CHAPTER 2

A New Look at Global Banking Vulnerabilities

Online Annex 2.1. Enhanced Global Stress Test—Data

Sample of banks

The enhanced Global Stress Test (GST) exercise is based on publicly available bank-level data for 29 countries and 869 banks, covering about 92 percent of global banking system assets (Table 2.1.1). The dataset is considerably larger than the original GST (Ding and others 2022). The data was obtained from Fitch Connect and contains bank-level time series of balance sheet and regulatory indicators at the highest level of consolidation under multiple accounting standards. End-2022 financial year reports were used as the starting points for the capital projections. Alternative sources were used to manually complement missing data points. The choice of the countries was guided by the multi-country DSGE macrofinancial model (Vitek, 2018) that generated the adverse macrofinancial scenarios. Additional banking systems—Hong Kong, Singapore, Luxembourg, and Russia—for which macrofinancial adverse scenarios were not available from the DSGE model were included in the simulation exercises for liquidity-solvency interactions (Annex 4), bringing the bank total to 924.

The GST sample includes both parent banks and their global subsidiaries provided that they are not operating in the same country. Aggregation of the stress testing results at the global level requires exclusion of the subsidiaries to avoid double counting. However, country specific results can be presented with foreign subsidiaries especially when they are systemically important at the country level (Table 2.1.1).

Enhancements to the GST models

Besides data, several enhancements were made to the GST satellite models projecting net interest income, valuation changes on bond portfolio, and loan losses. In order to model the additional impact of deposit outflows on capital, a new liquidity-solvency channel was introduced.

- Net interest income: The previous version of the GST projected this component using regressions for net interest margins (NIM) that did not depend upon short-term interest rates. The enhancements to the GST include bank-by-bank coefficients for pass-through from policy rates (proxied by short-term rates) to net interest margins where long enough time series exist. Where bank-by-bank estimation is not possible, country-level panel regressions are used. See Annex 2.2.

- Valuation changes on bonds: The previous version projected Other Comprehensive Income and Trading Income changes using a combination of regression and statistical models. The enhancements to the GST include direct estimation of valuation losses/gains from the marked-to-market portfolio for the solvency analysis (Annex 2.3); and from the held-to-maturity (HTM) portfolio for the liquidity-solvency analysis (Annex 2.4).

- Loan loss: The loan loss provisions use the original GST, modified to include the short-term interest rate (and a lag) and the long-term interest rate separately (instead of the term spread). The regression now includes the inflation rate so that the response of loan losses to the short-term interest rate could be interpreted as the response to the real rate.

- For the liquidity-solvency interaction exercise, selected balance sheet and regulatory information on liquidity conditions of banks were obtained from Fitch Connect to measure banks' liquidity buffers against potential deposit outflows (Table 2.1.3; Annex 2.4). Valuation losses for Held-for-Trading (HfT), Available-for-Sale (AfS) and Held-to-Maturity (HtM) securities from market risk analysis were used as inputs to estimate liquid assets and central bank counterbalancing capacity under different scenarios. Finally, short term interest rates of GST scenarios were used to calculate funding costs of central bank facilities—150 bps above short-term rates.

Granular bank-level data

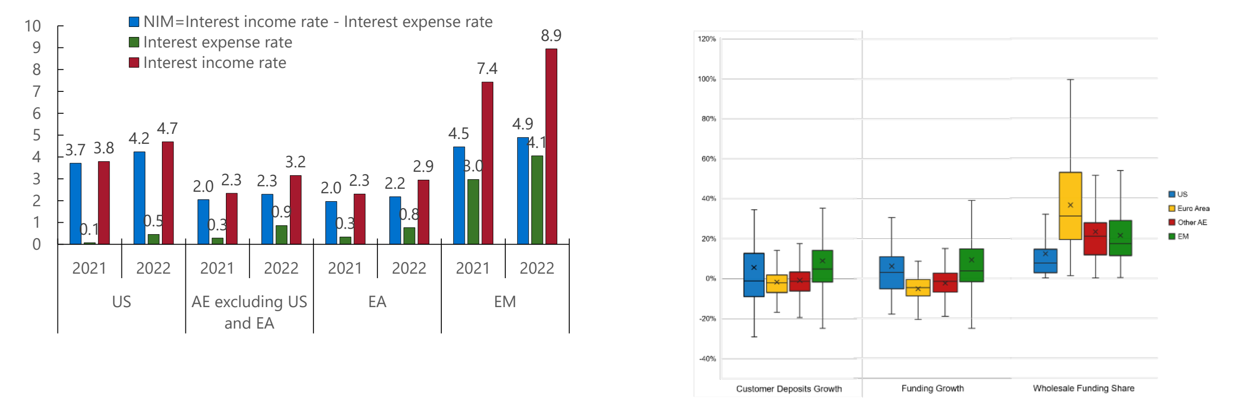
A broad range of balance sheet and regulatory indicators (Table 2.1.2 and Table 2.1.3) were used to project net profit and bank capital under various scenarios, including the liquidity test. Summary statistics on the evolution of the interest expense rate (proxied by the ratio of interest paid on liabilities to total interest-bearing liabilities), the interest income rate (proxied by the ratio of interest income on assets to interest bearing assets) and the net interest margin (NIM) (Figure 2.1.1) show that NIMs have increased in 2022 with higher interest rates across regions. The emerging economies stand out with higher levels of NIMs compared to other regions, while NIMs in the US are higher than other advanced economies. On the liabilities side, although median customer deposits have fallen in advanced economies in 2022 (presumably due to the monetary policy tightening), median funding growth has not necessarily decreased. For instance, US banks have been able to raise other sources of funding, such as from Federal Home Loan Banks (see also Annex 2.7).

Bank level data was used where possible (Table 2.1.4). For the analysis on valuation losses, additional information was collected from multiple sources on the duration (or remaining maturity) and coupon rates to facilitate the market valuation analysis for debt securities booked under the HfT, AfS and HtM categories (Annex 2.3). Specifically, for EU banks covered under the EBA transparency exercise, the remaining maturity of their AfS and HtM were collected separately using information on the maturity buckets of the sovereign securities holdings of the banks. For banks not covered under the EBA transparency exercise, the maturity buckets of total securities by banks were used to compute remaining maturity (or as a proxy of duration) wherever available in Fitch Connect. For duration or coupon rates that were not covered in either database, supply side data for sovereign bonds was collected from Bloomberg and used as substitutes. An overview of the duration data suggests longer duration for advanced economies than emerging markets, and longer duration for HtM securities than HfT and AfS securities.

Online Annex Figure 2.1.1. Net Interest Margin and Deposit Growth, 2021-2022

1. Interest Margin
(Interest Income Rate – Interest Expense Rate, In percentage points)

2. Customer Deposits Growth, Funding Growth and Wholesale Funding Share in 2022 (In percentage)



Source: FitchConnect; IMF staff estimates.
Notes: Interpretation of the box plot: The ends of the whisk represent the min and max values. The box represents the range between first and third quartile. The line in the box represents the median and the cross mark represents the mean.
Wholesale funding comprises deposits and liabilities from banks, pension funds, money market mutual funds and other financial intermediaries.

Scenarios

The scenarios used under the GST include one baseline and one adverse scenario. The baseline scenario was sourced from the published October 2023 WEO and includes key variables such as GDP growth, unemployment rate, short-term and long-term rate, inflation, and commodity and oil prices. With end-2022 data as the starting point, the three-year projection horizon for the stress test is 2023-2025 (Figure 2.1.2). Additional OLS regressions were used to project stock price growth and corporate bond spread under the baseline by linking these variables with GDP growth. The adverse scenario relies on the Global Macrofinancial Model by Vitek (2018) which calibrates adverse shocks measured as deviation from the baseline scenario. For valuation analysis of debt securities, the end-of-period interest rates were used for 2022 in lieu of period average rates to bring model-estimated fair value losses closer to the actual losses reported by banks by the end of 2022.

The adverse scenario features a severe stagflationary scenario. The severity of the scenario can be measured by the size of the two-year cumulative real GDP growth for 2023-24 and its standard deviation from the mean (Figure 2.1.2 and Table 2.1.4). In particular, the global growth is calibrated at 3½ standard deviation from the mean of the historical distribution, distributed across countries at 1.7-3.4 standard deviation across regions. Trade and financial spillovers across the 33 countries (29 used in this chapter) are embedded in the DSGE model (Vitek 2018). The shock to GDP growth is generated in all countries mainly through supply-side channels. Shocks to labor productivity, mark ups and oil prices are primary drivers of the severe shock to inflation that generates an (endogenous) response of monetary policy through higher policy rates (using a Taylor Rule). Additional confidence effects generate demand shocks. After the first year's severe recession, the policy rate reacts to the combination of the output gap and reduced inflation and comes down over 2024-25. However, the unemployment rate remains elevated through the projection horizon.

The scenario is especially severe in China in terms of its historical distribution. This is because, in addition to supply side shocks, there are shocks to the real estate sector output and price that causes a sharp decline in consumer confidence. Since the adverse stress test scenario needed a recession and there is no history of a recession in China, the cumulative GDP growth is very severe (3.4 standard deviation) as a deviation from the historical mean but not particularly severe (1.7 standard deviation) as a deviation from the baseline (Table 2.1.4).

Online Annex Table 2.1.1. GST Bank Sample

Country	Bank Sample with Subsidiaries		Bank Sample without Subsidiaries	
	Banks	Assets Coverage	Banks	Assets Coverage
Australia	17	92%	14	89%
Austria	50	96%	47	85%
Belgium	15	89%	12	51%
Brazil	38	94%	25	81%
Canada	16	97%	15	95%
China	136	98%	128	98%
Denmark	49	84%	47	83%
Finland	20	93%	16	92%
France	14	97%	13	94%
Germany	26	94%	17	79%
Greece	5	98%	5	98%
India	24	92%	23	92%
Indonesia	53	94%	39	82%
Ireland	10	93%	3	37%
Italy	44	94%	38	87%
Japan	27	72%	27	72%
Korea	37	98%	35	94%
Mexico	26	84%	18	30%
Netherlands	15	91%	11	87%
Norway	27	78%	25	71%
Portugal	10	83%	7	62%
Saudi Arabia	11	98%	11	98%
South Africa	6	95%	6	95%
Spain	18	92%	17	91%
Sweden	25	91%	24	86%
Switzerland	27	78%	25	78%
Türkiye	32	92%	23	79%
United Kingdom	33	78%	19	68%
United States	58	95%	48	88%
TOTAL	**869**	**92%**	**738**	**87%**

Source: FitchConnect; IMF Financial Soundness Indicator (FSI), and IMF staff estimates.
Note: Total assets use those reported under the IMF financial soundness indicator (FSI) or the entire Fitch banking sample as a secondary benchmark. For China, small regional and local banks are not captured in the total assets.

Online Annex Table 2.1.2. Selection of Key Variables Used in the GST

Balance Sheet	Income Statement	Regulatory
Total assets	Pre-tax profit	Risk weighted assets (RWA)
Total earning assets	Net interest income	RWA credit risk
Total securities	Net trading income	RWA market risk
Held-for-trading securities	Net fees and commission income	RWA operational risk
Available-for-sale securities	Net loan loss, or loan impairment charge	RWA other risk
Held-to-maturity securities	Other profit or loss items	Common equity tier 1 capital
Gross loans	Tax expense	Regulatory tier 1 capital
Total impaired loans	Comprehensive income	Total regulatory capital
Provision stock for loans	Net income before profit transfers	
Provision stock for asset other than loans	Dividends and other distributions	
Total provision stock		

Source: FitchConnect

Online Annex Table 2.1.3. Selection of Key Variables Used in the Liquidity Stress Test

Asset	Liabilities	Regulatory
Cash and equivalents	Total deposits	Common equity tier 1 capital
Cash and due from banks	Total customer deposits	Regulatory tier 1 capital
Deposits with banks	Customer term deposit	Total regulatory capital
Reverse repos and cash collateral		Risk weighted assets
Total securities		
Held-for-trading securities		
Available-for-sale securities		
Held-to-maturity securities		

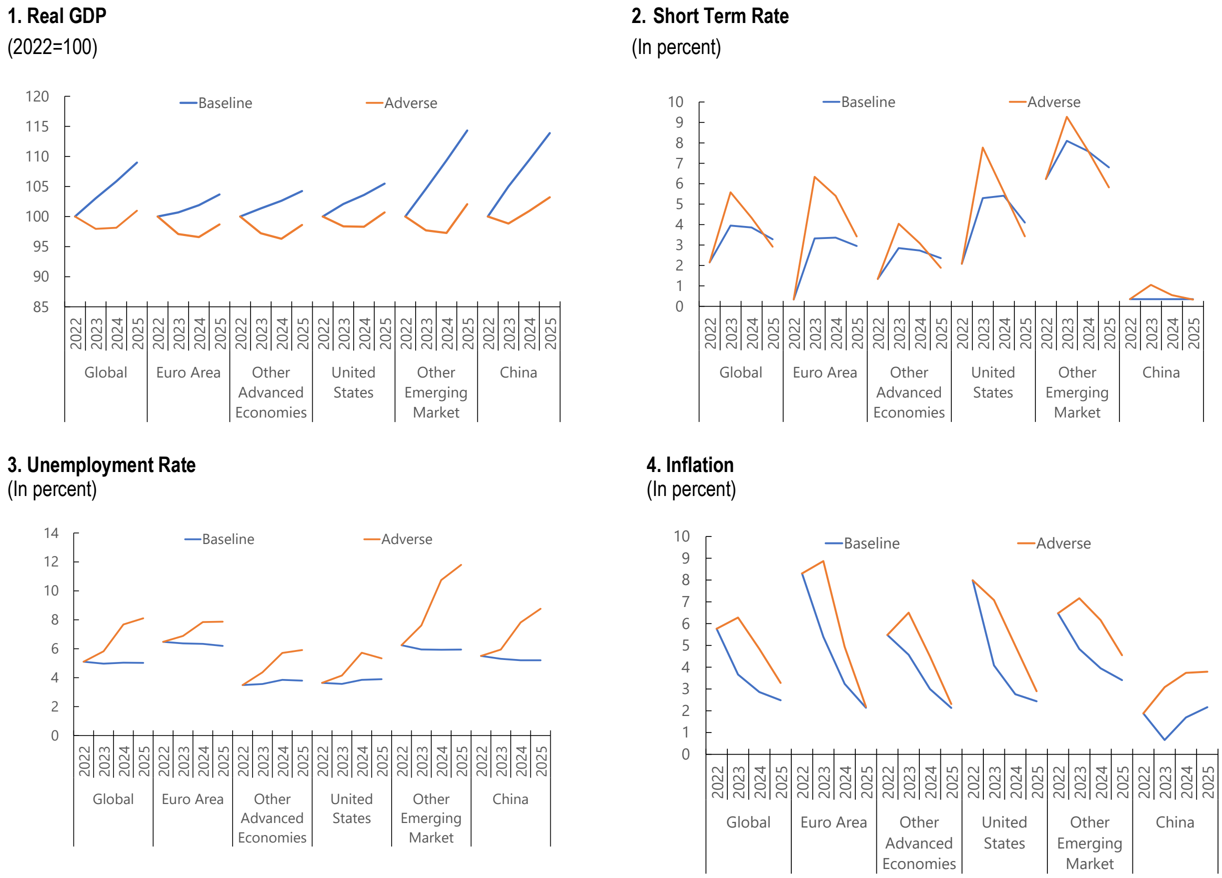
Source: FitchConnect

Online Annex Table 2.1.4. Coverage of Bank Specific Data (In percent)

	Share of Banks					Share of Bank Assets				
	HtM Securities	Hedging - back-testing approach	Hedging - derivative approach	Duration	Bank Specific NIM Betas	HtM Securities	Hedging - back-testing approach	Hedging - derivative approach	Duration	Bank Specific NIM Betas
Australia	76	88	53	35	59	95	99	29	6	97
Austria	38	34	12	4	36	90	87	37	49	63
Belgium	73	80	67	27	40	99	100	86	48	59
Brazil	76	82	18	37	29	93	98	46	22	65
Canada	69	94	81	0	88	98	99	99	0	99
China	97	99	42	47	0	100	100	86	76	0
Denmark	12	4	31	4	45	84	51	90	61	86
Finland	45	60	50	10	15	96	98	97	72	67
France	79	79	71	50	57	99	99	98	61	75
Germany	38	54	23	50	65	21	54	24	31	42
Greece	100	100	80	40	60	100	100	99	50	50
India	21	0	13	13	17	4	0	3	2	39
Indonesia	85	91	21	68	38	97	98	33	80	83
Ireland	40	80	70	50	30	60	82	88	72	26
Italy	95	93	50	20	43	100	99	50	76	73
Japan	52	89	15	15	34	89	98	25	75	33
Korea	68	97	32	22	24	97	100	94	1	61
Mexico	62	62	50	35	31	90	85	55	43	57
Netherlands	60	73	80	33	47	54	96	98	91	33
Norway	22	22	74	30	48	64	56	91	70	84
Portugal	100	90	90	20	60	100	94	94	50	82
Saudi Arabia	100	100	73	0	64	100	100	73	0	67
South Africa	100	100	83	17	83	100	100	93	13	98
Spain	94	94	89	50	50	99	99	80	92	72
Sweden	40	64	56	20	32	59	49	67	84	89
Switzerland	93	15	59	37	63	99	58	72	20	44
Türkiye	84	88	13	63	53	99	100	12	73	85
United Kingdom	73	79	79	0	36	94	96	92	0	80
United States	78	95	97	5	76	89	98	99	2	87
TOTAL	**73**	**69**	**47**	**29**	**45**	**92**	**87**	**76**	**45**	**68**

Source: Fitch Connect, bank annual and regulatory reports, and IMF staff estimates.
Note: Bank Specific NIM Beta includes banks for which we estimated bank specific interest income and interest expense betas.

Online Annex Figure 2.1.2. Global Stress Test Scenarios



Source: IMF *World Economic Outlook*; Vitek (2018); IMF staff estimates.

Online Annex Table 2.1.5. Scenario Severity - Real GDP: Two-Year Cumulative Growth (In standard deviation)

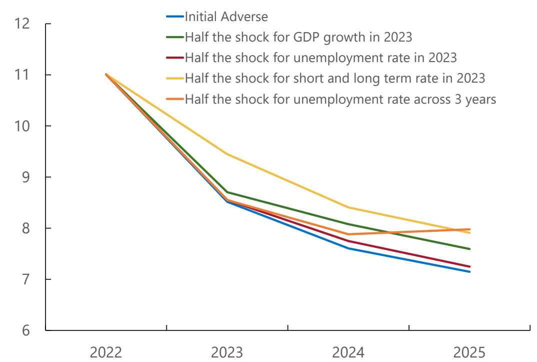
Country/Region	Deviation from historical mean	Deviation from baseline
Global	3.4	2.6
Other Advanced Economies	2.6	2.2
China	3.4	1.7
Other Emerging Market	3.1	3.0
United States	2.2	2.0
Euro Area	1.7	1.5

Adverse scenario for China—Sensitivity Analyses

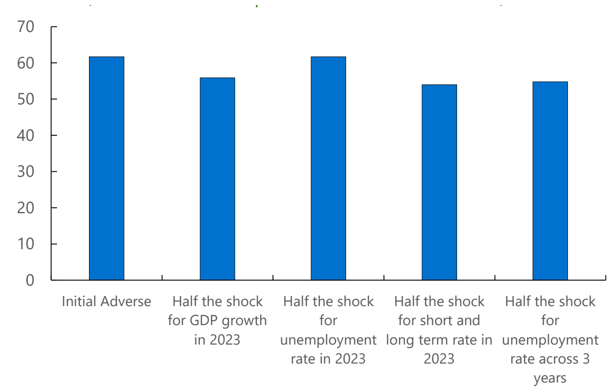
The capital depletion in the adverse scenario would be lower if the scenario were less severe, compared to the adverse scenario results (Figure 2.4 and Figure 2.5). For example, if the economy did not enter a recession in 2023, or if the shock to GDP growth were halved in 2023, everything else constant, then the CET1 ratio would settle to around 7 ½ percent in 2025. If, instead, the shock to the unemployment rate were halved in all the three years, then the CET1 ratio would be around 8 percent in 2025 (Figure 2.1.3). Whereas 62 percent of bank assets were found to be weak in the adverse scenario (Figure 2.5), 55 percent of bank assets would be weak if the unemployment rate shock were half in all three years.

Online Annex Figure 2.1.3 Global Stress Test Results: China

1. Sensitivity Analysis for China – CET 1 Ratio
(Adverse sceanario, in percent)



2. Sensitivity Analysis for China – Share of Assets of Weak Banks
(Adverse sceanario, in percent of total assets in China)



Source: FitchConnect; Vitek (2018); IMF staff estimates.

Online Annex 2.2. Estimation of Interest Income and Interest Expense Pass-through from Short-Term Rates ("Betas")

The objective of this analysis is to estimate the pass-through from the short-term interest rate to banks' interest income rate (IIR) and interest expense rate (IER), used in the enhanced GST exercise for the projection of net interest income (NII). Following the recent literature on the topic (for example, Drechsler, Savov and Schnabl (2021)), we refer to these pass-throughs as the IIR and IER betas, respectively. The IIR is defined here as the ratio of total interest income to interest-earning assets, while the IER is defined as the ratio of total interest expenses to interest-bearing liabilities (Table A1). The bank-by-bank sample is obtained from Fitch Connect, has an annual frequency from 1995 to 2022, and includes 733 banks from 28 countries. Lack of meaningful empirical results forced us to drop Chinese banks from this analysis. Instead, for projections of the net interest income for Chinese banks, it was assumed that it was constant, in percent of assets, over time.

The IER beta describes the impact of a change in the short-term interest rate on the *average* cost of funding of the bank. Therefore, it should not be interpreted as a deposit beta (i.e., the pass-through from short-term interest rates to new deposit rates). While the deposit betas would also be an object of interest, the variables needed to directly estimate them were not available in our dataset. Similarly, the IIR betas capture the pass-through from short-term rates to the *average* rate that banks earn on their assets and should not be interpreted as a lending beta (i.e., the pass-through from short-term rates to new lending rates).[1]

The econometric specification used to estimate the IIR and IER betas is a panel autoregressive distributed lag model (panel ARDL):

$$y_{c,i,t} = \alpha_{c,i}^{y} + \rho_i^{y} y_{c,i,t-1} + b_{0,c,i}^{y} r_{c,t}^{ST} + b_{1,c,i}^{y} r_{c,t-1}^{ST} + \gamma_{0,c}^{y} X_{c,t} + \gamma_{1,c}^{y} X_{c,t-1} + \varepsilon_{c,i,t}^{y} \qquad (2.2.1)$$

where c denotes the country, i denotes the bank, t denotes the year, and $y \in \{IIR; IER\}$. Parameter $\alpha_{c,i}^{y}$ is a bank-specific fixed-effect, $r_{c,t}^{ST}$ is the short-term interest rate, and X_t is a vector of macro controls. For simplicity, the regression specification in equation (2.2.1) is written as if $r_{c,t}^{ST}$ and $X_{c,t}$ were common across banks within the same country. However, for G-SIBs, we use bank-specific interest rates and macro controls, obtained as a weighted average across countries of the corresponding variables, where the weights are the exposures of the G-SIB at the consolidated level. So, for example, the $r_{c,t}^{ST}$ on the right-hand side of equation (2.2.1) for a G-SIB would be the exposure-weighted average of short-term interest rates across countries.

The real GDP growth is included as a control for the interest income regression—since banks derive higher interest income from stronger lending growth during periods of booms. Other macroeconomic controls included in the regressions are the VIX (as a proxy for the price of risk), the term spread, and a dummy for year 2020.

The term spread is defined as the difference between the long-term and the short-term interest rates. The choice of whether to control for the term spread or for the long-term interest rate (that is, whether to include $r_{c,t}^{LT} - r_{c,t}^{ST}$, or $r_{c,t}^{LT}$ in the macro controls vector $X_{c,t}$) has a significant impact on the estimates for the IIR and IER betas. Controlling for the term spread implicitly means that our estimates for IIR and IER betas correspond to a parallel shift (rather than a steepening or flattening) of the yield curve.

[1] To illustrate how these concepts differ, note that if bank 1 has a lower IIR beta than bank 2, this could be explained by bank 1 having a lower lending beta, but it could also be because bank 1's assets have longer duration or because bank 1 has a slower portfolio growth rate (so a larger share of bank 1's portfolio continues to earn the "old" rate after an interest rate hike).

In equation (2.2.1), the coefficients $\gamma_{0,c}^{y}, \gamma_{1,c}^{y}$ are common across banks of the same country, while ρ_i^{y} , $b_{0,c,i}^{y}$, $b_{1,c,i}^{y}$ are bank specific. We set $\gamma_{0,c}^{y}, \gamma_{1,c}^{y}$ to be common across banks so as to avoid having to estimate too many bank-specific coefficients with a short time series. Bank-specific coefficients are only estimated for those banks that have (at least) some 20 annual data points available in our dataset. Banks with only short time-series are assumed to have common coefficients (within each country) and are not included in Figure 2.7 in the main text nor in Figures 2.2.1 and 2.2.2 of this Annex, since the focus of the discussion is on bank-specific coefficients. Slightly less than half the banks in our sample (323 out of 733 banks) have a sufficiently long data series to be included in this analysis of bank-specific coefficients.

Once the coefficients ρ, b_0, b_1 are estimated from the panel ARDL model for each bank,[2] the IIR and IER betas are calculated as the impact of a permanent 100bps increase in $r_{c,0}^{ST}$ on the IER and IIR at different time horizons. In year-0, the impact would simply be given by $\beta_0 = b_0$. In year-1, however, we need to take into account the autoregressive and lagged effects, thus obtaining an impact $\beta_1 = (b_0 + b_1) + \rho b_0$. If we continue to iterate using the ARDL equation, we obtain that for any time horizon T≥1, the impact is $\beta_T = (b_0 + b_1) \sum_{k=0}^{T-1} \rho^k + \rho^T b_0$. Since the scenarios used for the stress testing exercise have a 3-year window, an interest rate shock in the first year of that window would have an immediate pass-through of β_0, and a pass-through of β_2 in the last year of the stress test. For this reason, the main text refers to β_2 as the long-term beta.

Figure 2.2.1 displays the histogram of IIR and IER betas for all countries in the sample, for year-0 (i.e., β_0) in the first column and for year-2 (i.e., β_2) in the second column. Consistent with theory, most banks have betas below 1, so there is generally an incomplete pass-through from short-term interest rates to IIR and IER. In year-0, the median pass-through is 0.43 for IIR and 0.42 for IER at the global level (Table 2.2.1). In year-2, both distributions are shifted to the right relative to year-0, indicating that the pass-through increases over time. The medians in this case are 0.74 for IIR and 0.68 for IER. There is some variation across regions, with median IER betas increasing by 20-110 percent and IIR betas increasing 30-130 percent between year-0 and year-2. The US particularly stands out, with a median IIR pass-through in year-0 close to the global median (0.44 for US, 0.43 for the global), but a year-2 pass-through close to 1 which is well above the global median of 0.74.

Online Annex Table 2.2.1. Median Estimates of IIR and IER Betas

	Median IIR betas		Median IER betas	
	β_0^{IIR}	β_2^{IIR}	β_0^{IER}	β_2^{IER}
ALL	0.43	0.74	0.42	0.68
US	0.44	1.02	0.35	0.72
EA	0.49	0.65	0.50	0.69
EM (excluding China)	0.50	0.74	0.53	0.64
Other AE	0.35	0.67	0.38	0.65

Next, we analyze whether the IER betas are correlated with banks' funding structure. Theory would suggest that banks with a larger deposit "franchise" (as a share of their funding) should have lower IER betas. This is because banks have market power over depositors who tend to keep deposits at their current bank even if they could earn a higher interest rate by switching to a different bank. On the other hand, if banks are highly-dependent on market-based funding, then we would expect the IER beta to be higher since banks would need to pay the market interest rate. For each bank, we compute the ratio of deposits to total funding for each period in our sample, and take the average over time. Figure 2.2.2

[2] The c, i subscripts and y superscript are omitted in this paragraph to simplify notation.

displays scatter plots for bank-specific IER betas (in year-2, residualized by their country average[3]) and ratios of deposits-to-funding, together with a least squares regression line. That is, the regression line corresponds to the following econometric specification (estimated either at the global or regional level):

$$\beta_{2,c,i}^{y} = \delta_c^{y} + \mu\, \overline{dtf}_{c,i} + u_{c,i}^{y} \qquad (2.2.2)$$

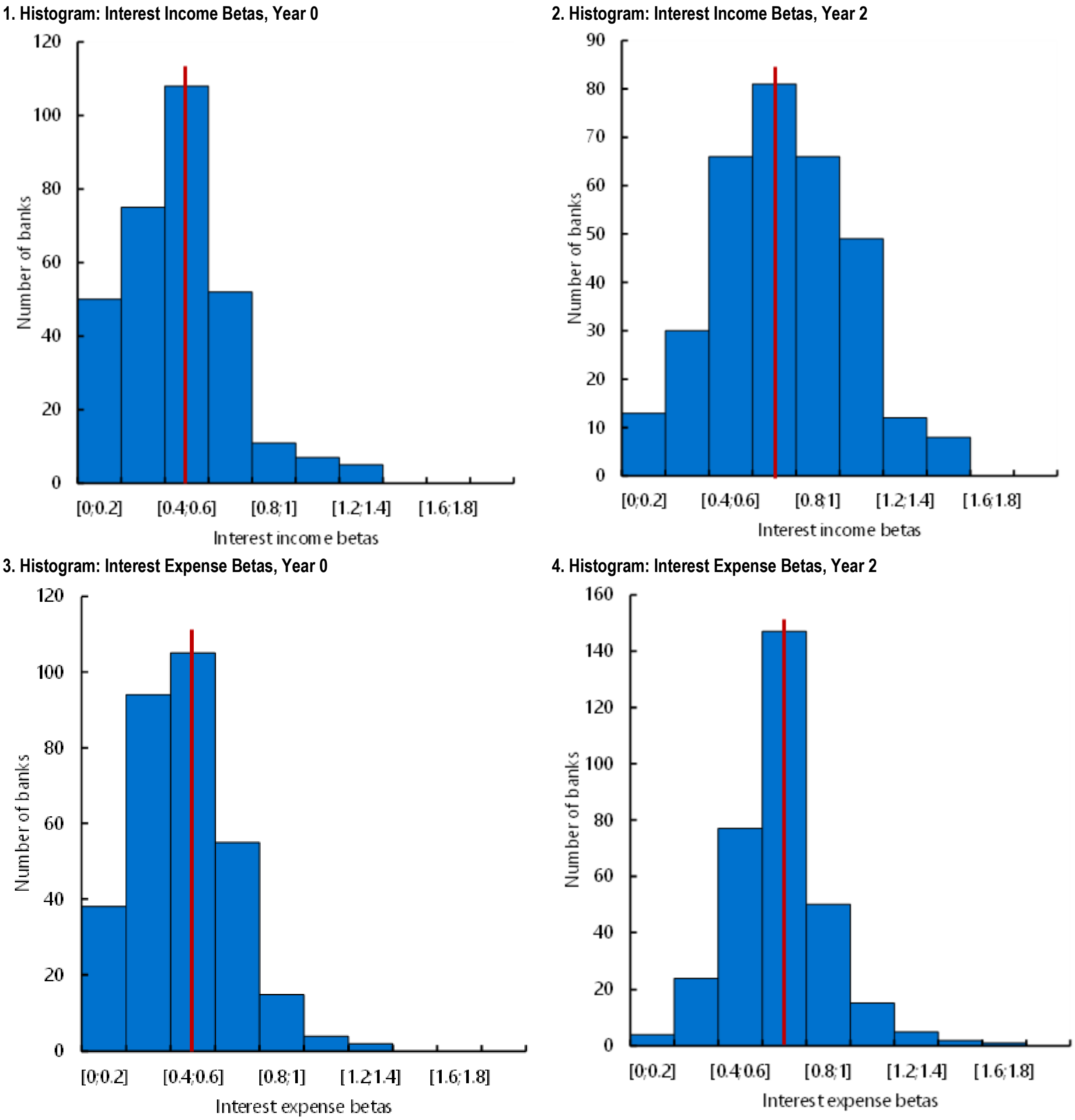
where $\overline{dtf}_{c,i} = \frac{\sum_{t=1}^{T} dtf_{c,i,t}}{T}$ is the bank-specific sample-average deposit-to-funding ratio. Both at the global and the regional level (except for emerging markets), the slope of the regression line (i.e., μ in equation (2.2.2)) is consistent with the theory: banks with a larger share of funding from customer deposits tend to have lower IER betas. This correlation between funding structure and IER betas is particularly strong for the US (Figure A2).

Online Annex Table 2.2.2. Variable Definitions

Variable		Description
Left hand-side variable (y)	Interest expense rate (IER)	$\frac{Total\ Interest\ Expense_t}{Average\ Interest\ Bearing\ Liabilities_t}$
	Interest income rate (IIR)	$\frac{Total\ Interest\ Income_t}{av\{TEA_t + PR_t - NPL_t\ ;\ TEA_{t-1} + PR_{t-1} - NPL_{t-1}\ \}}$ where TEA = Total Earning Assets net of loan loss provisions stocks (PR). NPL =Nonperforming Loans When the variables are not available in FitchConnect to compute the denominator above, we instead use: $\frac{Total\ Interest\ Income_t}{Average\ TEA_t}$
r_t^{ST}		Short-term interest rate
Macro controls: X_t	Term spread	$r_t^{LT} - r_t^{ST}$, where r_t^{LT} is the long-term interest rate
	VIX	N/A
	Real GDP growth	N/A
	Dummy 2020	N/A
dtf_t		$\frac{Total\ Customers\ Deposits_t}{Total\ Funding_t}$

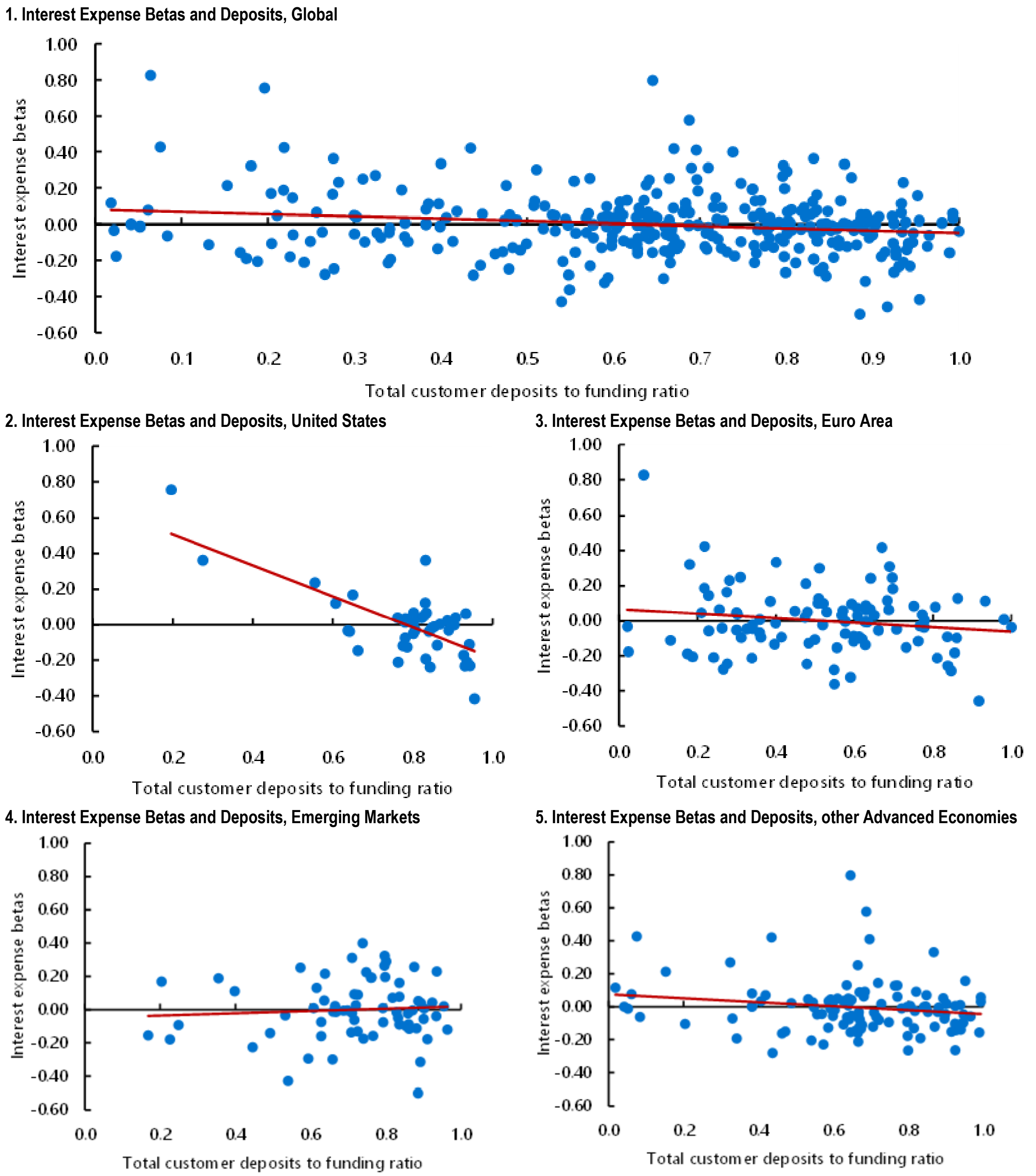
[3] While this analysis could be carried out country-by-country (thus avoiding the need to residualize), for several countries there is only a small number of banks in the sample. For this reason, a regional analysis was preferred.

Online Annex Figure 2.2.1. Interest Income and Expense Betas, Global



Source: IMF staff calculations.
Note: The red vertical lines indicate the medians.

Online Annex Figure 2.2.2. Interest Expense Betas and Deposits-to Funding Ratio



Source: IMF staff calculations.

Online Annex 2.3. Estimation of Fair Value Changes of Debt Securities

Estimation of Unrealized Fair Value Changes in HfT and AfS Securities

The Held-for-Trading (HfT) and Available-for-Sale (AfS) securities were revalued based on a fully fledged discounted-cashflow approach (see Table 2.3.1 for different categories of securities). [4] It calculates the present value of all expected future cashflows generated by a debt security and thus is better suited to capture the non-linear impact of large interest rate changes on the market value of debt securities, often referred to as convexity, which prevents potential over-estimation of valuation losses (gains) in response to rising (declining) yields. Specifically, the valuation takes the following form:

$$P_t = C * \frac{1-(1+r_t)^{-n}}{r_t} + \frac{Par\ value}{(1+r_t)^n}$$

Where P_t refers to bond price at time *t*, *C* refers to annualized coupon payment, r_t refers to yield-to-maturity at time *t*, *n* refers to number of years until maturity. In both the baseline and adverse scenarios, the whole yield curve assumptions are set by linearly interpolating the short- and long-term yields in each year over the risk horizon 2023-2025. An yield curve shock changes r_t, and therefore the bond price and set the corresponding valuation shock compared to the initial price. This approach accounts for all the non-liminalities, including convexity, and usually gives more modest valuation impact than a linear proxy using modified duration (the first derivative of the above formula with respect to interest rate), especially for larger interest rate shocks.

The projection of valuation losses over the risk horizon also assumes that banks will maintain its maturity structure and thus their duration profile. This is equivalent to assuming that as securities mature on banks' balance sheet, the funds will be reinvested into new bonds with maturity structure that would lead to the same maturity profile at the bank level.

Also, instrument, country, and counterparty breakdown of securities is not systematically available from our database. Therefore, the chapter assumes all the security portfolios are invested in sovereign bonds of the home jurisdiction unless national authorities have provided additional data. For instance, a U.S. bank's bond investments are all in U.S. treasuries, including those held by its U.K. subsidiary. Japanese banks hold notable amount of equities and cash for repo transactions in their AfS, which are taken out for the valuation loss calculation from interest rate change using data provided by the Bank of Japan.

The results of the fair value analysis are driven by three main factors: the remaining maturity of a bond, the outstanding amount (on globally consolidated basis), and the shock to yield-to-maturity. The discounted-cashflow formula suggests that larger price impact on debt securities is associated with higher remaining maturity, larger outstanding amount, or larger shocks to the yield-to-maturity (Figure 2.3.2). For instance, the large valuation losses for German and Turkish banks under the adverse scenario can be explained by both the long duration and large yield shock, whereas for Japan the main driver is high holdings of sovereign securities by banks (e.g., the volume effect). The results for the UK and the US seem to be driven equally by all three factors. Adopting a definition of weak banks as those experiencing losses of more than 4 percentage points of capital in the first year under the adverse scenario suggests that smaller banks and banks in the advanced economies experience larger losses than others, and thus are more vulnerable under stress.

[4] Data comes from Fitch Connect. For missing bank data on the share of HfT, AfS and HtM securities out of total securities, aggregated shares on the country level were used as substitutes. There is no data in Fitch Connect that allows the distinction between domestic and foreign securities or securities by currency.

Estimation of Unrealized Fair Value Changes in HtM Securities

The fair value analysis also measures the potential unrealized gains or losses for HtM securities as part of the asset liquidation scenario under the liquidity stress test when central bank facilities are not available, even as they are not typically marked-to-market as per the accounting classification (see Table 2.3.1). Unlike the HfT and AfS securities which were only revalued over the risk horizon, the HtM securities were revalued *both at the starting point* and *over the risk horizon* using the discounted cashflow approach.

The starting point valuation adjustment rely on three approaches:

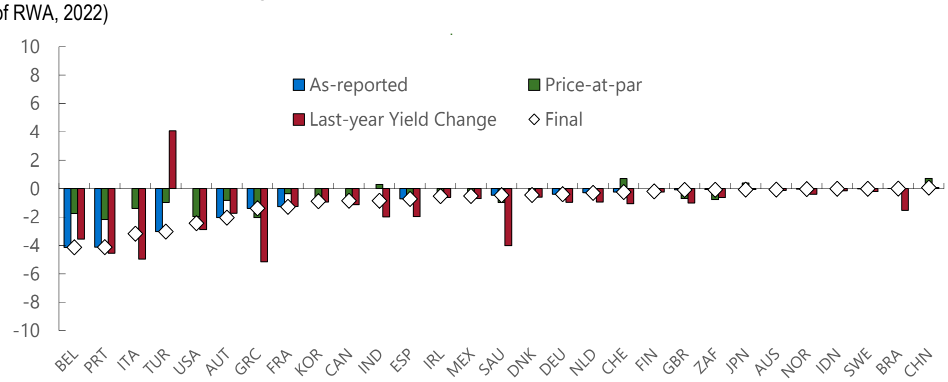
1) "Price-at-Par" method: This method assumes all HtM bonds were issued at par value and held by the banks in the HtM category since they were issued. As such, the yield-to-maturity should be equal to coupon rates at issuance. Over time, the yield-to-maturity could fluctuate and deviate from the coupon rates, leading to valuation changes of the bond away from its par value. Using this concept, the exercise compared the yield-to-maturity to the coupon rates at end-2022 and used the updated values of both to re-calculate the bond price. The percentage change relative to the par value is treated as the cumulative valuation gains or losses of the HtM securities at the starting point of the stress test.

$$P_{t0} = Par\ value$$
$$r_{to} = c$$
$$P_{to} = c * Par\ value\ * \frac{1-(1+r_{to})^{N_{issue}}}{r_{to}} + \frac{Par\ value}{(1+r_{to})^{N_{to}}}$$
$$P_{t} = c * Par\ value\ * \frac{1-(1+r_{t})^{N_{t}}}{r_{t}} + \frac{Par\ value}{(1+r_{t})^{N_{t}}}$$
$$\Delta P = \left(\frac{P_t}{P_{t0}} - 1\right) * HtM\ securities_{t0}$$

2) "Last-year Yield Change" method: This method captures the price impact due to yield changes during the last year (2022), since interest rate prior to 2022 has been persistently low and close to zero lower bond.
3) "As-Reported" method: This method used the reported market value and calculated the percentage change relative to the book value at individual bank level, which was then aggregated to country level weighted by banks' HtM securities.

Online Annex Figure 2.3.1

HTM Securities Unrealized Valuation Change at T0
(In percent of RWA, 2022)



Source: FitchConnect, Bloomberg, Harver Analytics and IMF staff estimates.

The final estimates follow a pecking order by using the "As-Reported" method first wherever applicable at the bank or country level, and then the average of the "Price-at-Par" approach and "Last-year Yield Change" approach for the missing observations as proxies (text figure). [5] The results indicate higher valuation losses at the starting point in 2022 (in percentage point of CET1 ratio) for Belgium, Italy, Portugal, and Greece primarily due to their higher holdings of HtM securities.

Estimation of Hedging Effect on Fair Value Changes

A market valuation analysis without incorporating banks' own hedging strategy could lead to over-estimation of market losses, as banks frequently use derivatives such as interest rate swaps and options, to mitigate valuation impact of their debt securities holdings against adverse movements in interest rates. The exercise relies on two supplementary approaches to quantify hedging effect:

1) "Back-testing" method: This method compares actual reported AfS valuation change reported by the banks during 2022 against the model-based estimate of valuation losses of the AfS securities using discounted-cashflow approach (Figure 2.3.3). The hedging ratio can then be calculated as:

$$Hedging\ ratio = 1 - \frac{Reported\ AfS\ valuation\ change}{Model - based\ AfS\ valuation\ change}$$

One caveat of this approach is that it may over- or underestimate hedging substantially if a bank holds notable foreign securities in jurisdictions with distinct interest rate patterns from that of home country. Because of data constraints, the chapter assumes all security investments (including those held by overseas subsidiaries) are in sovereign securities issued by the bank's home jurisdiction unless additional data are provided by national authorities. If a bank invests in foreign securities in countries that experienced much larger interest rate changes than the home country, the reported AfS valuation change could be artificially larger than the model-based estimate assuming all securities are domestic, reducing estimated hedge ratio substantially. For example, the low hedging ratio for Japanese banks (that do not disclose hedging information in annual reports) appear to reflect such peculiar portfolio structure and interest rate development in 2022.

2) "Derivative-based" method: this method complements the "Back-testing" method by estimating the ratio of the notional value of the interest rate derivative contract on the asset side over the total interest earning assets, based on Jiang and others (2023) (Figure 2.3.3). For the G-SIBs included in the GST sample, this method also computes the hedging ratio using information reported under the section of fair value hedging accounting from either the regulatory or annual reports.

The final estimates follow a pecking order by first taking the reported hedging ratios for the G-SIBs, and then the minimum of the ratios under the "Back-testing" and the "Derivative-based" methods for the non-G-SIBs to allow for conservative (i.e., less mitigating effects) estimates of hedging.[6]

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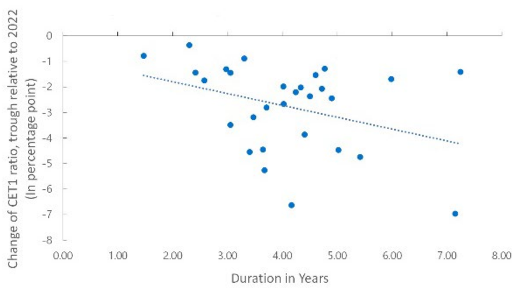
[5] Our results are broadly comparable with the unrealized valuation changes of the HtM securities for 2022 reported for the Euro Area banks in the latest (2023) EBA stress test. EBA reports almost €120 billion valuation loss pre-hedging as of February 2023 while our results are around €145 billion as of December 2022 with a larger banking sample. See EBA (2023) for reference.

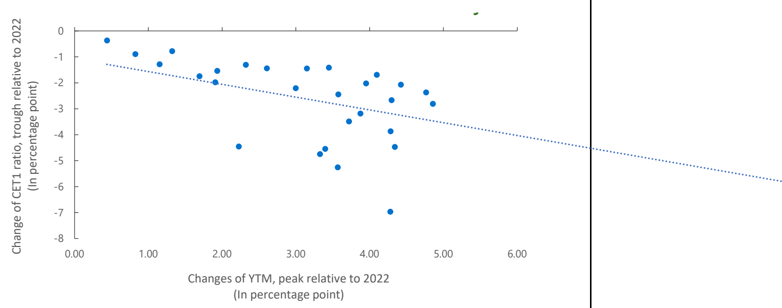
[6] A comparison of the hedging ratio between the EBA stress test exercise and the GST exercise yields similar estimates for 2022 on aggregate, with a slightly higher estimate from the GST, despite the fact that the EBA focuses on hedging effect on HtM securities whereas our analysis focuses on hedging effect on HfT and AfS securities which are normally more actively hedged. See EBA (2023) for reference.

Online Annex Figure 2.3.2. Results of the Bond Valuation Analysis

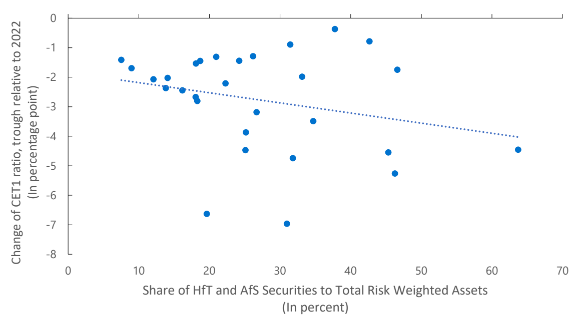
1. Drivers of Valuation Losses on Fair Value Securities under Adverse Scenario – Average Duration



2. Drivers of Impact on Valuation Losses on Fair Value Securities under Adverse Scenario – Shock to Yield to Maturity



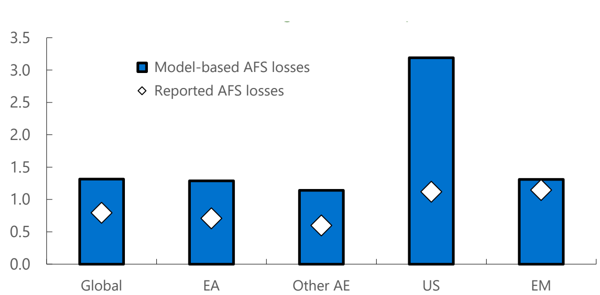
3. Drivers of Valuation Losses of HfT and AfS Securities under Adverse Scenario – Share of HfT and AfS Securities to Risk Weighted Assests



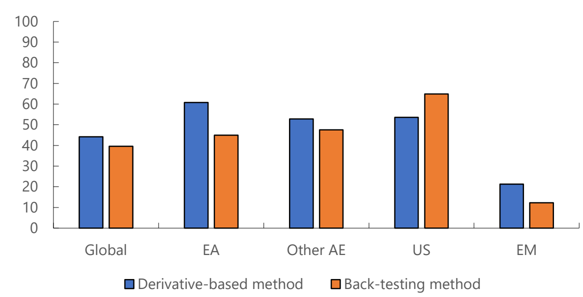
Sources: FitchConnect, Haver Analytics, Bloomberg and IMF staff estimates.
Note: The impact on CET1 ratio is shown without hedging effect.

Online Annex Figure 2.3.3. Hedging Effect on Fair Value Changes

1. Back – Testing of Hedging Effect on AFS Securities
(Absolute valuation changes in 2022, in percent of RWA)



2. Hedging Ratio – Comparison of Estimating Approaches
(Weighted average by HfT and AfS securities, in percent)



Sources: FitchConnect, Haver Analytics and IMF staff estimates.

Online Annex Table 2.3.1. Impact of Bond Valuation Change: Accounting, Regulatory and Investor Perspectives

Book	Accounting (US GAAP, IFRS 9)[1,2] rule	Impact on Basel III Indicators[3]	Investor views
Held for trading (HfT)	Marked-to-Market (MtM), ΔMtM, as part of realized profits/losses in the income statement (taxed)	ΔMtM impact capital through retained earnings	MtM
Available for sales (AfS)	MtM, ΔMtM = unrealized gains and losses as Other Comprehensive Income (OCI)[2] in the income statement, and equity + provisions (tax-deductible)	Unrealized gains/losses added to/deducted from capital. Provisions reduce earnings and capital.	MtM
Held to maturity (HtM)	Book value, ΔMtM = unrealized gains and losses not part of the income statement or balance sheet; credit risk provisions. Can be sold before maturity.[4]	Provisions reduce earnings and capital. MtM for High Quality Liquid Assets (HQLA) calculations and for normal-times central bank facilities.	MtM

1/ The International Financial Reporting Standard (IFRS) is adopted in many jurisdictions, including EU members. However, several major jurisdictions—such as the U.S., Japan, China, and India—largely continue to use their domestic accounting principles.

2/ The table uses US Generally Accepted Accounting Principles (GAAP) terminology. In IFRS 9, HfT, AfS, and HtM are expressed as fair value through profit and loss, fair value through OCI, and amortized cost, respectively.

3/ Basel III has not been adopted universally—especially in emerging market and developing economies—since Basel rules are set up for internationally active banks. Even among advanced economies, including the U.S. and Japan, small and medium-sized banks could exclude unrealized gains and losses even from AfS securities from regulatory capital (consistent with Basel II (called "AfS filter") but not Basel III.

4/Typically, banks can continue booking unsold part of HtM bonds in HtM. However, U.S. GAAP sets a much stricter rule requiring banks to reclassify their entire HtM portfolio as AfS if they sold any portion of HtM securities, with limited exceptions.

Online Annex 2.4. Liquidity-Solvency Interactions

The simulation exercises adopt a "reverse stress test" approach to assess the potential capital impact of a full range of deposits run-off rates under two settings: i) banks have full access to central bank liquidity facilities (CBF) to cover liquidity shortfalls, pledging HtM bonds after selling other bonds, and, if necessary, other less liquid assets, and ii) banks have no access to CBF, and need to sell HtM bonds and recognize valuation losses.[7] The exercise uses the sample of 869 banks and 29 countries of the Global Stress Test, using bank-by-bank financial statements from Fitch Connect as of December 2022.

The simulation assumes banks meet deposit outflows with a specific sequence of asset liquidation: first using cash and cash equivalents, followed by HfT and AfS securities, and lastly resorting to HtM securities. All securities are marked-to-market following the GST bond valuation methodology (see Annex 2.3), for different scenarios (baseline and adverse) and run-off rates. It is also assumed that banks suffer the run at the end of 2023—the first year of the stress test horizon 2023-2025. Using these assumptions, we first determine the size of the liquidity shortfall (LS) for each bank (b), conditional on deposit run-off rate (rr) and scenario (s):

$$LS_b^{rr,s} = Max\{rr \times D_b \; - \; (C_b + HfT_b^s + AfS_b^s);\; 0\,\}$$

where D is the total customers deposits, C is banks' cash and cash equivalents, using balance sheet accounts 'Cash and due from banks' and 'Deposit with banks', and HfT and AfS is the corresponding marked-to-market securities under GST scenarios. Banks facing deposit outflows have two broad options when they run out of the most liquid assets. First, they incur higher expenses from pledging HtM securities at central bank facilities in return for cash, reducing retained earnings and capital. If a bank runs out of HtM securities, the last resort is emergency liquidity assistance with the central bank. Second, they can sell HtM securities at the current (and discounted) market price and incur capital losses by realizing the marked-to-market losses on bonds that were hitherto in book value terms. Then, the exercise estimates the impact of deposit outflows on banks' capital with and without central bank facilities.

When banks have full access to CBF, the capital impact is estimated as the annualized increase in funding costs (equivalent to assume deposit outflows and corresponding borrowing from central banks last for a year) assuming banks can access CBF with 150 bps over short term rates for each country and GST scenario (ST_c^s).[8] If a bank runs out of eligible collateral (e.g. marked-to-market HtM securities), central banks are assumed to extend ELA with expanded collateral or, if needed, unsecured arrangements at the same interest rates. Since deposits are usually much cheaper than central bank facilities, banks' overall cost of funding rises.

On the other hand, when banks have no access to CBF, they need to sell HtM bonds at a loss to cover liquidity shortfalls (also see Annex 2.3). However, in this case the amount of HtM securities at market value limit the amount of asset sales and some banks could fail because they run out of liquid assets before meeting all deposit outflows. Specifically,

[7] The solvency to liquidity interaction is not currently included in the interest expense rate component of the GST. While weak solvency generally increases bank funding cost in principle, empirical models did not detect the impact of lower capital ratio on funding cost. It is likely that the annual data used in this exercise did not pick up short-lived stress episodes where such interactions are most common.
[8] In practice, a less conservative approach on two assumptions would lower the estimated capital impact of increasing funding costs: i) the costs of central bank facilities, especially systemic ELA, could be set lower—even lower than policy rates— to contain systemic stress, and ii) severe liquidity events are usually resolved one way or another in a much shorter horizon than 1 year.

$$CapImpact_b^{rr,s} = \begin{cases} \dfrac{LS_b^{rr,s} \times [ST_c^s + 150\ bps]}{RWA_b} & if\ CBF\ are\ available \\ \dfrac{Min\{LS_b^{rr,s}, HtM_b^s\} \times VLR_b^s}{RWA_b} & if\ CBF\ are\ not\ available \end{cases}$$

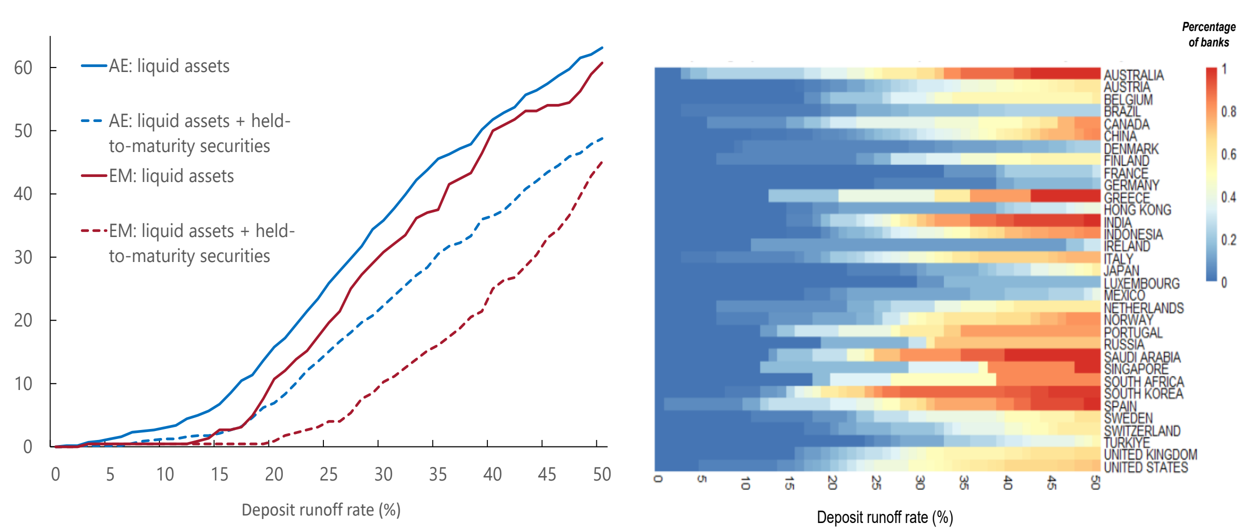
where RWA_b are the banks' risk weighted assets and VLR is the valuation loss rate of HtM securities for each bank and scenario estimated with the GST bonds valuation methodology. It is important to note that valuation losses do not consider potential additional fire sale losses due to market illiquidity; however, in practice this could be a relevant source of additional losses if banks need to sell their bonds in a systemic stress episode.

Figure 2.4.1 shows the percentage of banks exhausting liquid assets (i.e. cash, cash equivalents and HfT and AfS securities) for different deposit outflow rates as of December 2022. Regional level results show that banks in emerging markets can sustain slightly higher deposit outflows than those in AEs. Most AE banks can absorb 5-10 percent outflows without needing to sell or pledge HtM, and most EM banks can sustain 15 percent of outflows (panel 1). Country level results show important differences across countries: while banking systems of most countries hold sufficient liquid assets to withstand large deposit outflows, in other countries like Australia, Saudi Arabia, South Korea, Spain and United States, more than 40 percent of banks by number deplete their liquid assets at a run-off rate of 25 percent (panel 2).

Figure 2.4.2 shows aggregate capital impact with and without central bank facilities. Results show that such facilities could mitigate the losses noticeably across regions: while aggregate increase in funding costs is 9 bps of RWA for AE and 4 bps for EM with 25 percent deposit outflows, valuation losses selling HtM bonds amount to 20 bps of RWA for both AE and EM. Overall, in both cases aggregate capital impact is moderate, but many individual bank and country level results suggest that impacts could be considerably larger.

Online Annex Figure 2.4.1. Percent of banks depleting liquid assets at different deposit outflow rates 1/

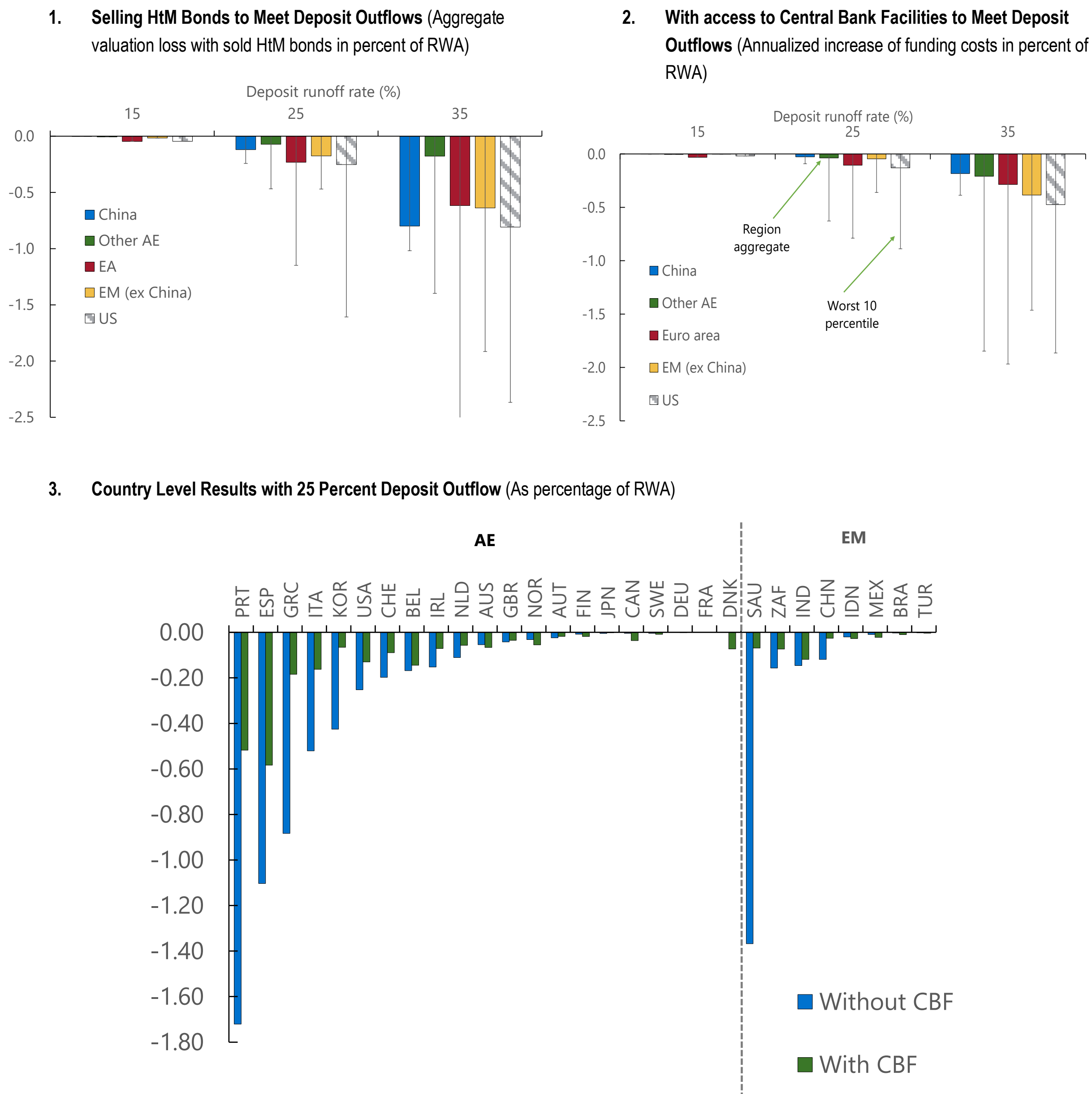
1. Results at Region Level **2. Results at Country Level**



Source(s): FitchConnect, EBA transparency exercise, Bloomberg, IMF staff estimates. The Global Stress Test (GST) contains 924 banks across 33 countries. While liquidity buffer results for all banks and countries are shown here, not all countries were included in the solvency exercise since the Global Financial Model (Vitek, 2018) does not have macrofinancial scenarios for four of them--Luxembourg, Singapore, HongKong, and Russia.

1/ Liquid assets are proxied as the sum of cash, cash equivalents and HtF and AfS bonds using financial statements information of December 2022. HtM securities are marked-to-market at the end of 2022 following the GST bond valuation methodology.

Online Annex Figure 2.4.2. Impact of Liquidity-to-Solvency Interactions on Bank Capital Ratio with and without Central Bank Facilities: Adverse Scenario 1/



Source(s): FitchConnect, EBA transparency exercise, Bloomberg, IMF staff estimates.

1/ Using end 2023 bond revaluation in the adverse scenario (see Annex 2.3). Without CBF, selling HtM bonds at end 2023 when deposit outflows hit banks, results in valuation loss from interest rate changes in 2022 (actual) and 2023 (adverse scenario), assuming the book value of HtM is proxied by end 2021 valuation. Once a bank runs out of securities, it is considered as failed and does not incur any additional losses (e.g., by selling illiquid assets with massive haircuts). When banks have access to CBF, central banks are assumed to charge 150 bps on top of short-term interest rates under adverse scenario. If a bank runs out of security collateral (all assumed to be eligible for central bank repos at market values), the bank is presumed to obtain unsecured ELA at the same interest rates.

Online Annex 2.5. Literature Review, KRI Framework, and KRI Thresholds

Literature Review

Early Warning Indicators and Supervisory Best Practices

1. The academic literature has suggested that three types of early warning indicators[9] are useful to predict banking crises and bank distress: (1) macro-financial indicators, including real GDP growth, real interest rate, inflation, credit to the private sector, and others; (2) balance sheet indicators, primarily following the CAMEL rating system popular among bank supervisors, where the acronym refers to the five key dimensions of Capital, Assets, Management, Earnings, and Liquidity[10]; and (3) market indicators, such as price-to-book ratio, excess returns, dividend payments, standard deviation of returns and trading volume.

2. The aggregate macro-financial indicators are most useful for predicting systemic weakness and broader banking crises and a rich literature already exists.[11] In our analysis, we focus on the last two groups of indicators to make full use of our cross-country quarterly bank-level data and high-frequency market data to identify individual vulnerable banks.

Investor Behavior and Market Discipline: Bank Security Selloffs and Deposit Runs

3. The banking turmoil in the Spring of 2023 has drawn attention to the amplification effect that investor behavior can have once signs of stress appear in banks' solvency and liquidity metrics. While ultimately banks may drop below critical regulatory capital levels given sufficient negative shocks, a withdrawal of market support—through a combination of a fall in equity valuations, a steep rise in funding costs, and a rapid withdrawal of deposits—is much more likely to precede any such event and hasten a banks demise. Studies show that depositors may punish risky banks by withdrawing deposits and requiring higher interest rates. [12] High funding costs reflect an elevated market risk premium and hence perceived default risk and may also lead to deposit runs. In addition, depressed equity valuations (most easily proxied by a low price to book ratio) indicate pessimism on the part of investors regarding a bank's future profitability and will likely make it difficult for the bank to raise additional capital if needed and stay viable.

Construction of the Dataset for the Key Risk Indicator (KRI) Framework

4. Quarterly data on a broad range of balance sheet and income statement-based metrics are collected for publicly listed banks to generate a comprehensive sample of banks that encompasses various measures of key risk trends. This dataset is further enhanced by incorporating aggregate consensus forecast financial data and daily market pricing information from third-party proprietary sources.[13]

5. Reporting requirements differ significantly across regions. Thus, the construction of a standardized bank dataset involves a delicate balancing act between relevance, timeliness and granularity of the information collected on the one hand and the inclusion of an adequate and representative sample of institutions within the dataset on the other. For instance, although quarterly data are more suited to the objectives of an early warning system, it is important to note that the scope of banks included in the set is constrained by the reporting frequency and standards in some jurisdictions, and availability of aggregate consensus forecast data.

6. The period and sample of banks have been determined to maximize consolidated data availability reported at the ultimate parent level.[14] To ensure the adequacy and consistency of the information, we cross-referenced financial data and searched for extreme outliers as quality checks. The approach allowed the identification of over 3750 banks in 43 countries across six regions

[9] Studies on macro-financial indicators: Barrell et al., 2010; Chen et al., 2021; Davis and Karim, 2008, etc. Studies on micro balance sheet indicators: CAMEL: Betz et al., 2014; Ferriani et al. 2019; Gonzalez-Hermosillo, 1999, etc. Studies on market indicators: Campbell et al., 2008; Curry et al., 2007

[10] Several studies also find that size (log of total assets) of financial institutions to be relevant, with larger banks less likely to fail. (Cole and Wu, 2009; Wheelock and Wilson, 2000.)

[11] See Laeven and Valencia, 2018, for IMF work on this topic.

[12] Studies on depositor discipline: Martinez Peria and Schmukler, 2001; Berger and Turk-Ariss, 2011, etc. Studies on deposit insurance and reduced market discipline: Demirgüç-Kunt and Huizinga, 2004; Ioannidou and Penas, 2010. Studies on market prices and returns: Distinguin et al., 2006; Flannery, 2001. This depositor discipline appears to be stronger for banks relying more on uninsured deposits (Berger and Turk-Ariss, 2011), while steps taken to reduce financial stability risks and shield depositors from losses, such as expanding deposit insurance coverage and rescuing troubled banks, are commonly believed to lower market discipline and increase risk-taking. Large, systemically important banks are also often perceived as too-big-to-fail and less subject to market discipline.

[13] The proprietary third-party sources include Bloomberg LP, S&P Capital IQ, and Visible Alpha. The Visible Alpha dataset includes standardized financial data and metrics that include company filings data, aggregate consensus and revised aggregate consensus data that enables analysis across banks and geographies.

[14] See Annex 6.1, "Intra-Group Consolidation," Financial Soundness Compilation Guide 2019, International Monetary Fund, Washington, DC. See, Financial Soundness Indicators - FSIs Home - IMF Data

comprising of Asia, China, Europe, Latin America, Middle East and North Africa, and North America.[15] The sample accounts for US$ 116tn in total assets and represents approximately 65 percent of global banking system assets in 2022. The breakdown of the data by percent of total assets in the sample shows banks in Asia and China have the largest share (46 percent) followed by Europe (26 percent), North America (25 percent), Latin America (2 percent) and Middle East and North Africa (2 percent) (Figure 2.12.1, Chapter 2).

7. Covering the period from 2018 to 2023, the dataset includes two key periods of stress: the COVID-19 pandemic and the March 2023 banking turmoil. Importantly, this data set presents an important innovation compared to standard literature by incorporating aggregate consensus analyst forecasts for the evolution of bank balance sheets, income statements, and key financial ratios. This enables the analysis of forecasted trends up to the fourth quarter of 2023.[16] In addition, the consensus forecasts allow us to gauge investor expectations at various historical points, enhancing the capture of the ex-ante sentiment of market participants. This is crucial for a deeper understanding of the role market discipline can potentially play during banking stress.

KRI Selection

8. Twelve financial ratios and market variables were identified to form the core set of KRIs (Table 1). The selection process for these core KRIs was guided by several criteria including, data coverage, literature review, the CAMELS framework, best banking supervision practices and econometric analysis. We used the CAMELS framework to identify key risk indicators. Bank supervisors widely use the CAMELS risk framework to assess the overall health of a bank and issue periodic supervisory ratings for banks they supervise. The CAMELS risk framework consists of six risk components that include various risk metrics to assess capital adequacy, asset quality, management performance, earnings, liquidity, and sensitivity to market risk. We focus on the first five CAMELS components since global quarterly data on sensitivity to market risk is scarce and comparability is limited. We use the IMF's Financial Soundness Indicators, which were developed in collaboration with the international community to support the assessment of strengths and vulnerabilities of financial systems; and the quarterly Risk Dashboard metrics published by the European Banking Authority to also identify core KRIs.[17] In addition, we applied econometric analysis to confirm that a deterioration in CAMEL variables, all else equal, are statistically associated with future stresses—large declines in stock prices, stock price excess returns, and deposits—at the bank level (See Empirical Evidence for the Relevance of Key Risk Indicators in Identifying Vulnerable Banks section). The following table describes the rationale for the KRI selection based on the CAMELS risk framework.

[15] Asia includes India, Indonesia, Japan, Malaysia, Philippines, Singapore, South Korea, Taiwan and Thailand; Europe includes Austria, Belgium, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Italy, Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland, and the United Kingdom; Latin America includes Brazil, Chile, Colombia, Mexico and Peru; Middle East and North Africa includes Egypt, Kuwait, Qatar, Saudi Arabia and Türkiye; and North America includes Canada and the United States.

[16] Please note that when the dataset was last updated, in September 2023, the availability of actual balance sheet, income statement, and financial ratio financial information was limited for 2Q23. Aggregate consensus analyst forecasts are also used for 2Q23-4Q23, and for 2Q23 if actual 2Q23 data was not available at time of data collection.

[17] See Financial Soundness Indicators - FSIs Home - IMF Data and Risk Dashboard and European Banking Authority (europa.eu).

Online Annex Table 2.5.1. CAMEL Key Risk Indicators Rationale and Definitions

Component	Indicators	Rationale
Capital adequacy	Equity to total Assets	Equity to total assets measures the degree by which the value of assets is being financed using equity as compared to debt. The lower the ratio, the more a bank is leveraged by debt.
	Tier 1 Capital to Risk-Weighted Assets	Tier 1 regulatory capital to risk-weighted assets indicates the level of regulatory capital to absorb losses. If the Tier 1 capital ratio is decreasing, it could be due to rapid risk-weighted asset growth or capital erosion.
Asset Quality	Nonperforming Loans to Total Loans (NPLs)	The NPL ratio identifies and measures problems with asset quality in the loan portfolio, with an increasing ratio signaling deterioration in the bank's loan portfolio.
	Coverage Ratio	The coverage ratio measures the extent to which NPLs are already covered by provisions and provides a measure of future losses that would be incurred if all NPLs were written-off.
	Loan Growth	Measuring quarterly loan growth helps identify rapid loan growth that increases provision expenses, impacts profitability and capital adequacy.
Component	Indicators	Rational
Management	Indirectly observable through market metrics.	Management is the most qualitative of the risk factors and it is highly correlated to compliance with internal policies and external regulations. In standard regulatory practices this would include the results obtained during supervisory examinations of internal control systems. Throughout this exercise we have substituted management indicators for market metrics that proxy investor's perception of management performance
Earnings	Return on Equity (ROE)	Earnings focuses on the bank's ability to create appropriate returns to be able to grow, retain competitiveness, and generate capital. Return on equity (ROE) was selected as the best proxy to measure how efficient a bank is in utilizing its capital to generate profits, and the internal ability to generate capital through retained earnings. A lower ROE means that a bank is not able to use its capital efficiently.
Liquidity	Net Loan to Deposit	The net loans to deposit ratio measures the banking organization's reliance on non-deposit funding for loan growth, the higher the ratio, the higher the risk of dependency on alternative or more expensive funding sources should deposits run-off or loan growth exceed deposit growth.
	Total Deposit to Total Liabilities	Total deposit to total liabilities measures the dependency on deposit funding, the higher the ratio, the less dependence on more expensive funding sources.
	Deposit Growth	Quarterly deposit growth measures sequential negative changes, a rapid reduction in deposits can adversely affect liquidity, and credit growth.
Market Metrics	Dividend growth forecast	Analyst forecasts of dividend growth is a simple ex-ante benchmark of future performance. Market expectations of dividend cuts can provide a negative signal about medium term bank profitability as investor expect management to implement dividend cuts from their current levels. Dividend forecast comprise analyst expectations of one-year ahead dividends at each point in time and is therefore a forward looking metric.
	Market Leverage	Market leverage is the ratio between total assets and market capitalization. This is a high-frequency benchmark of leverage and loss absorbing capacity; higher market leverage alerts market participants that changes in assets value could erode the market value of equity
	Price to book	Price to book value represents the ratio between the market value and the book value of equity and is used by investors to quantify the value of future bank performance. Low Price/Book ratios are typically driven either by a market view that current bank asset quality is low, or assets are mismarked (i.e., the reported book value is too high), or that future bank profitability will be lower than is needed to compensate for equity risk (i.e., forward looking return on assets is low). In both situations banks will face a high cost of future capital raises, which may entail significant dilution of current shareholders. This makes banks vulnerable to shock scenarios where capital buffers may be depleted.

Calibration of Key Risk Indicator Thresholds

Different criteria have been used to set the key risk indicator thresholds in the chapter. For the ratios of Tier 1 capital to risk-weighted assets and of nonperforming loans to total loans and for changes in quarterly deposits, uniform thresholds have been used across regions; for the price-to-book ratio, bank-specific thresholds have been set to account for bank-specific characteristics; and for the other eight key risk indicators, the thresholds have been calibrated to incorporate regional differences. Some additional criteria have also been used to establish the threshold values for the key risk indicators:

- *Quartiles*. Depending upon the key risk indicator, either the first-quartile or third-quartile value has been used to set a threshold to capture potentially vulnerable banks by region. The quartiles are generated using the full sample period and therefore do not represent 25 percent of the banks at each specific point in time. For certain metrics, a more stringent threshold of the 90th percentile has been chosen.
- *Supervision*. Publicly available data for the first quarter of 2023 from the European Bank Authority's Risk Dashboard have been incorporated into the indicators regarding the Tier 1 capital ratio, nonperforming loans, return on equity, and loan-to-deposit ratios.[1]
- *Historical data trends*. For European Union credit institutions, publicly available consolidated bank data on nonperforming loans from the fourth quarter of 2014 to the first quarter of 2023 have been incorporated, as have bank data on nonperforming loans by asset size group from the first quarter of 1984 to the first quarter of 2023 for banks insured by the US Federal Deposit Insurance Corporation.[2]
- *Data on failed banks*. For four banks that experienced sizable deposit outflows prior to their failure between March and May of 2023, data on the net loan-to-deposit ratio, ratio of total deposits to total liabilities, and quarterly changes in total deposits from the second quarter of 2022 to the first quarter of 2023 have been incorporated.
- *Bank-specific dynamics* for the price-to-book ratio since the current time series that reflect idiosyncratic bank characteristics and cannot be easily compared across banks or regions have been incorporated. These dynamics are used to set one standard deviation from the historical mean as a sign of transitory concern and are combined with stringent "hard" thresholds that provide a more structural view.

Online Annex Table 2.5.2. CAMEL Key Risk Indicators Thresholds

CAMELS	KRI	Asia	China	Europe	Latin America	Middle East and North Africa	North America	Rationale
Capital	Ratio of equity to total assets	<7	<7	<5	<9	<11	<9	Regional quartile
	Ratio of Tier 1 capital to risk-weighted assets				<12			Quartile, supervision 1/2/
Asset Quality1/2/	Ratio of NPLs to total loans				>8			Supervision, historical 2/
	Loan growth (Q/Q)	>10	>5	>11	>10	>7	>5	Regional quartile
	NPL coverage ratio	<75	<70	<40	<100	<85	<70	Regional quartile
Earnings	ROE	<6	<9	<6	<11	<10	<9	Quartile
Liquidity	Deposit growth (Q/Q)				<-5			2023 data on failed banks2/
	Net loan-to-deposit ratio	>95	>90	>150	>110	>100	>95	Regional quartile, supervision 1/
	Ratio of total deposits to total liabilities	<70	<65	<50	<50	<65	<55	Regional quartile and data on failed banks 2/
Market	Dividend growth forecast				<0			Market signaling
	Price-to-book ratio				< 1 standard deviation from mean			Bank-specific dynamics
		<0.50	<0.40	<0.45	<0.90	<0.75	<0.95	Regional quartile
	Market leverage	47×	51×	63×	18×	21×	14×	Regional 90th percentile

Source: IMF staff calculations.

Note: Incorporates publicly available key risk indicator thresholds from the first quarter of 2023. KRI = key risk indicator; NPLs = nonperforming loans; Q/Q = quarter over quarter.

[1]See European Banking Authority, "Risk Dashboard" (https://www.eba.europa.eu/risk-analysis-and-data/risk-dashboard).

[2]See European Central Bank, "ECB Publishes Consolidated Banking Data for End-March 2023," press release, August 3, 2023 (https://www.ecb.europa.eu/press/pr/date/2023/html/ecb.pr230803~17b58985ea.en.html), and US Federal Deposit Insurance Corporation, "FDIC Quarterly Banking Profile" (https://www.fdic.gov/analysis/quarterly-banking-profile).

Empirical Evidence for the Relevance of Key Risk Indicators in Identifying Vulnerable Banks

Empirical findings substantiate the significance of the key risk indicators used in this chapter to identify vulnerable banks. A series of logit regressions are conducted to assess the indicators' predictive capability in regard to three types of bank stress events: high negative excess returns, large drops in equity price, and instances of deposit flight, all of which could lead to banks having difficulty in respect to funding liabilities or raising equity capital. For each type of event, a dummy variable is conducted indicating the event's occurrence if a certain threshold is crossed. Given that indicators from the same CAMELS category can display high correlations, and to ensure a wider coverage of banks in the regression analysis, the choice is made to use a single indicator per category from the key risk indicator list presented in Figure 2.4.1 Panel 1 as independent variables. The first difference of each key risk indicator is then taken to show how changes in each key risk indicator can predict the likelihood of bank stress events unfolding in the following quarter. Therefore, $KRI_{ij,t-1}$ is a vector of 5 KRI indicators in the first difference. The logit model uses an unbalanced panel data set at the individual bank (i) level, with quarterly (t) frequency for the period of 2Q18 to 1Q23. Bank asset sizes and country fixed effects (α_j) are also controlled for:

$$StressEvent_{ijt} = \beta\ KRI_{ij,t-1} + \alpha_j + \varepsilon_{ij,t-1} \quad (1)$$

Figure 1, panel 1 shows that the selected key risk indicators from all five dimensions have strong powers regarding predicting bank stress events over the past five years. Notably, an increase in provisions to average loan ratios, indicating potential deterioration in asset quality, increases the likelihood that banks will face extremely high negative excess returns and price drops. Along the same lines, increases in banks' return on assets (indicating higher earnings), ratio of total deposits to total liabilities (indicating higher liquidity for the bank), and price-to-book ratios all predict a lower probability of equity sell-offs and large negative excess returns. Both an increase in the ratio of equity to total assets and an increase in return on assets decrease the chance of deposit flight in the following quarter. Results remain robust after adding other macro control variables. Panel 2 presents the receiver operating characteristic (ROC) curves for predicting large negative excess returns with and without KRIs. For the model with only bank sizes and country fixed effects, the prediction rate is about 70%, when adding KRIs, the prediction rate increases only modestly to 75%. Further econometric work is needed to fully determine the predictive power of the model, which will be possible when a longer time series is available for analysis.

Online Annex Figure 2.5.1. Empirical Results: Predictability of KRIs on Bank Stress Events

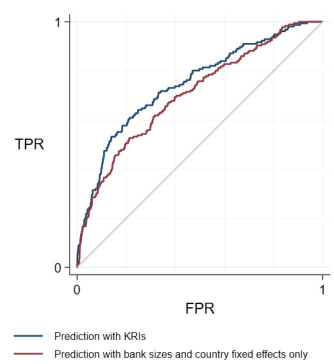
KRIs are mostly statistically significant in predicting stress events

1. Regression Result Table

	Negative excess returns > 15%	Negative excess returns > 20%	Stock price drop > 20%	Deposit outflow > 5%
C: Total Equity to Total Assets	0.004	0.021	0.127	-0.250**
	(0.04)	(0.13)	(1.22)	(-2.26)
A: Provisions to Average Loans	0.381***	0.354***	0.286***	-0.053
	(5.08)	(4.12)	(3.68)	(-0.50)
M: Price/Book Ratio	-0.979***	-0.455*	-0.418*	0.151
	(-4.16)	(-1.92)	(-1.94)	(0.46)
E: ROA	-0.284***	-0.149	-0.269***	-0.223*
	(-3.30)	(-1.49)	(-3.10)	(-1.90)
L: Total Deposits to Total Liabilities	-0.040**	-0.069***	-0.038**	0.048*
	(-2.40)	(-2.92)	(-2.08)	(1.88)
N	5,841	4,883	5,669	5,643
Log (Assets)	Y	Y	Y	Y
Country FE	Y	Y	Y	Y

KRIs improve the predictability of events with large negative excess returns (>20%).

2. ROC Curves for Models with and without KRIs



Sources: Bloomberg, L.P; Visible Alpha; and IMF staff calculations.

Note: In Panel 1, the *t* statistics appear in parentheses. Negative excess returns and stock price drops are at the weekly level, and deposit outflows are at the quarterly level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. In Panel 2, a model with no predictive power would be a 45° line. The greater the predictive power, the more bowed the curve, and hence the area beneath the curve is often used as a measure of the predictive power. TPR: True positive rate, FPR: False positive rate.

Online Annex 2.6. Money Market Funds as Alternatives to Bank Deposits

The recent cycle of interest rate increases in the United States has brought significant shifts in bank deposits to the forefront. From March 2022 to July 2023, $750 billion in deposits exited the US commercial banking system, with outflows peaking during the regional bank turmoil in March 2023. During the same period, more than $650 billion flowed into money market funds. Such substantial shifts raise concerns about the increasing risk of destabilizing outflows of deposits during episodes of turmoil in the banking sector. Interestingly, other countries experiencing strong cycles of interest rate increases did not observe similar shifts (Figure 1, panel 1), likely because the regional bank turmoil in the United States did not significantly affect confidence in the banking systems of other jurisdictions. However, variations in the structure and pricing of money market funds across jurisdictions may have played a role.

Market structures of money market funds differ across jurisdictions. Money market funds can be considered alternatives to bank deposits because they typically carry limited risk, offer returns consistent with money market rates, and aim to provide liquidity on demand for investors (FSB 2021). Since the global financial crisis, a global effort has attempted to strengthen regulations governing money market funds, with a focus on reducing liquidity mismatches in these funds and enhancing liquidity management tools. As a result, market structures and sizes have adjusted in distinct ways across jurisdictions. For example, US government money market funds, which experienced significant inflows in March 2023, have expanded substantially in recent years and now account for nearly 80 percent of US taxable money market funds. In contrast, EU money market funds with equivalent characteristics account for only 10 percent of total EU money market funds. In Europe, money market funds are concentrated within a limited number of countries, each characterized by distinct money market fund classifications and currency compositions, which could complicate attempts to use them as substitutes for bank deposits.

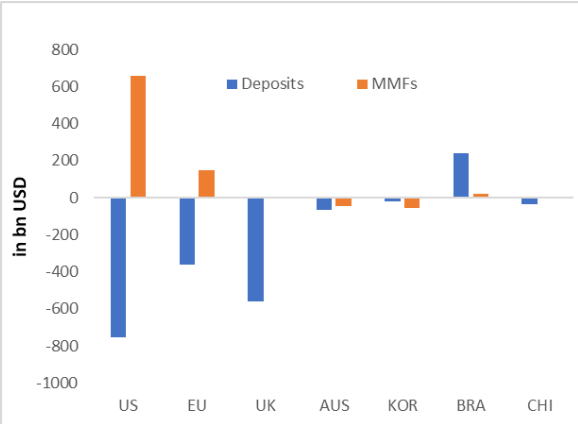
In the current cycle of interest rate increases, the yield advantage of money market funds over bank rates is significantly larger than in previous US cycles or in other jurisdictions. Normally, yields from money market funds adjust more swiftly once a cycle of interest rate increases is underway, whereas bank deposits tend to lag. The variation in responses reflects the distinct nature of money market funds and bank deposits. The former are diversified portfolios of short-term assets offering yields that closely track policy rates in highly competitive primary funding markets. On the other hand, banks have historically faced little pressure to raise deposit rates given the value of the banking system relationship for customers and the unwillingness of depositors to leave for higher returns. The yield differential played a pivotal role in making money market funds more attractive compared with bank deposits during the latest cycle of interest rate increases in the United States, during which money market funds had the largest yield advantage since 2000. At the same time, US money market funds typically have a higher yield advantage compared with those in the euro area (Figure 1, panel 2). Looking forward, banks may need to raise interest rates faster to avoid deposit outflows to money market funds, given the larger interest rate differentials available and the lower frictional costs of moving deposits in the internet banking era.

Online Annex Figure 2.6.1. Money Market Funds and Bank Deposits

The recent cycle of interest rate increases led to large inflows to Money Market Funds, mainly in the US

1. **Deposit and MMF Flows during the Latest Cycle of Interest Rate Increases**

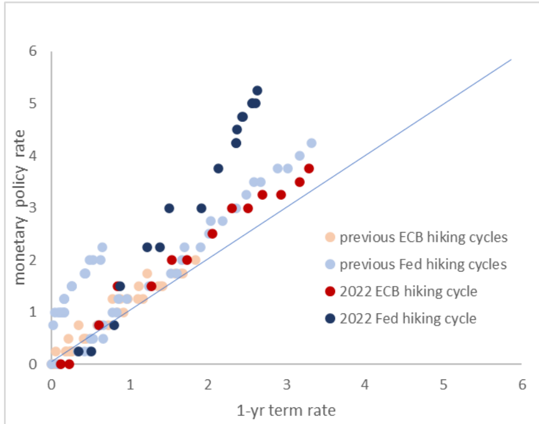
(US$ billions)



The yield advantage of Money Market Funds in the US contributed to the relatively higher inflows observed.

2. **Bank One-Year Rates versus Monetary Policy Rates (as a proxy for Money Market Fund yields)**

(Percent)



Sources: Bloomberg, L.P; Bank of England; European Central Bank; European Fund and Asset Management Association; Bank of Korea; and IMF staff calculations.

Note: In panel 2, the monetary policy rate for the Federal Reserve is the lower bound of the federal funds rate; that for the European Central Bank (ECB) is the deposit facility rate. The bank rate for the United States is the average rate for one-year certificates of deposit; that for the euro area is the one-year term rate. The rates represent cumulative changes since the beginning of the interest rate increase cycle. Only periods of interest rate increases are considered. Data labels in the figure use International Organization for Standardization (ISO) country codes. EU = European Union; Fed = Federal Reserve; MMF = money market fund.

Online Annex 2.7. Liquidity Support to Financial Systems—Practice

Central banks usually have several tools for injecting liquidity to banks to achieve distinct objectives: normal-time instruments and emergency liquidity assistance (see Dobler and others 2016). Normal-time instruments include open-market operations a central bank executes to implement monetary policy and on-demand standing facilities that require eligible collateral assets. Central banks also play the role of the lender of last resort to maintain financial stability, which is operationalized through a set of rules governing emergency liquidity assistance. They are usually collateralized as well. But unlike normal-time instruments, emergency liquidity assistance is usually accompanied by more intense supervision. In cases in which central bank reserve deposits are the critical component of banks' liquid assets—as is observed frequently in emerging markets and developing countries with underdeveloped money markets—lowering reserve requirements increases banks' usable liquidity irrespective of the policy's objective (monetary or financial stability).

Sometimes, other agencies provide liquidity. For example, since 2022, US regional banks have increased collateralized borrowings from Federal Home Loan Banks. Some countries, such as fully dollarized economies, do not even have a central bank. In these cases, normal-time instruments do not exist, and emergency liquidity support needs to come from the government or industry-financed funds.

Central bank liquidity facilities differ in many dimensions across countries, objectives, and tools. Key characteristics include term, cost, size, collateral, and collateral valuation. Central banks design parameters regarding each of these characteristics to match the facilities' objectives and contain moral hazard and protect taxpayers against losses. Terms are often overnight for normal-time facilities, but many central banks also have term facilities for prolonged episodes of liquidity stress. Central banks may provide a fixed size of liquidity allocated via auctions or may satisfy all demand for a given price (full allotment). The first approach could help conserve limited lender-of-last resort resources, such as foreign exchange liquidity. As for costs, normal-time facilities often involve surcharges above policy rates. Emergency liquidity assistance for idiosyncratic cases usually carries penalty spreads—often 100-300 bps—over the policy rate to discourage moral hazard. Nonetheless, some countries have provided systemic liquidity support at or below policy rates, though this is not recommended. Emergency liquidity assistance often takes broader sets of assets—including loans and, in some cases, even equity and physical assets—as collateral than normal-time facilities. When a bank runs out of eligible collateral, some central banks provide unsecured credit. But this is also not the best practice, and the IMF usually recommends treating such cases as solvency challenges and accompanying government guarantees. Collateral are usually (and should be) assessed at fair value and accompany additional haircuts. However, the Federal Reserve's Bank Term Funding Program in March 2023 took collateral at face value. Moreover, several major emerging market central banks, such as those in Brazil and China, do not apply market valuation to collateral provided to secure emergency liquidity assistance (IMF's Monetary Operations and Instruments Database).

As market finance and nonbank financial institutions have played greater roles, central banks have started to provide systemic liquidity support to nonbank counterparties (King and others 2017; Chapter 2 of the April 2023 Global Financial Stability Report). Liquidity provision through banks is sufficient even for market-wide events as long as banks on-lend central bank liquidity to other parties. However, it may not work well amid systemic events involving liquidity. In those cases, emergency liquidity assistance beyond banks may be needed to safeguard financial stability.

Central banks have also been the buyer of last resort with regard to asset purchases (Adrian and others 2021). For example, during the COVID-19 pandemic, many central banks in emerging market and developing economies had to sell their international reserves—including US Treasuries—which added volatility in Treasury markets, despite the safety of the assets. In response, the Federal Reserve Board introduced a foreign and international monetary authority's repo facility so that foreign central banks can repo in US Treasuries for dollar liquidity.

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