads are high at the outset of an expansionary period and they slowly decrease throughout the boom to reach a local trough ahead of an ensuing recession. This strong empirical regularity is reflected by imposing a positive sign constraint in the model for loan loss rates (term spreads down during booms, realized loan loss rates down too). For NIMs, the sign on the term spread coefficient is expected to be positive, as the widening of term spreads after the onset of a recession reflects the fact that banks' funding costs (incl. deposit rates) drop due to an expansionary central bank policy response, while loan interest rates may decrease more slowly, depending on how strong is a fall in credit demand. In the model, imposing a sign restriction was not necessary as the estimated LRMs on terms spreads in the NIM models had a positive sign in all specifications across countries.

Stock price growth and corporate bond spreads: The rationale for the imposed constraints is broadly in line with that for real GDP and unemployment.

VIX: A strong increase in VIX is associated with disruptions in financial markets and economic recessions, suggesting the positive sign on loan loss rates. Effects on fees and commissions are ambiguous because more volatile markets (irrespective of the direction of a move) can mean more underwriting business and related income for banks. There is no direct channel (albeit perhaps indirect) from the VIX to NIMs.

C. Decomposing Net Loan Loss Rates into Default Rate and Loss Given Default

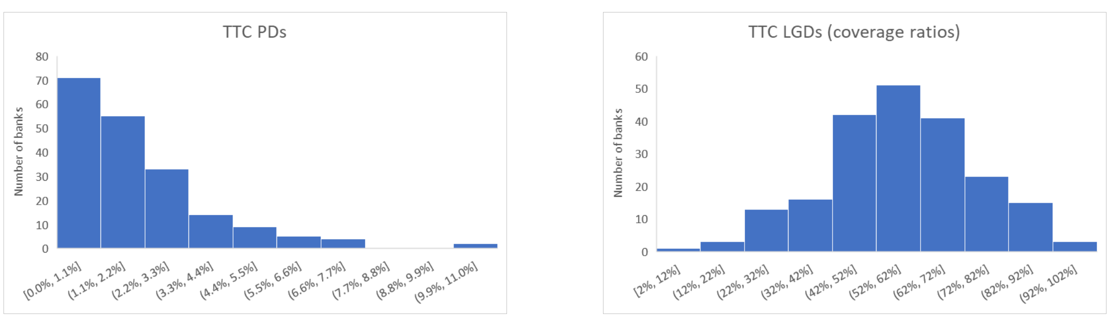
Net loan loss rates were decomposed into expected default rates and loss given default. The decomposition was required to compute the projected performing exposure stocks and the related ratios (Online Annex Table 4.1.2) and to derive NII and compute other P&L and balance sheet items. The principle underlying the methodology from Frey and Jacobs (2012) has been used to do the decomposition.

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^{TTC}) 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 (PD_i^{TTC} in the equation). The asset correlation was set to 10 percent. Online Annex Figure 4.1.1 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.

Online Annex Figure 4.1.1. TTC PD and LGD Proxies for All Banks
(Locational data, 261 entities)



Step 2: Imply a 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:

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

Step 3: Imply the PiT LGDs.

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

D. Analysis on Corporate and Consumer Loan Loss Provisions

This section explains the technical details regarding data and specifications employed in the satellite analysis regarding the bank provisioning in Box 4.1.1. The objective of this analysis is to disentangle the impact of changes in risk of corporate versus household borrowers in terms of banks' aggregate loan loss provision dynamics.

Data are based on the quarterly consolidated bank financials in 15 advanced economies and 9 emerging economies (Online Annex Table 4.1.4). The sample period spans from 2005Q1 to 2020:Q1 with 910 banks included. The data sources are similar to those for the broader GST methodology, and include in addition SNL and data on LGD from EBA.

Online Annex Table 4.1.4. Quarterly Global Bank Panel Data Universe

Universe	Sample Universe
Data Period	2005:Q1 – 2020:Q1 Quarterly
Data Source	SNL, EBA, and Bloomberg
Country Coverage	
Advanced Economy (15)	AUT, BEL, CAN, DEU, DNK, ESP, FIN, GBR, ITA, KOR, NLD, NOR, SGP, SWE, USA
Emerging Economy (9)	CHN, IDN, IND, MEX, MYS, POL, RUS, THA, TUR
Industry Category	Bank (commercial, development, investment), saving banks, bank holding company
Consolidation	Consolidated basis

This satellite analysis is intended to complement the global stress testing exercise to account for decomposing the aggregate loan loss impact into that stemming from the corporate and household sector-related risks. The following local projection method (Jordà 2005) was employed to that end:

$$LLP_{i,c,t+h} - LLP_{i,c,t-1} = \alpha_i + \alpha_t + \beta_h \cdot CorpExposure_{i,t-1} \cdot \Delta CorpEL_{c,t} + \gamma_h \cdot ConsExposure_{i,t-1} \cdot \Delta ConsEL_{c,t} + controls + \epsilon_{i,c,t} \quad (1)$$

where i refers the index of bank, c refers the country, α_i is the bank fixed effect, α_t is time fixed effect, LLP is the loan loss provision per average loans, $CorpExposure$ is the share of the exposure to the corporate loans such as C&I loans, $ConsExposure$ is the share of the exposure to the household loans such as unsecured consumer loans and mortgages, $\Delta CorpEL$ and $\Delta ConsEL$ are the change in expected losses based on the riskiness of corporate loans and consumer loans as described in below. The set of controls includes 3 lags of the dependent variable, changes in riskiness, and a set of bank-level characteristics (NIM, cost-to-income ratio, corporate exposure, log assets, and log loans).

The changes of riskiness of corporate loans ($\Delta CorpEL$) and consumer loans ($\Delta ConsEL$) are given as follows:

$$\Delta CorpEL_{c,t} = LGD_{c,corporate} \cdot \left(PDcorporate_{c,t} - PDcorporate_{c,t-1}\right) \ (2)$$

$$\Delta ConsEL_{c,t} = LGD_{c,consumer} \cdot \left(PDconsumer_{c,t} - PDconsumer_{c,t-1}\right) \ (3)$$

where $PDcorporate_{c,t}$ is the country average of the probability of default (PD) proxied by one year expected default frequency of nonfinancial private firms obtained from Moody's KMV; $LGD_{c,corporate}$ and $LGD_{c,consumer}$ are the LGD for corporate and retail sector obtained from EBA (countries outside the EBA dataset are assumed to have average LGD); $PDconsumer_{c,t} = \rho \cdot Z_{c,t-1}$ where $Z_{c,t}$ is the harmonized unemployment rate obtained from OECD, and ρ is a coefficient estimated by regressing the PD of default for retail loans from EBA on the unemployment rate.[4]

The equations were estimated using OLS. In order to give to each country a weight equal to the size of its economy, each observation is weighted by the GDP of the country divided by the number of observations relative to the same country.

A decomposition of provisions can be performed based on the right-hand side of equation (1), which can be split into two components: a corporate risk-related component (fourth term of right-hand side of (1) $=\beta_h \cdot CorpExposure_{i,t-1} \cdot \Delta CorpEL_{c,t}$) and a household risk-related component (fifth term on the right-hand side of (1) $=\gamma_h \cdot ConsExposure_{i,t-1} \cdot \Delta ConsEL_{c,t}$).

Therefore, given a change in corporate and consumer riskiness, the share of changes in provisions due to corporate provisions in each quarter is equal to

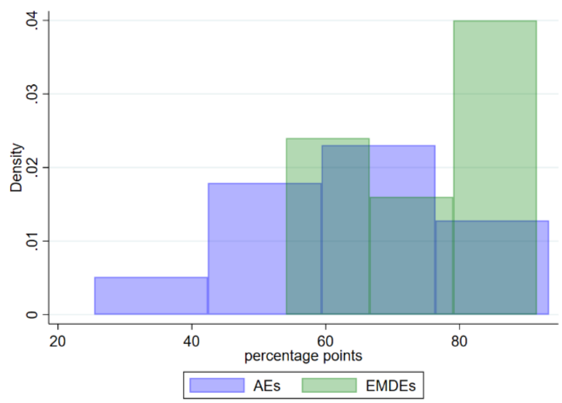
$$ShareCorp_{c,h} = \frac{\beta_h \cdot CorpExposure_{i,t-1} \cdot \Delta CorpEL_{c,t}}{\beta_h \cdot CorpExposure_{i,t-1} \cdot \Delta CorpEL_{c,t} + \gamma_h \cdot ConsExposure_{i,t-1} \cdot \Delta ConsEL_{c,t}}$$

Online Annex Figure 4.1.2. illustrates, for the economies in the main GST sample, the share of the increase in LLP (in 2020) coming from the increase in corporate risk due to COVID-19. In fact, it possible to use the satellite model to predict these shares also for countries outside the estimating sample, as long as data on corporate exposure and PDs are available.

[4] The coefficient ρ is used to normalize the unemployment rate, so that a change in unemployment has the size of a change in PDs. The PDs from EBA are not included directly in the main estimating equation as data are available only for a relatively short time period.

Online Annex Figure 4.1.2. Share of the Increase in LLP coming from Corporate Risk

(country-level distribution)



E. Quantification of the Impact of Government Guarantees

A simple methodology is used to quantify the potential impact of Government guarantees on bank provisioning. A detailed assessment of each country's policy, together with the related implementation challenges, is beyond the scope of this exercise; such an endeavor might also require confidential data on the composition of bank lending portfolios. It is therefore preferred to rely on the following simplifying assumptions

a. guarantees have full uptake and are kept in place for the whole analysis period: while the initial uptake has been low in some jurisdictions, it is difficult to forecast the final uptake.

b. guarantees covers only credit to non-financial corporations: these policies have been mainly implemented to protect NFC, however some of these programs may also offer some coverage to households.

c. all banks in a country are all equally covered by the guarantees: this assumption may be problematic if guarantees are directed to support a specific set of firms (e.g., SME, touristic sector) and some banks lend disproportionally more to such firms. However, data availability constraint the analysis in this respect.

d. guarantees do not impact the probability of a borrower defaulting: guarantees could, instead, impact default if they decrease banks' incentives to properly monitor borrowers or improve economic conditions by protecting bank solvency and financial stability.

Given this set of assumptions, guarantees are represented as policies that decrease the LGD of corporate loans proportionally to the size of the program and on the size of the corporate lending of each bank. As an example, if a country's guarantees scheme is equal to 5 percent of the domestic credit to non-financial corporations, then it is inferred that 5 percent of the losses on corporate will be absorbed by the Government. In this example, the LGD for corporate lending decreases by 5 percentage points. Consequently, the loan loss provisions, normalized by the average loans, for a bank i, in country c are calculated as follows

$$LLP_{i,c} = (1 - ShareCorp_i) * LLP_{household} + ShareCorp_i * \left(LGD_{c,corporate} - g_c\right) ** PD_{i,c}$$

Where g_c is the ratio of the size of the guarantees program to the credit to NFC, $ShareCorp_i$ is the share of provisioning coming from corporate risk (in absence of guarantees), and $LGD_{c,corporate}$ is the loss given default on corporate loans estimated, at the country level, from EBA.[5]

The GST's loan loss provision model (see Sections A, B, and C) provides the total provisioning for each bank, while the additional satellite analysis provides the decomposition in terms of household versus corporate sector. These inputs allow for the computation of provisioning with Government guarantees.

[5] If $LGD_{c,corporate} < g_c$, then it is assumed $LLP_{i,c} = (1 - ShareCorp_i) * LLP_{i,household}$

F. Mitigation Policies: Taxonomy and Impact on Banks

This section briefly describes the analyses used to estimate the impact of mitigation policies on banks' solvency over the stress test period, 2020 to 2022. It covers the information sources used, a policy taxonomy from the perspective of financial impact on banks, decisions regarding which classes of policies are included in the scope of analysis, and a general discussion of approaches employed to estimate each policy's financial impact on banks.

Data sources

Since the start of the COVID-19 pandemic, several organizations have created databases to track national and multilateral economic and financial policies intended to mitigate its impact. The scope of these databases varies widely, and this Chapter relies on those focused on macroeconomic and financial sector policies. The databases include:

Online Annex Table 4.1.5. Main Source Databases

Organization	Scope / Focus	Geographic Focus	Number of Policies	URL
European Systemic Risk Board	Monetary, macroprudential, debt moratoria and fiscal measures, market rules	Europe	1,113	https://www.esrb.europa.eu/home/search/coronavirus/html/index.en.html
Financial Stability Board	Monetary and fiscal policy, borrower solvency, bank balance sheet and operations	Global	2,119	
IMF	Financial sector regulation and supervision	Global	353	
Keefe, Bruyette and Woods	Financial sector policies	US, Europe, Japan	118	
Yale School of Management	Monetary and fiscal policy, credit facilities and guarantees, liquidity facilities, macroprudential policy	Global	3,705	https://som.yale.edu/faculty-research-centers/centers-initiatives/program-on-financial-stability/COVID-19-tracker
IMF	Fiscal policies: Spending, borrower support, guarantees	Global	Country aggregates	
UBS	Fiscal stimulus measures	Global	Country aggregates	

As the table suggests, the first five of these databases present information on a policy-by-policy basis. Most of these databases identify, for each policy, the country or other geographic scope, body responsible, announcement date, policy description, classification according to the authors' taxonomy, and links to supporting documents. These five databases provide the raw information to estimate the impact of policies that 'directly' impact banks' capital position – a notion explained in the next section. The final two databases provide supplementary information to estimate the effects of policies that indirectly affect capital positions through loan-loss provisioning.

Taxonomy of Mitigation Policies

Virtually all economic policy responses to the COVID-19 shock, from the broadest monetary and fiscal policies to the most specific macroprudential measures, could in principle affect banks' financial performance and position. However, this Chapter's quantification of mitigating policies' impact includes a relatively narrow subset of policies. It excludes very broad policies that affect general macroeconomic and systemic financial conditions, such as economic growth, employment, and the monetary and interest rate environment. These effects are, in principle and probably in practice, more appropriately captured through the macroeconomic scenarios that determine banks' overall financial performance.

The quantification exercise also excludes a class of policies that support bank solvency indirectly by lowering bank provisions. These come in three broad categories. The first is policies that borrowers' probability of default—for example, tax breaks, new loans, repayment holidays and other forms of support for corporates and households. These are to some extent captured through the macro scenarios' impact on probability of default, and as a practical matter are difficult to quantify analytically because the ex-post size of any support program is not specified in advance. The second, corporate guarantees, are not captured from individual policy pronouncements, but as a by-product of the aggregate guarantees estimates provided by the IMF's Fiscal Affairs Department. and reduce borrowers' probability of default—repayment holidays, policies' impact on bank performance must be specific and quantifiable—a criterion that excludes very broad fiscal stimulus measures (for example, jobs or public works programs).

A second broad category of policies affect banks' recognition and provisioning for loan losses. Some supervisors explicitly allow banks to defer recognition of or provisioning in cases where the borrower is deemed to have deteriorated as a consequence of the COVID-19 shock but is otherwise financially sustainable. In some cases, too, regulators allow banks to dampen the pro-cyclical effects of policies, like IFRS 9 or 'current expected credit loss' recognition, regarded as potentially pro-cyclical. The rationale for excluding these policies from explicit quantification is similar – they are in principle captured through the macroeconomic scenario, and in any case are exceptionally difficult to quantify ex ante.

Finally, this analysis excludes a broad range of other announced policies with no analytically discernable effect on banks' solvency positions (business continuity, measures to ease operational burdens, bans on short selling, and many others) or which operate mainly to support bank funding liquidity (either foreign or domestic currency).

This quantification exercise focuses on a class of policies that operate directly on bank capital—either reported capital positions or the gap between their current positions and effective minimum capital requirements. There policies operate in three ways: by lowering the denominator of a capital ratio (either risk-weighted assets or the 'leverage exposure' denominator of the leverage ratio; by reducing capital deductions (often through mandatory suspension of dividends or buybacks); or by eliminating or softening the requirement for specified layers of capital buffer (typically the countercyclical capital buffer, capital conservation buffer, or systemic risk buffer) (Online Annex Figure 4.1.3).

Online Annex Figure 4.1.3. Taxonomy of Policies that Directly Affect Bank Financial Position

Policy Class	*Policy Type*	*Model Treatment*
Capital Adequacy: *Explicitly Quantified*	• Lower measured RWA / leverage exposure	• Reduces ratio denominator; raises ratio
	• Lower capital deductions	• Raises forecast capital numerator
	• Lowers solvency threshold	• Lower required buffers
Borrower Support: *Embedded or Included Ex-Post*	• New loan programs • Repayment relief	• Mitigation effect is assumed embedded in stress test model probability of default
	• Loan guarantees	• Country total guarantees applied as ex-post reduction of LGDs
Loss Recognition: *Embedded in Stress Test Provisions*	• IFRS/CECL relaxation • Recognition deferrals	• Implicitly embedded in stress test provision model

With this taxonomy in place, the policies in the databases listed earlier were each reviewed and either excluded from consideration (the vast majority of measures) or classified according to their effect on bank capital. This exercise was conducted for the 29 countries considered in this chapter. In addition, pan-European policies under the auspices of the European Central Bank, the European Banking Authority (EBA), or other policy bodies were considered separately and, where appropriate, applied only to the capital positions of banks overseen by the Single Supervisory Mechanism and EBA supervisory exercises.

Quantification of Mitigation Effects

Each policy that affects bank capital position does so through one of five financial accounts: two measures of capital (CET1 and Tier 1), two balance sheet size measures (risk-weighted assets and leverage exposure) that serve as denominators of capital ratios, and one measure of change in minimum capital requirement (CET1 buffers).

Each policy's impact is in principle estimated based on its unique structure. In practice, a few common policies, which account for the bulk of total policy impact on bank capital across all jurisdictions, are calculated on the basis of a few common patterns. Examples include:

e. All capital buffers are expressed relative to risk-weighted assets, so elimination or reduction of these buffers is likewise estimated with reference to future risk-weighted assets. (Note that risk-weighted assets are typically constant or nearly constant over the forecast period.)

f. The impact of cancellation of dividends is treated simply on the basis of forecast dividends on common equity in the stress test model. Dividend cancellation policies in all instances are applied over a specific time frame (usually 2020). The model conforms to this description and assumes resumption thereafter of dividends forecast in the stress test model.

g. The impact of policies cancelling share buybacks is modelled assuming that buybacks in 2020 would have remained constant with levels reported for 2019. The effect of buybacks is also limited to the policy's stated time horizon.

h. In a few jurisdictions, banks' deposits with the central bank and holdings of domestic government bonds have been excluded from leverage exposures for the purposes of calculating regulatory leverage ratios. The effects of this exclusion are straightforward.

More unique policies are modelled to mimic their stated terms, to the extent possible given disclosed data. The following few examples, neither exhaustive nor fully representative, are presented for illustrative purposes:

i. U.S. regulators announced, for newly overdue mortgages, a suspension of the increase in risk-asset weighting that normally accompanies deterioration of the credit. In this case, we note that system-wide overdue mortgages increased from about 3.0 percent before the COVID-19 episode, to about 7.9 percent by the end of May. The estimation approach assumes, for simplicity, that the risk-weighting rises from 20 percent to 80 percent on credit downgrade. This change in risk-asset weighting is applied to each bank's reported on-balance sheet mortgages outstanding.

j. Loans granted under the U.S. Payroll Protection Program have been excluded from risk-weighted assets and leverage exposures for the purpose of measuring capital ratios. Each US bank's quantity of PPP loans outstanding is unknown. However, the size of the total program has been reported as $659 billion. The model assumes that banks included in the stress test (over 80 percent of US bank assets) account for all of the PPP loans. Further, it assumes that the RWA density on PPP loans is the same as each bank's overall credit RWA density (credit RWA as a percent of total loans).

These estimates of policy impact on individual balance sheet metrics are then converted into pro-forma effects on bank capital ratios. These bank-specific effects drive the bank-specific capital mitigation effects that determine bottom-up analyses of post-mitigation capital position, capital requirements, and solvency. These bank-specific results are then simply aggregated to country, regional and global estimates.

References

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