ONLINE ANNEX 1.1. TECHNICAL NOTE

A. Sensitivity of EM Term-Premia to Inflation Measures and the U.S. Term-Premia[1]

1. The empirical analysis follows Wright (2011), who shows a link between inflation uncertainty and term premia, and Moench (2019) who looks on variation of global bond term premia and its sensitivity to shocks in U.S. target rate. The staff analysis focuses on the term premia rather than bond yields to exclude the effects of expected policy rate changes both in the U.S. and emerging markets. Estimation uses the local projections approach in Jorda (2005) and estimates the following panel:

$$\boldsymbol{TP_{i,t-1\to t+h} = \alpha_{i,h} + \beta_h \gamma_{i,t} + \delta_h X_{i,t} + u_{i,t+h}}$$

2. The dependent variable $\boldsymbol{TP_{i,t-1\to t+h}}$ is the cumulative change in the 10-year term premium (percentage points) from *t-1* to *t+h* with *h = (0,…,6)* months. The term premium is defined as the expected return that investors get beyond the expected rate path. The estimation follows the dynamic affine term structure model of Adrian, Crump and Moench (ACM, 2013) and includes a sample of 16 emerging markets.[2] Where available, we use official end of day curve data from local pricing sources.

3. The impulse variable $\gamma_{i,t}$, in turn, is one of the four explanatory variables:

- $\boldsymbol{TP_{US,t}}^{\Delta}$ is the change in the U.S. 10-year term premium estimate following the ACM methodology.
- $\boldsymbol{CPIExp_{i,t}}^{\Delta}$ is the change in survey-based inflation expectations for the next twelve months. The inflation expectations are computed as the average of the point forecasts for year-on-year price growth.
- $\boldsymbol{CPIUnc_{i,t}}^{\Delta}$ and $\boldsymbol{GDPUnc_{i,t}}^{\Delta}$ are changes in the Consensus Forecast survey dispersion for next-year inflation and real-GDP growth, measured as standard deviations of the point forecasts for each month. We use these variables as a proxy to inflation and economic uncertainty following Rich et. al. (1992).

4. We include country fixed effects $\boldsymbol{\alpha_{i,h}}$ to control for bias from unobserved country specific features. $\boldsymbol{X_{i,t}}$ denotes a vector that contains explanatory variables other than $\gamma_{t,i}$ as well as three lags for the dependent, impulse and explanatory variables. Increasing the number of lags does not affect the results. The coefficients of interest $\boldsymbol{\beta_h}$ measure the average response of term

[1] The authors of this section are Dimitri Drakopoulos, and Dmitri Petrov.

[2] The sample includes Brazil, Chile, China, Colombia, Hungary, India, Indonesia, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Thailand, and Turkey.

premium $\boldsymbol{TP_i}$ across countries **i** in period $t+h$ with $h = (0,\ldots,6)$ months. The panel data sample spans from September 2007 to December 2020 and includes 160 monthly observations.

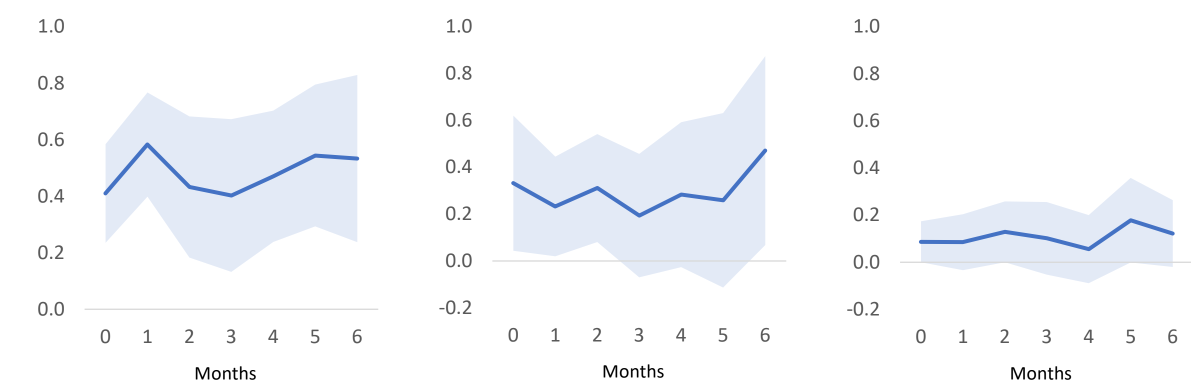
5. Figure 1.1.1 shows the estimated coefficients of the term premium to the external and domestic impulses. More than half of the change in the U.S. term premium is persistently pass on to the emerging markets,[3] consistent with previous findings of Albagli et. al. (2019) and Bowman et. al. (2016) who document the impact of the U.S. monetary policy shocks on emerging markets term premium, as well a broader impact of financial condition changes in emerging markets (see WEO April 2021). In contrast to previous studies, focusing on surprise monetary tightening captured by policy rate expectations dynamics, this analysis contributes through capturing the relationship between long-term term premia of the yield curves.

Similarly to Wright (2011), we find a connection between inflation uncertainty and term premium in a similar panel setting. However, while both measures have consistently trended lower over the last decade, the short-run dynamics between inflation uncertainty and term premia is somewhat less pronounced but still observable in our country sample. Changes in 12 months ahead inflation expectations have limited contemporaneous effects on term premia while growth uncertainty does not appear significant.

Online Annex Figure 1.1.1. EM Term Premium Sensitivity to Inflation Measures and the US Term Premium

The panel shows the estimated coefficients of emerging markets term premium to 1 percentage point shock in the U.S. term premium, inflation survey dispersion and 12-month inflation expectations.

1. U.S. Term Premium (Percentage points change) | **2. Inflation Survey Uncertainty (Percentage points change)** | **3. Inflation Survey Expectations (Percentage points change)**



Sources: Bloomberg Finance L.P.; National Settlement; Clearing and Valuation Agencies; and IMF staff calculations.
Note: Coefficient estimates are reported with 90% confidence interval with robust standard errors (Driscoll-Kraay, 1998).

References

Adrian, Tobias, Richard K. Crump and Emanuel Moench. 2013. "Pricing the Term Structure with Linear Regressions." *Journal of Financial Economics*, Vol. 110, No. 1, pp. 110–138.

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[3] Country levels analysis shows that there is significant variation in the sensitivity with high-yielding emerging markets generally having higher betas to changes in the U.S. term premium. Results are unchanged in a simpler specification excluding macroeconomic variables.

Albagli, Elias, Luis Ceballos, Sebastian Claro, and Damian Romero. 2019. "Channels of US Monetary Policy Spillovers to International Bond Markets." *Journal of Financial Economics*, Vol. 134, pp. 447–473.

Bowman, David, Juan M. Londono, and Horacio Sapriza. 2016. "U.S. Unconventional Monetary Policy and Transmission to Emerging Market Economies." *Journal of International Money and Finance*, Vol. 55, pp. 27–59.

Driscoll, John C., and Aart C. Kraay. 1998. "Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data". *Review of Economics and Statistics*, Vol. 80, pp. 549–560.

Mönch, Emanuel. 2019. "The Term Structures of Global Yields." Bank for International Settlements, Vol. 102, pp. 3–15.

Rich, Robert W., J.E. Raemond, J. S. Butler. 1992. "The Relationship Between Forecast Dispersion and Forecast Uncertainty: Evidence from a Survey Data – ARCH model." *Journal of Applied Econometrics,* Vol. 7, pp. 131–148.

Wright, Jonathan H. 2011. "Term Premia and Inflation Uncertainty: Empirical Evidence from an International Panel Dataset." *The American Economic Review*, Vol. 101, No. 4, pp. 1514–1534.

B. Corporate Sector Analysis[4]

6. The analysis in Chapter 1 of the April 2021 GFSR proposes a simple framework for policymakers to better target future policy support in the corporate sector. As part of the framework, an assessment of corporate sector indicators is carried out for a sample of firms.

Sample

7. The sample covers large advanced and emerging market economies with systemically important financial sectors: Brazil, China, France, Germany, India, Italy, Japan, Mexico, Poland, Russia, Spain, Turkey, United Kingdom, and United States. The analysis is carried out on a firm level, and the results are aggregated by GICS level 2 sector (Annex Table 1.1.1) and by firm size.

8. Firms are separated by size into three groups (*large*, *mid-sized*, and *small*) that have considerably different funding sources (based on the classification used in the *October 2019 GFSR Chapter 2* on debt-at-risk). While *large firms* have full access to capital markets, *small firms* rely predominantly on bilateral bank loans. It should be noted that *mid-sized firms* here are defined differently from small and medium-sized enterprises (SMEs). SMEs—based on the definitions by the European Union and United States--have assets below approximately $50 million and thus would be among *small firms* (also with assets below $50 million).

9. The sample includes about 19,500 firms (Annex Table 1.1.2). Most of them are publicly traded firms, but there are about 2,500 privately held firms. Mid-sized and small firms comprise over one half of the sample. Emerging market economies and all the sectors are well represented relative to the total sample size.

10. The data source is S&P Capital IQ. The analysis uses the latest balance sheets, as of the third quarter of 2020, to incorporate the impact of the COVID shock and the effect of existent policies of firms. Other data sources, such as Orbis, would considerably expand the sample (see, for the example, the debt-at-risk analysis in Chapter 2 of the October 2019 GFSR) but would have data lagged by two or three years. Given the sectoral nature of the COVID shock and the massive policy support, the priority is given to firms with the most current publicly available data. The analysis could also be applied to a wider population of firms. Notably, country authorities with access to larger datasets, for example, from national chambers of commerce or tax departments could carry out the analysis to have a more comprehensive assessment of the corporate sector, including very small firms.

[4] The authors are Nassira Abbas, Sergei Antoshin, Shuyi Liu, Tom Piontek, Aki Yokoyama, and Xingmi Zheng.

Online Annex Table 1.1.1. Classification of Non-Financial Corporates by Sector and Firm Size

Sectors are classified based on the level 2 GICS sectors.

Level 1 GICS	Level 2 GICS	vulnerable sub-sectors
Consumer Discretionary	Automobiles and Components	autos
Consumer Discretionary	Consumer Services	restaurants, hotels, leisure
Consumer Discretionary	Retailing	small retail
Energy	Energy	energy
Industrials	Transportation	airlines
Real Estate	Real Estate	office REITs
Communication Services	Media and Entertainment	
Communication Services	Telecommunication Services	
Consumer Discretionary	Consumer Durables and Apparel	
Consumer Staples	Food and Staples Retailing	
Consumer Staples	Food, Beverage and Tobacco	
Consumer Staples	Household and Personal Products	
Industrials	Capital Goods	
Industrials	Commercial and Professional Services	
Materials	Materials	
Utilities	Utilities	

Firms are classified into three buckets by firm size based on their main sources of funding and hence by the expected impact of COVID-related policy support.

classification by firm size	total assets	typical sources of funding
large	>$500 million	bonds, equities, syndicated loans, bank loans
mid-sized	>$50 million and <$500 million	equities, bank loans, syndicated loans for larger firms
small	<$50 million	mainly bank loans, some equities for larger firms, credit cards for smaller firms

Sources: Bloomberg Finance L.P.; S&P Capital IQ; S&P Leveraged Commentary and Data; and IMF staff calculations.

Online Annex Table 1.1.2. Sample of Non-Financial Corporates

There are about 19,500 firms in the global sample, of which small and mid-sized firms comprise over one half of the sample, and about 2,500 firms are private.

number of firms	total	large	mid-sized	small
by region				
United States	4,180	1,999	1,000	1,181
Europe	877	484	272	121
Japan	3,443	1,290	1,629	524
China	6,107	3,879	2,005	223
other EMs	4,903	790	1,313	2,800
by ownership				
all public firms	16,825	6,382	5,990	4,453
all private firms	2,685	2,060	229	396
by sector				
Automobiles and Components	559	280	213	66
Consumer Services	3528	1795	1077	656
Retailing	727	210	277	240
Energy	1127	344	404	379
Transportation	665	238	257	170
Real Estate	631	386	139	106
Media and Entertainment	248	135	62	51
Telecommunication Services	822	302	263	257
Consumer Durables and Apparel	717	242	248	227
Food and Staples Retailing	180	54	61	65
Food, Beverage and Tobacco	2244	900	779	565
Household and Personal Products	843	286	244	313
Capital Goods	1335	365	551	419
Commercial and Professional Services	926	577	149	200
Materials	829	332	238	259
Utilities	278	135	105	38
Health Care Equipment and Services	1226	321	436	469
Pharmaceuticals, Biotechnology and Life Sciences	1073	363	475	235
Semiconductors and Semiconductor Equipment	161	94	33	34
Software and Services	640	445	138	57
Technology Hardware and Equipment	751	638	70	43
total	19,510	8,442	6,219	4,849

Sources: S&P Capital IQ; and IMF staff calculations.

Indicators

11. The assessment of firms is carried out using a range of corporate indicators. The indicators are selected from these main sources: IMF FSAPs (summarized in IMF (2021) on the corporate sector), academic literature on non-viable (zombie) firms, and rating agencies' methodologies. The framework considers three types of indicators (see Annex Table 1.1.3 for definitions and thresholds), similarly to Tressel and Ding (2021):

- **Liquidity stress indicators** are meant to predict a shortage of cash or liquid assets in the near term, so that a firm has to borrow or make other adjustments. Smaller firms have fewer funding sources, lower buffers, and fewer other options, such as a sale of non-core assets, and—faced with high liquidity stress—may default on their debt.
- **Solvency stress indicators**[5] signal a possible erosion of the equity position to zero in the near term, which in some countries legally binds a firm to file for bankruptcy. Firms can raise equity from the markets or from the owners.
- **Viability indicators**[6] are envisaged to gauge whether a firm will become profitable a few years from now, after the post-COVID recovery has taken hold. Weaker firms, especially in the COVID-sensitive sectors, may face enduring profitability challenges due to structurally lower demand and sectoral transformation.

12. Firms' EBIT projections are based on analysts' forecasts for individual firms obtained from one of the largest panels of forecasters (IBES provided by S&P Capital IQ). For firms without analysts' forecasts, the projected changes based on sectoral averages are applied to their latest (2020Q3) EBIT to forecast EBIT in 2021. Liquidity stress is envisaged to translate into solvency stress, as firms with projected liquidity gaps in 2021 are assumed to fill the gaps by raising debt. As a result, for such firms, interest expense rises proportionally to the increase in debt (assuming the effective interest rate remains constant), which further weakens net earnings and equity.

13. Several indicators are selected for each type of vulnerability to ensure robustness of the approach. The thresholds are selected based on: (1) nominal values for well-established, intuitive indicators, for example, 0 for cash balance and equity; (2) suggested thresholds from the literature; (3) average thresholds from rating agencies' methodologies for CCC-rated firms which have the highest probability of default among graded firms; (4) where no guidance is available, a distributional measure corresponding to the weakest 5th percentile (the 5th percentile is selected as it corresponds approximately to the threshold for CCC-rated firms based on credit spreads).

14. Finally, two robustness checks are implemented using (1) Altman Z scores (Altman (2000)), and (2) National University of Singapore/CRI probabilities of default (PDs).

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[5] The solvency stress indicators include: 2021 projected equity position, net debt-to-earnings ratio, gross debt-to-earnings ratio, and debt-to-equity ratio.

[6] The viability indicators include: 2021–23 projected interest coverage ratio (ICR, EBIT divided by interest expense), projected earnings before interest and taxes (EBIT)-to-revenues ratio, debt-to-assets ratio, price-to-book equity ratio, and the price-to-book equity ratio relative to a firm's sectoral average.

Online Annex Table 1.1.3. List of Liquidity, Solvency, and Viability Indicators

The key indicators are based on the metrics used in the IMF's FSAPs, academic literature, and rating agencies' methodologies.

	Indicators	Threshold for high stress	Time of assessment	References
	Main approach			
	Liquidity indicators			
1	projected cash	<0	2021	IMF (2021)
2	interest coverage ratio (ICR) = EBIT / interest expense	<1	latest (2020Q3)	IMF (2021)
3	liquidity buffer ratio = (cash + undrawn committed facilities + FCF) / 12m debt maturities	<1	latest (2020Q3)	Fitch (2020)
4	current ratio = current assets / current liabilities	<5th percentile	latest (2020Q3)	IMF (2021)
	Solvency indicators			
5	projected equity	<0	2021	IMF (2021)
6	net debt/EBIT	>CCC-rated firms	latest (2020Q3)	Fitch (2020), S&P (2013, 2018)
7	gross debt/EBIT	>CCC-rated firms	latest (2020Q3)	Fitch (2020), Moody's (2020)
8	equity/assets	20%	latest (2020Q3)	
	Viability indicators based on projected balance sheets			
9	ICR and firm's age	<1 for 3 years; exclude young firms	2021-23	Adalet McGowan et al (2017)
10	EBIT margin = EBIT / revenue	<CCC-rated firms	2023	Fitch (2020), Moody's (2020)
11	gross debt/assets	>0.5 and increasing	2021	Fukuda and Nakamura (2011)
	Viability indicators based on current market valuations			
12	price-to-book equity ratio	<1	2021	
13	price-to-book equity ratio relative to firm's sector	<5th percentile	2021	Banerjee and Hofmann (2018)
	Robustness check 1: Altman Z scores			
14	Altman Z scores for public firms in advanced economies	Altman thresholds	latest (2020Q3) / 2021	Altman (2000)
15	Altman Z" scores for private firms in advanced economies and all firms in emerging mar	Altman thresholds	latest (2020Q3) / 2021	Altman (2000)
	Robustness check 2: National University of Singapore's estimated PDs			
16	Estimated probabilities of default	>95th percentile	2021	NUS model

Sources: Fitch Ratings; National University of Singapore/CRI database; S&P Capital IQ; Moody's; and IMF staff.
Note: FCF=free cash flow.

Results

15. The assessment of liquidity and solvency is carried out for 2020 and 2021 (Annex Table 1.1.3), while the assessment of viability is conducted using current market prices which embed market expectations and projections of balance sheets over the next three years.

16. Individual liquidity indicators show that liquidity stress is elevated at small firms[7] (Annex Figure 1.1.2, panel 1). Among the indicators, the interest coverage ratio (ICR) yields the highest share of debt with high risk, while the cash indicator suggests a lower share of debt with high risk, as expected, as it takes time for a firm with negative operating profits to deplete its cash holdings.

17. Some solvency indicators—based on leverage—suggest elevated risk even at large firms (Annex Figure 1.1.2, panel 2). This is also to be expected as firms have entered the COVID period with high debt levels (as discussed in recent GFSRs) and have borrowed record amounts of new debt since February 2020. On the other hand, the equity indicator points to a lower share of debt with high risk, as firms with negative changes in retained earnings have existing equity as a buffer. Notably, while leverage is elevated at large firms, their equity position is generally strong.

18. The composite liquidity risk indicator is deemed to be high if at least three out of the four (a simple majority) individual indicators are assessed as high. Similarly, the composite solvency risk indicator requires at least three out of the four individual solvency risk indicators to be high.

19. There is a considerable differentiation across sectors given the sectoral nature of the COVID shock, as well as pre-existing vulnerabilities in some sectors (Figure 1.1.3, panels 1 and 2). There are common vulnerable sectors in advanced and emerging market economies, such as energy, real estate, and retail. However, there are some important differences. For example, in advanced economies, biotech firms are often growth firms with weak earnings and low equity but still enjoy full market access and can continue as a business for years. In emerging markets, telecommunication services are highly vulnerable, likely because this is a people-intensive sector with a large presence of call centers.

20. Viability is assessed using both balance-sheet projections-based indicators and market valuation-based indicators (Figure 1.1.4, panels 1 and 2). Balance sheets are projected based on analysts' forecasts for individual firms using the IBES panel of forecasters. The composite viability risk indicator for firms with no data on market prices is based on balance sheets and requires two out of the three individual indicators to signal high risk. The composite market valuations-based viability risk indicator for firms with data on market prices is based on market prices and requires both individual indicators to signal high risk. The composite viability risk indicator for firms with market price data is deemed to be high if both balance sheets and market prices suggest high risk. This requirement may understate the share of firms with high viability risk (or non-viable firms) by design. These firms would not receive government support

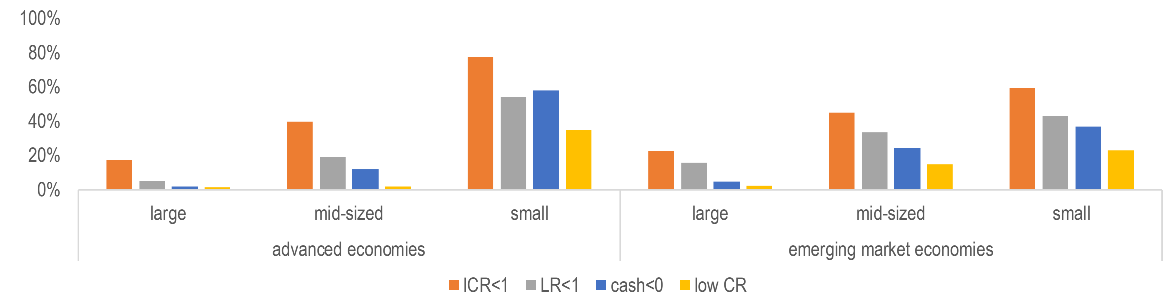
[7] The results based on balance sheet indicators for small firms in emerging market economies appear to be generally better than those for small firms in advanced economies. This is explained by greater market access for weak small firms in advanced economies. For example, the weaker balance sheets of small firms in advanced economies, the shares of debt of small firms with the price-to-book ratio below 1 are 45 percent and 62 percent in advanced economies and emerging markets, respectively.

according to the framework, and it is envisaged that policymakers should err on the side of caution to minimize economic scarring and externalities (such as wider job losses).

Online Annex Figure 1.1.2. Individual Indicators of Liquidity and Solvency Risks by Firm Size

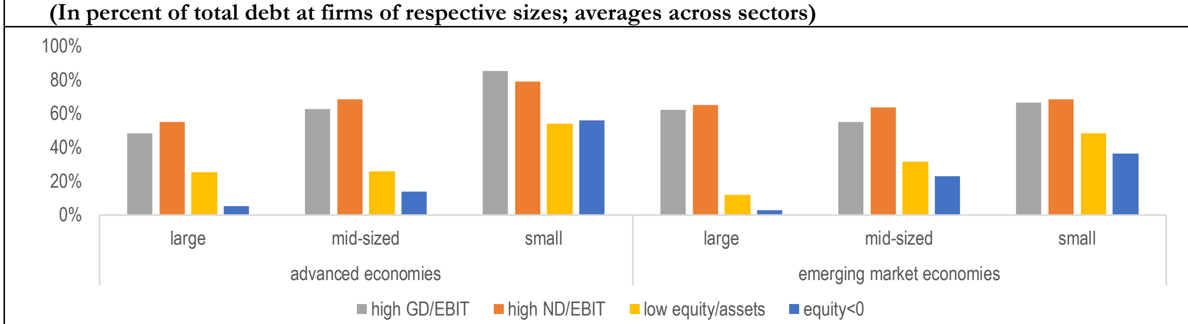
Liquidity indicators point to elevated stress at small firms.

1. Share of Debt at Firms with Elevated Liquidity Stress Indicators
(In percent of total debt at firms of respective sizes; averages across sectors)



Some solvency indicators suggest elevated risks even at large firms.

2. Share of Debt at Firms with Elevated Solvency Stress Indicators
(In percent of total debt at firms of respective sizes; averages across sectors)

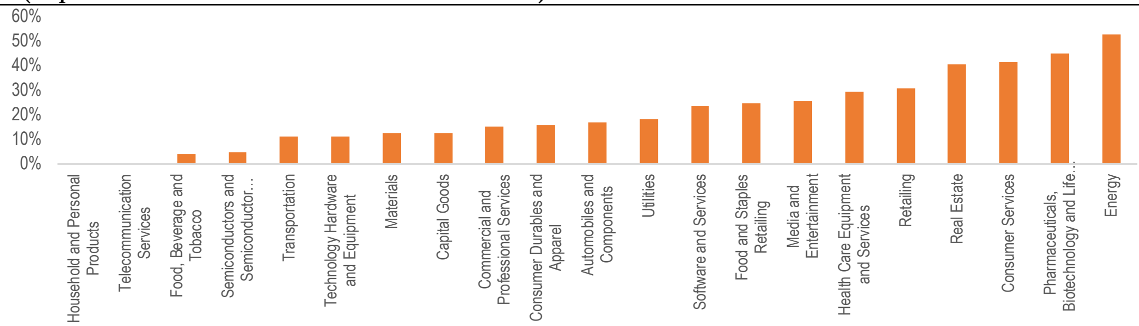


Sources: S&P Capital IQ; and IMF staff calculations.
Note: cash=projected cash; EBIT=earnings before interest and taxes; ICR=interest coverage ratio (EBIT divided by interest expense); LR=liquidity ratio (the sum of projected cash and undrawn credit divided by short-term debt); low CR=current ratio (current assets divided by current liabilities) below the 5th percentile threshold; equity=projected equity; high ND/EBIT=net debt (gross debt minus cash) divided by earnings before interest and taxes above 5.7 (the average threshold for CCC-rated firms used by rating agencies); high GD/EBIT=gross debt divided by EBIT above 7.4 (based on rating agencies); low equity/assets=equity divided by assets below 20 percent.

Online Annex Figure 1.1.3. Composite Solvency Indicators by Sector

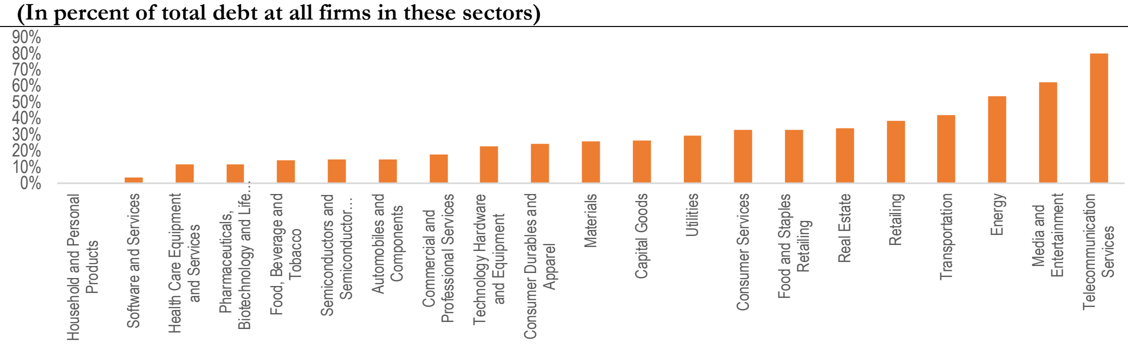
A wide range of firms across all sectors face solvency risk …

1. Share of Debt at Mid-Sized Firms in Advanced Economies with Elevated Solvency Stress
(In percent of total debt at all firms in these sectors)



… while at large firms, risks are concentrated only in a few sectors.

2. Share of Debt at Mid-Sized Firms in Emerging Market Economies with Elevated Solvency Stress
(In percent of total debt at all firms in these sectors)

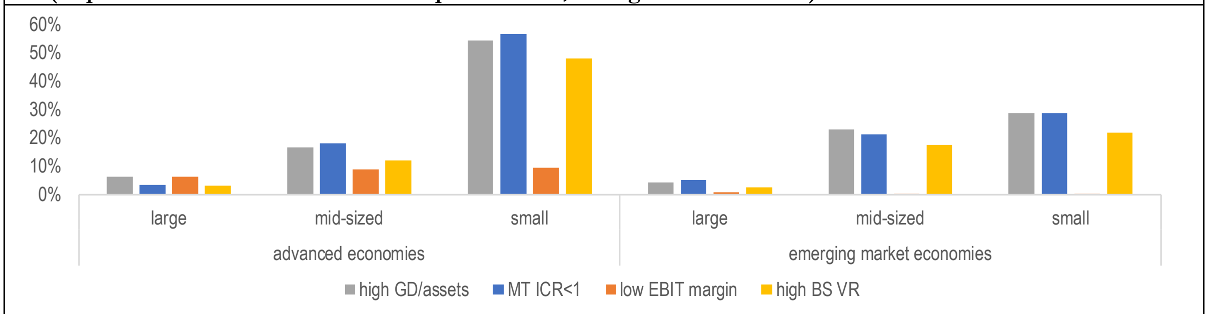


Sources: S&P Capital IQ; and IMF staff calculations.
Note: the overall liquidity, solvency, and viability stress indicators are computed as combinations of the respective components. For example, the overall liquidity stress indicator is assessed as "elevated" if at least three of the four individual liquidity indicators exceed their respective thresholds.

Online Annex Figure 1.1.4. Individual Indicators of Viability by Firm Size

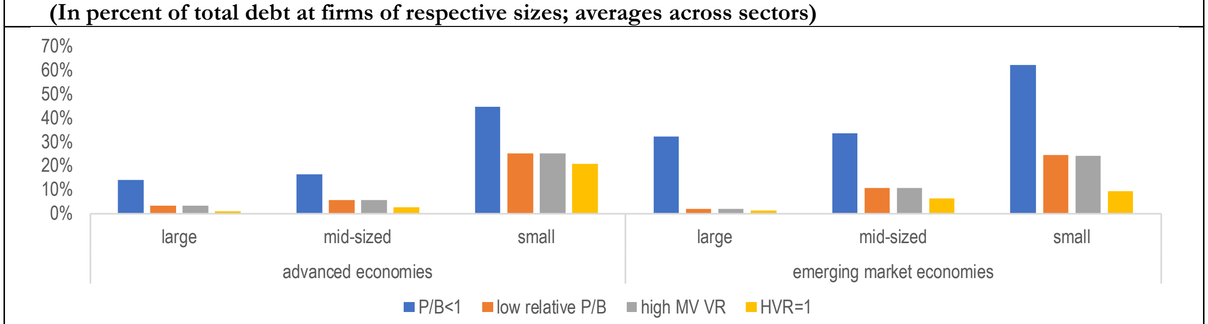
The share of firms with poor viability is considerable based on balance-sheet measures in advanced economies …

1. Share of Debt at Firms with Poor Viability
(In percent of total debt at firms of respective sizes; averages across sectors)



… and is currently relatively low based on market valuation measures in all countries.

2. Share of Debt at Firms with Poor Viability
(In percent of total debt at firms of respective sizes; averages across sectors)



Sources: S&P Capital IQ; and IMF staff calculations.
Note: EBIT=earnings before interest and taxes; MT ICR=medium-term interest coverage ratio (EBIT divided by interest expense) or ICR in each of the years 2021-23 for mature firms (with age greater than 5 years); low EBIT margin=EBIT divided by revenues below 4 percent (based on rating agencies); high GD=gross debt divided by assets above 0.5 and growing; P/B=price-to-book; BS VR = balance sheet-based viability composite indicator; MV VR = market valuation-based viability composite indicator; HVR = composite viability indicator.

21. As with liquidity and solvency, small firms are the ones that have the largest share of non-viable entities. Notably, in emerging markets, small firms have stronger balance sheets based on liquidity, solvency, and balance sheet-based viability than those in advanced economies but have considerably lower market valuations based on price-to-book ratios.

22. As a robustness check, the Altman Z scores are computed using the formulas for listed firms, private firms, and firms in emerging markets (Annex Figure 1.1.5, panel 1). The Altman Z scores were designed as predictors of defaults and combine elements of liquidity, solvency, and market-based viability (for advanced economies) risks. They confirm qualitatively that small firms are riskier than large firms, on average. The assessment of risk in advanced economies based on Altman Z scores is generally similar to that in this framework. However, the Altman Z scores suggest that default risks are suppressed in emerging markets—which goes against some simple corporate stress metrics, such as ICRs, in emerging markets.

23. The second robustness check is the estimated PDs from the University of Singapore (Annex Figure 1.1.5, panel 2). The estimated PDs are based on firms' balance sheets and market prices and include elements of liquidity, solvency, and market-based viability risks. The PDs point to modest risks in advanced economies and elevated risks in emerging markets. Notably, the PDs do not suggest that small firms in advanced economies are weak—in contrast with the findings in this analysis based on a wide range of indicators.

24. A sensitivity analysis aims to address two sources of uncertainty: (1) the uncertainty in forecasts of earnings, and (2) the construction of composite indicators. The first type of uncertainty is demonstrated by the effect of using upside (mean forecast plus two standard deviations of forecasts) and downside (mean forecast minus two standard deviations of forecasts) assumptions of earnings on the share of debt at firms with projected negative equity (Figure 1.1.6, panel 1). The shares of debt at firms with negative equity change by up to 2 percentage points of debt of all firms.

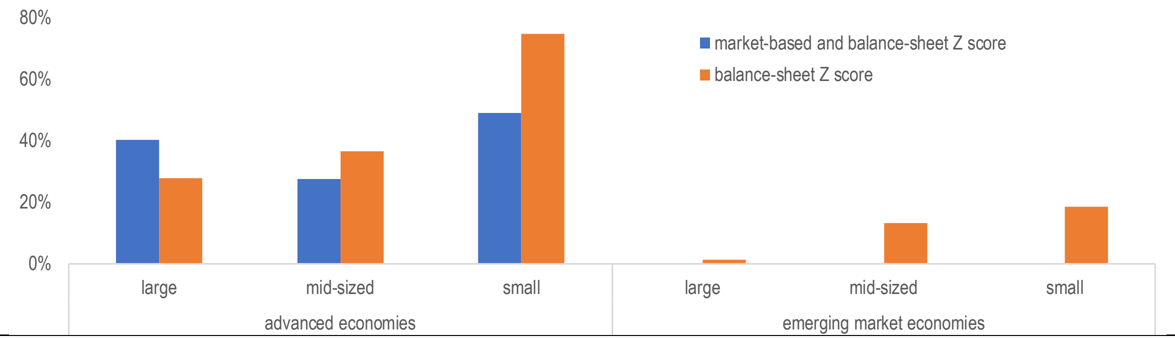
25. The second type of uncertainty is illustrated by requiring four or two—instead of three—individual indicators to signal high risk for the composite solvency indicator to show high risk (Figure 1.1.6, panel 2). The share of debt with high solvency risk changes notably depending on the number of indicators employed, especially when only two indicators are required to signal stress. This is because two leverage indicators suggest the highest stress level across the individual indicators. In this case, the use of three indicators may be a balanced approach because high leverage is at least partly offset by very low interest rates which need to be taken into account in solvency risk assessment.

26. The sensitivity analysis here is envisaged to be used by policymakers to calibrate policy support given a fiscal space constraint. For example, if fiscal resources are limited to support viable firms, policymakers could use pessimistic assumptions about earnings and a more punitive composite viability risk indicator to minimize the number of viable firms and thus the amount of required support.

Online Annex Figure 1.1.5. Robustness Checks

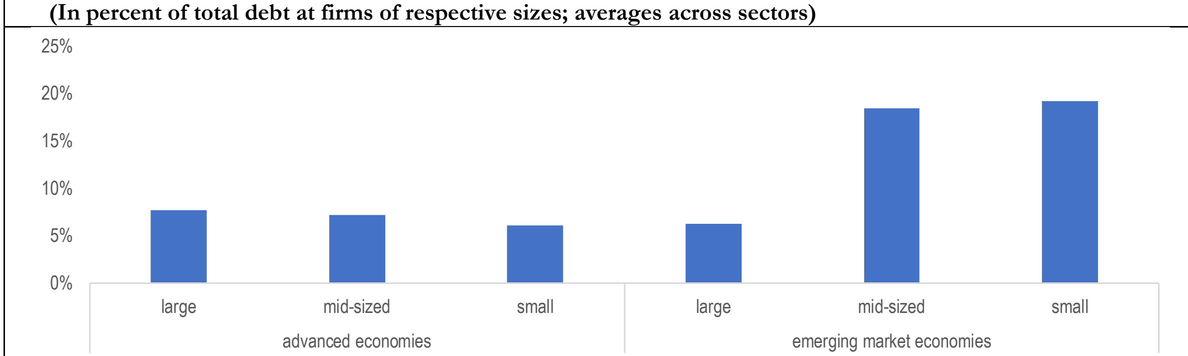
The Altman Z scores based on balance sheets qualitatively confirm the results for advanced economies and suggest low risk in emerging markets, while the market-based Z scores point to high risk even at large firms in advanced economies.

1. Share of Debt at All Firms with Low Altman Z Score
(In percent of total debt at firms of respective sizes; averages across sectors)



In contrast, the estimated probabilities of default based on both balance sheets and market prices suggest high risk in mid-sized and small firms in emerging markets and elevated risk in the COVID-sensitive sectors.

2. Share of Debt at All Firms with High Estimated Probabilities of Default
(In percent of total debt at firms of respective sizes; averages across sectors)

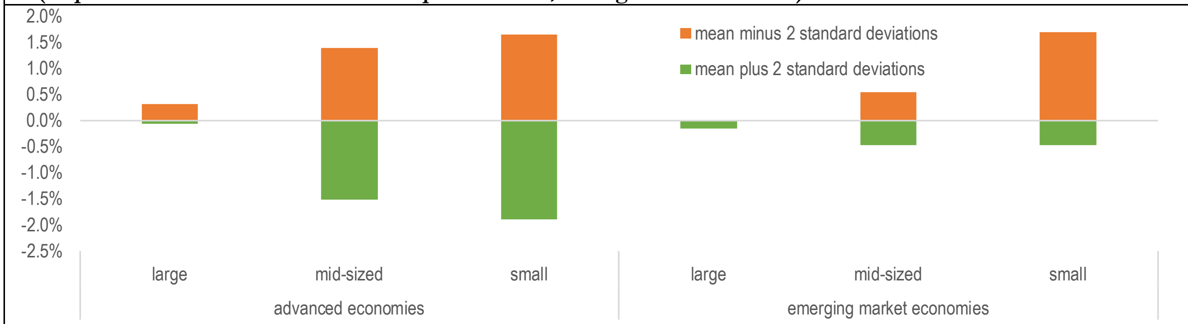


Sources: National University of Singapore/CRI database; S&P Capital IQ; and IMF staff calculations.

Online Annex Figure 1.1.6. Sensitivity Analysis

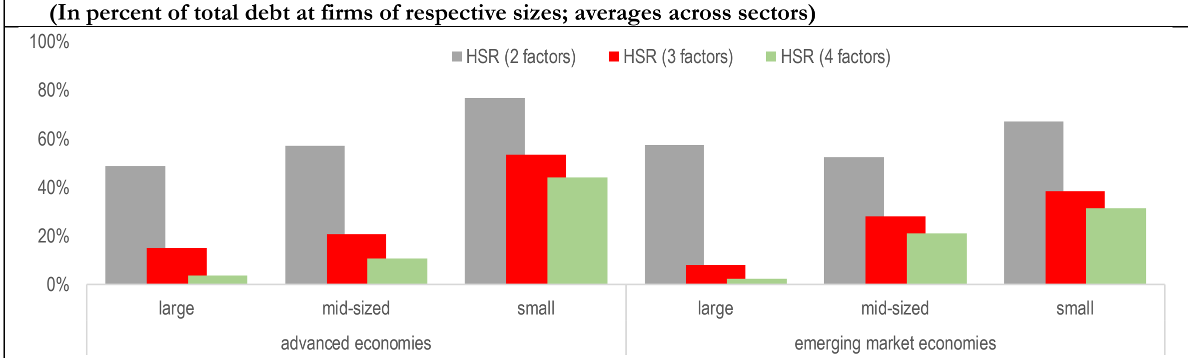
Solvency risk assessment changes based on forecasts of earnings.

1. Share of Debt at Firms with Negative Equity Under Different Assumptions about Future Earnings Relative to Mean Forecasts
(In percent of total debt at firms of respective sizes; averages across sectors)



The composite stress indicators depend on the construction method.

2. Share of Debt at All Firms with High Solvency Risk
(In percent of total debt at firms of respective sizes; averages across sectors)



Sources: S&P Capital IQ; and IMF staff calculations.
Note: the overall solvency stress indicators are computed as combinations of the respective components. The overall solvency stress indicator is assessed as "high" if at least two, three, or four of the individual liquidity indicators exceed their respective thresholds. The selection based on four out of four indicators method yields the greatest share of firms with elevated solvency stress compared to other methods to combine the individual stress indicators.

References

Altman, Edward. 2000. "Predicting Financial Distress of Companies: Revisiting the Z-Score and Zeta Models." Unpublished manuscript. http://pages.stern.nyu.edu/~ealtman/Zscores.pdf

Banerjee, Ryan, and Boris Hofmann. 2020. "Corporate zombies: Anatomy and life cycle." Bank for International Settlements, Working Paper No. 882 (September).

Blanchard, Olivier, Thomas Philippon, and Jean Pisani-Ferry. 2020. "A New Policy Toolkit Is Needed as Countries Exit COVID-19 Lockdowns." Peterson Institute for International Economics, Policy Brief (June).

Brunnermeier, Markus and Arvind Krishnamurthy. 2020. "Corporate Debt Overhang and Credit Policy." BPEA Conference Draft (Summer).

Caballero, Ricardo J., Takeo Hoshi, Anil K. Kashyap. 2008. "Zombie Lending and Depressed Restructuring in Japan." *American Economic Review* Vol. 98, No. 5 (December).

Díez, Federico, Romain Duval, Jiayue Fan, Jose Garrido, Sebnem Kalemli-Özcan, Chiara Maggi, Soledad Martinez-Peria and Nicola Pierri (2021). "Insolvency Prospects Among Small-and-Medium-Sized Enterprises in Advanced Economies: Assessment and Policy Options." Forthcoming IMF Staff Discussion Note.

Fitch Ratings. 2020. "Sector Navigators: Addendum to the corporate rating criteria."

Fukuda, Shin-ichi, and Jun-ichi Nakamura. 2011. "Why did 'zombie' firms recover in Japan?" The World Economy 34(7), 1124–1137.

International Monetary Fund. 2021. "COVID-19 and Corporate-Sector Stress: Macrofinancial Implications and Policy Responses." forthcoming. http://dm-edms.imf.org/cyberdocs/viewdocument.asp?doc=7008127&lib=DMSDR1S

Lam, W. Raphael, Alfred Schipke, Yuyan Tan, Zhibo Tan. 2017. "Resolving China's Zombies: Tackling Debt and Raising Productivity." (November).

McGowan, Adalet, Dan Andrews and Valentine Millot. 2017. "The working dead? Zombie firms and productivity performance in OECD countries." OECD Economic Department Working Papers No.1372.

Moody's Investors Service. 2020. "Moody's financial metrics key ratios by rating and industry for global nonfinancial corporates: 2020 update."

S&P Global Ratings. 2013 (updated on 2018). "Corporate Methodology."

Tressel, Thierry, and Xiaodan Ding, 2021, "Global Corporate Stress Test: COVID-19 Impact and Medium-term Implications." Forthcoming IMF Working Paper.

C. Capital Impact from the Phase-out of Moratoria and Guarantees[8]

27. This annex presents the methodology used to estimate the potential capital impact from the withdrawal of repayment moratoria and state guaranteed loans. The top-down exercise focuses on EBA-supervised banking systems and relies extensively on EBA data disclosures. The sample selection is primarily driven by data availability, as most jurisdictions do not have consistent and granular disclosures on loans under these borrower-support measures.

Repayment Moratoria

28. The impact on the CET1 capital ratio from the phasing out of moratoria mainly comes from the additional reserves needed, hence reducing the numerator of the capital ratio. There are two main sources of additional reserves: low reserve coverage and credit quality deterioration.

29. First, there are additional reserves needed as a result of generally lower reserve coverage ratios than those of regular loans. (Online Annex Figure 1.1.7, panel 2). When moratoria end, banks need to raise the reserve coverage on these loans to the same standard as they do on regular loans. It is assumed that the reserve coverage ratio, by IFRS9 stages, would rise to the maximum level seen in the last 3 years. (Online Annex Figure 1.1.7, panel 1)

30. Second, there are additional reserves needed are a result of downgrades of credit quality into Stage 2 and NPLs. The projection of new flows into riskier loan categories is based on the transition rate observed on the total loan book between end-2019 to 2020:Q3. Effectively it is assumed that asset quality over the next 3 quarters - most programs would have expired by then - would follow the same path as observed during the COVID period. The transition rate from Stage 1 to Stage 2 is calculated as the net change in outstanding balance of Stage 2 loans, divided by the starting balance of Stage 1 loans; the same calculation is used for the transition rate from Stage 2 and NPL. (Online Annex Figure 1.1.7, panel 2) The additional reserve needed on these new flows are then calculated as mentioned above.

31. These assumptions are likely to under-estimate the extent of asset quality deterioration in the months ahead, as NPL formation could accelerate going forward and write-off is not considered given data unavailability. While EBA provides similar IFRS9 breakdown of loans with moratoria, the data is only available for 2020:Q2 and 2020:Q3, which shows very mixed dynamics across countries. This likely reflects differences in the pace of program implementation and in the provisioning practices with regard to repayment moratoria across countries.

[8] The author of this section is Yingyuan Chen.

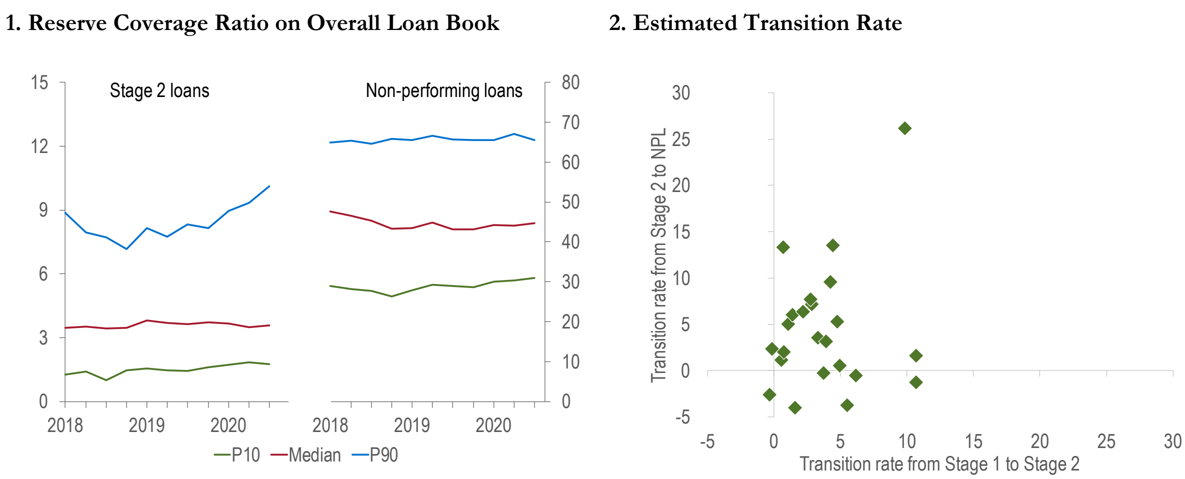
Guaranteed Loans

32. State guaranteed loans carry zero risk weights. After the guarantee expires, banks may need to replenish their loan book with regular loans, which require much higher reserve coverage and risk weights (typically increased from 0 to 100 percent on loans other than mortgages. In computing the impact on capital ratio as guarantees expire, generally the effect of an increase in the denominator due to higher risk weights is larger than the reduction in the numerator due to higher loan-loss provisions. Credit risks associated with the guarantees provided on the new loans are not considered in this exercise, as the loss in case of default are largely born by the state.

33. The total capital impact is then expressed as:

$$Capital\ impact = \frac{CET1 - \Delta\, reserve\ (loans\ with\ moratoria) - \Delta\, reserve\ (replacing\ guaranteed\ loans)}{RWA + \Delta RWA\ (replacing\ guaranteed\ loans)} - \frac{CET1}{RWA}$$

Online Annex Figure 1.1.7. Coverage Ratio and Estimated Transition Rate



Sources: EBA; and IMF staff estimate.
Note: in panel 2, write-off is not considered.

D. Drivers of Bank Buffer Usability: Sensitivity Analysis[9]

34. A sensitivity analysis was conducted using a standard (organic) capital generation and valuation model for an "average" bank, based on our 72-bank sample. The average bank: $200 billion in assets, RWA density of 55 percent, a CET1 ratio (equal to its medium-term target) of 12 percent, minimum CET1 requirements of 9.5 percent (including a Combined Buffer Requirement of 4.5 percent), a market-implied cost of equity (CoE) of 11 percent and a yield of 5.5 percent on (AT1) debt.

35. Two different bank return profiles relative to the baseline, while keeping the rest of the bank characteristics constant: A "low-return" bank (with a RoCET1 of <6 percent) and a "high-return" bank (with a RoCET1 >20 percent). Furthermore, two important assumptions are made for modelling the incremental asset base (new loans) generated by the capital buffer draw-down. Specifically, it is assumed that both the return-on-assets and the RWA-density of the incremental asset base are equal to the bank's back-book of loans (assumptions that may be optimistic and may skew results in favor of buffer usability). In the sensitivity analysis, these assumptions are evaluated by looking at how the outcome of the two models changes as we change each of these two key assumptions, keeping all other variables constant (Online Annex Figure 1.1.8).

Online Annex Figure 1.1.8. Sensitivity analysis: Key Factors for Buffer Usage

Key Metrics	Scenarios / Return profile	❷ Supervisory Hurdle Number of years to rebuild buffers used (hurdle at ≤ 5 years)									❸ Management Hurdle Banks that make a RoI ≥10% (from buffer usability) by Year 3								
RoE* before using the buffers (%)	*Scenario*	*24%*	*21%*	*19%*	*16%*	*13%*	*11%*	*8%*	*6%*	*3%*	*24%*	*21%*	*19%*	*16%*	*13%*	*11%*	*8%*	*6%*	*3%*
	Low	2	2	3	3	4	4	6	9	>20	✓	✓	✓	✓	✓	✓	✓	✗	✗
	High	2	2	3	3	4	4	6	9	>20	✓	✗	✗	✗	✗	✗	✗	✗	✗
Buffer usability (% Combined Buffer Requirement)	*Scenario*	*0%*	*13%*	*25%*	*38%*	*50%*	*63%*	*75%*	*88%*	*100%*	*0%*	*13%*	*25%*	*38%*	*50%*	*63%*	*75%*	*88%*	*100%*
	Low	1	2	4	6	8	9	11	13	15		✗	✗	✗	✗	✗	✗	✗	✗
	High	1	1	1	2	2	3	3	4	4		✗	✗	✗	✗	✗	✗	✗	✗
ROA of new assets (multiple vs back-book)	*Scenario*	*2.0x*	*1.8x*	*1.5x*	*1.3x*	*1.0x*	*0.8x*	*0.5x*	*0.3x*	*0.0x*	*2.0x*	*1.8x*	*1.5x*	*1.3x*	*1.0x*	*0.8x*	*0.5x*	*0.3x*	*0.0x*
	Low	7	7	8	8	8	9	10	10	11	✗	✗	✗	✗	✗	✗	✗	✗	✗
	High	2	2	2	3	3	3	3	3	3	✓	✗	✗	✗	✗	✗	✗	✗	✗
RWA density of new assets (% assets)	*Scenario*	*25%*	*33%*	*40%*	*48%*	*55%*	*63%*	*70%*	*78%*	*85%*	*25%*	*33%*	*40%*	*48%*	*55%*	*63%*	*70%*	*78%*	*85%*
	Low	7	7	8	8	8	9	9	9	9	✗	✗	✗	✗	✗	✗	✗	✗	✗
	High	2	2	2	2	2	2	3	3	3	✓	✓	✓	✗	✗	✗	✗	✗	✗
Cash payout after using the buffers (% net earnings)	*Scenario*	*0%*	*11%*	*23%*	*34%*	*45%*	*56%*	*68%*	*79%*	*90%*	*0%*	*11%*	*23%*	*34%*	*45%*	*56%*	*68%*	*79%*	*90%*
	Low	4	5	6	7	8	11	17	>20	>20	✗	✗	✗	✗	✗	✗	✗	✗	✗
	High	2	2	2	2	2	3	4	6	15	✓	✓	✓	✓	✗	✗	✗	✗	✗
RWA growth after using the buffers (%)	*Scenario*	*-4%*	*-3%*	*-2%*	*-1%*	*0%*	*1%*	*2%*	*3%*	*4%*	*-4%*	*-3%*	*-2%*	*-1%*	*0%*	*1%*	*2%*	*3%*	*4%*
	Low	3	3	4	5	8	>20	>20	>20	>20	✓	✗	✗	✗	✗	✗	✗	✗	✗
	High	2	2	2	2	2	3	3	4	5	✓	✓	✓	✗	✗	✗	✗	✗	✗
Change in CET1 target/requirements (% of RWAs)	*Scenario*	*-2.0%*	*-1.5%*	*-1.0%*	*-0.5%*	*0.0%*	*0.5%*	*1.0%*	*1.5%*	*2.0%*	*-2.0%*	*-1.5%*	*-1.0%*	*-0.5%*	*0.0%*	*0.5%*	*1.0%*	*1.5%*	*2.0%*
	Low	2	4	5	7	8	10	12	13	15	✓	✗	✗	✗	✗	✗	✗	✗	✗
	High	1	1	2	2	2	3	3	4	4	✓	✓	✓	✗	✗	✗	✗	✗	✗

Sources: Country regulatory authorities; and IMF staff calculations.

[9] The author of this section is Jose Abad.

E. Emerging Markets: Samples and Country Definitions

36. Figure 1.5.3 includes: Albania, Algeria, Angola, Argentina, Armenia, Azerbaijan, Belarus, Bolivia, Bosnia and Herzegovina, Brazil, Bulgaria, Chile, Colombia, Costa Rica, Croatia, Dominican Republic, Ecuador, Egypt, El Salvador, Georgia, Ghana, Guatemala, Hungary, India, Indonesia, Jamaica, Jordan, Kazakhstan, Lebanon, North Macedonia, Malaysia, Mauritius, Mexico, Morocco, Pakistan, Panama, Peru, Philippines, Poland, Romania, Russia, Serbia, South Africa, Sri Lanka, Thailand, The Bahamas, Tunisia, Turkey, Ukraine, Uruguay, Vietnam,