

# Measuring Systemic Banking Resilience

## A Simple Reverse Stress Testing Approach

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## Abstract

Reverse stress tests can be a useful tool to evaluate bank resilience to a credit shock, especially in environments where financial data are limited or opaque. This paper develops a simple and transparent country-level banking sector resilience indicator that focuses on tail risks, the Consolidated Distance to Breakpoint. Based on individual bank reverse stress test results, this novel metric quantifies the increase in nonperforming loans needed to deplete capital buffers for a subset of the most fragile banks that collectively represent at least 20 percent of total banking system assets, a level commonly associated with a systemic banking crisis. The paper calculates the Consolidated Distance to Breakpoint using public data for more than 1,500 banks in 59 emerging

market and developing economies during the COVID-19 pandemic. The paper explores the value added of this metric in relation to widely used country-level macro-financial and soundness indicators. The results show that the association of the Consolidated Distance to Breakpoint with these macro-financial and financial soundness indicators is limited. This suggests that this new indicator encapsulates complementary information, possibly because aggregate measures may obscure challenges in individual banks. As such, the Consolidated Distance to Breakpoint metric could serve as a useful input to establish a basic understanding of a banking sector's resilience.

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# Measuring Systemic Banking Resilience: A Simple Reverse Stress Testing Approach

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## 1. Introduction

The assessment of banking system stability in emerging and developing economies (EMDEs) is often impaired by the lack of reliable and complete financial data. Most systemic risk measures, such as the Conditional Value at Risk (Adrian & Brunnermeier, 2016), the Marginal Expected Shortfall (Acharya et al., 2017; Acharya et al., 2017), or the Expected Capital Shortfall (Brownlees & Engle, 2017) rely on detailed market data which are not readily available in most EMDEs. In addition, market data primarily cover large listed commercial banks and thus may not capture challenges at unlisted banks (including mutual banks or state-owned banks), whose potential distress could still be relevant for systemic banking sector resilience.

In this paper, we develop a simple and transparent country-level metric, the Consolidated Distance to Breakpoint (CDBP), which provides a basic approximation of system-wide bank resilience to credit shocks. We start from a simple “reverse stress test” framework and apply it to basic bank-level accounting data. We then focus on the tail of the most vulnerable banks in the system and propose a new aggregate metric of systemic distress.

Our new metric quantifies the rise in non-performing loans (NPLs) necessary to trigger undercapitalization in a subset of the most fragile banks that collectively represent at least 20 percent of banking system assets (“Banks at Risk”), a threshold commonly associated with a systemic banking crisis (see Reinhart, 2021a, for a taxonomy of financial crises). The larger the necessary rise in NPLs, the more resilient the banking system appears to be.

We only focus on credit risk, the most common source of financial instability in EMDEs, although banks often face a wide range of other risks, including liquidity, foreign exchange, and market risks. Other relevant factors are also not considered, including contagion and second-round effects, implications of contingent liabilities, and the strength of the bank resolution framework. Therefore, our framework is inherently limited in scope and should ideally be complemented with additional stress tests and quantitative and qualitative supervisory information.

To illustrate the potential application of this new metric of systemic banking resilience, we explore the value added of the CDBP during the COVID-19 pandemic. The spread of COVID-19 prompted many policy makers to introduce a wide range of policy support measures including debt moratoria, credit guarantees, and regulatory forbearance (Feyen et al., 2021), which has rendered bank balance sheets less transparent in some jurisdictions. In this context, we apply our CDBP framework to offer preliminary evidence of systemic bank resilience based on data of over 1,500 banks in 59 EMDEs.

To evaluate the value added of the CDBP, we investigate its empirical association with commonly used country-level macro-financial and soundness indicators. The results of these preliminary analyses show that this new metric may contain additional information not already encapsulated in these commonly used indicators, suggesting that it could complement them. As such, the CDBP could be used for basic monitoring purposes, particularly in countries with limited availability of reliable financial data.

In the remainder of the paper, we first cover methodological aspects and describe assumptions, caveats, and limitations. We then apply the framework to bank data covering the pandemic episode and relate the CDBP measure to several macro-fiscal indicators and financial soundness indicators. The last section concludes.

## 2. Methodological framework

Stress testing is a useful (off-site) tool to analyze the resilience of banking systems to adverse events and can complement other supervisory information, tools, and actions. A reverse stress test is a targeted exercise that quantifies how much current viability conditions should change for a bank to hit a pre-determined adverse outcome (Basel Committee on Banking Supervision, 2009). Reverse stress tests can be particularly useful in countries where supervisory capacity and enforcement are weak, resulting in a lack of complete and reliable data which prevents the application of more sophisticated analyses, or when the effects of an ongoing crisis, such as COVID, obscure data reliability.

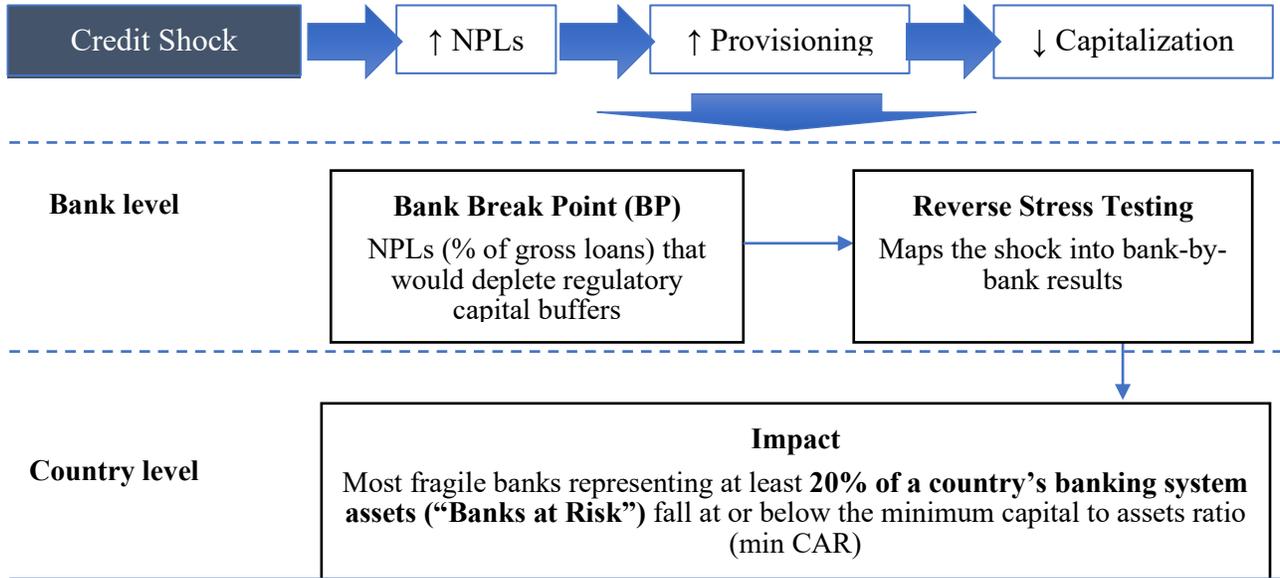
In this paper, we extend the reverse stress test framework by computing a banking system resilience measure from reverse stress test results for individual banks. Our approach hypothesizes an increase in the non-performing loans (NPLs) ratio for each bank to identify the point at which it “breaks”, the Break Point (BP). Specifically, because an increase in NPLs is accompanied by new provisions for loan losses, the BP is the NPL level at which the new provisions deplete the bank’s buffers above minimum capital requirements. For each bank, we then compute the “Distance from Break Point” (DBP) as the difference between the BP and the actual NPL ratio.

Next, we aggregate this bank-level information at the country level by sorting banks according to their DBP to identify the group of most fragile banks (i.e., the lowest DBP) that collectively represent at least 20 percent of total banking system assets. For banks with the same DBP value, we select the largest banks first. The 20 percent threshold is commonly used to identify a systemic banking crisis (Laeven & Valencia, 2013).<sup>2</sup> We define this set of vulnerable banks as “Banks at Risk” which could consist of a few large institutions or several smaller ones. In a final step, we consolidate the balance sheets of the “Banks at Risk” and calculate their consolidated Break Point (CBP) to arrive at the Consolidated Distance from Break Point (CDBP).

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<sup>2</sup> The threshold could be set at different values, depending on the granular composition of domestic banking sectors. For example, in economies where the banking sector counts hundreds of banks, the threshold could be set at a higher value to reflect the fact that distress may be related to a large number of small banks.

**Figure 1: Outline of the reverse stress test framework (credit shock)**



In the reverse stress test, we assume that the increase in additional provisioning for loan losses due to an increase in non-performing loans (NPLs) is fully absorbed by bank capital.<sup>3</sup> Therefore, our given adverse scenario entails computing the amount of provisioning needed to wipe out capital buffers, which are defined as the difference between regulatory capital held by individual banks and the country minimum capital requirement.<sup>4</sup> We only focus on credit risk, since it is the main risk for most banks in EMDEs, although currency and liquidity risks are often relevant as well. Formally, we model a credit shock that consumes existing capital buffers following an increase in NPLs as follows:

$$\begin{aligned} & \text{Minimum capital requirement } (MCR)_c \\ &= \frac{\text{Total Regulatory Capital}_i - [(\text{Bank Break Point}_i - \text{NPL ratio}_i) \times \text{NPL Provision Ratio} \times \text{Gross Loans}_i]}{\{\text{RWA}_i - [(\text{Bank Break Point}_i - \text{NPL ratio}_i) \times \text{NPL Provision Ratio} \times \text{Gross Loans}_i] + \text{ImpactRWA}_i\}} \end{aligned} \quad (1)$$

where the subscripts ( $c$ ) and ( $i$ ) denote a country and bank, respectively.  $MCR$  is the minimum regulatory capital requirement for all banks in a country. *Total Regulatory Capital* (TRC) is the amount of total regulatory capital held by each bank. The term *(Bank Break Point – NPL ratio)* is the increase in the NPL ratio (in percentage points) which depletes a bank’s capital buffers. *NPL Provision Ratio* is the percentage of provisions set aside for the new non-performing loans.<sup>5</sup> *Gross Loans* is bank gross loans. *RWA* is the amount of risk-weighted assets. *ImpactRWA* is the increase in RWA related to the non-provisioned portion of the new NPLs. It is computed as follows:

<sup>3</sup> We assume that banks do not have profits to cover for the increase in provisioning. Although this means that we are overestimating the impact of an increase in NPLs, some observers note that this approach is prudent (see, for example, Cihák, 2007, page 15). In a robustness test presented in the paper, we relax this assumption. Results remain qualitatively the same.

<sup>4</sup> We do not consider additional capital buffers applied at the bank level (e.g., systemic capital buffers). Subject to the availability of information, the empirical approach could be adjusted to reflect the bank, country and time-varying elements of additional capital buffers.

<sup>5</sup> In some jurisdictions, provisions are set aside for special mention loans too and there is the option to reserve general provisions for pass (performing) loans.

$$ImpactRWA_i = (BP_i - NPL\ ratio_i) \times Gross\ Loans_i \times (100\% - NPL\ Provision\ Ratio) \times (100\% - RWA_i/Total\ Assets_i) \quad (2)$$

where the exposure net of provisions is risk-weighted using as a weight the difference between 100%<sup>6</sup> and the risk weight attached to the original loan before turning NPL (assumed to be the same as the risk-weight density, the aggregate risk weight to total assets: RWA/Total Assets).

For banks in EMDEs, problem loans are often divided into three main categories according to the credit quality of each loan: substandard, doubtful, and loss loans. Each category requires a different level of provisioning.<sup>7</sup> In line with previous work (see, for example, Cihák, 2007, Ong et al., 2010; and Ong, 2014), we assume that under an adverse scenario, the provisioning rate for new NPLs (*NPL Provision Ratio*) is 55%. This ratio represents an average and assumes that new NPLs are equally distributed among the three categories and that the provisioning rates are 20% against substandard loans, 50% against doubtful loans, and 100% against loss loans (the exact average is 56.7%). We apply this provisioning ratio to the entire NPL exposure, thus ignoring the value of any collateral.<sup>8</sup> We also assume that provisioning requirements reduce both the value of regulatory capital as well as risk-weighted assets (RWA).<sup>9</sup>

We calculate a bank's Break Point (BP) as the NPL ratio that causes a decrease in total regulatory capital (TRC) to the minimum capital threshold (MCR). Using Equation (1), the BP for bank *I* can be computed as follows:

$$BP_i = \frac{TRC_i - MCR_c \times RWA_i}{[(55\% \times Gross\ Loans_i) - MCR_c \times (55\% \times Gross\ Loans_i) + MCR_c \times RWATerms_i]} + NPL\ ratio_i \quad (3)$$

where *RWATerms* is:

$$RWATerms_i = (100\% - 55\%) \times Gross\ Loans_i \times (100\% - RWA_i/Total\ Assets_i) \quad (4)$$

We compute a bank's Distance from Break Point (DBP) by comparing a bank's BP to its actual NPL ratio:

$$DBP_i = \max \{BP_i - Bank\ NPL\ Ratio_i, 0\} \quad (5)$$

We set the DBP to 0 if a bank is already undercapitalized (i.e., when a bank's BP is lower than its NPL ratio).

To aggregate the individual bank results to the country-level, we calculate the consolidated DBP (CDBP) for a subset of the most vulnerable banks. We do so by sorting banks according to their DBP. We define

<sup>6</sup> According to the Basel Committee on Banking Supervision (2019), the unsecured portion of any loan for which provisions are no less than 20% of the outstanding amount of the loan should carry a weight of 100%.

<sup>7</sup> See the Bank Regulation Supervision Survey – available at <https://www.worldbank.org/en/research/brief/BRSS> - for detail on asset classification systems across 161 jurisdictions around the world, see Anginer et al. (2019) for a detailed explanation.

<sup>8</sup> In general, provisioning is applied to the outstanding amount of NPLs minus the value of collateral. The value of collateral is in turn reduced by pre-defined haircuts established by supervisors. As we miss key information on the value of collateral and supervisory haircuts, we apply the value of provisioning to the entire NPL exposure.

<sup>9</sup> This approach is in line with Ong (2014, p. 29).

the subset of “Banks at Risk” as the most vulnerable banks that collectively represent at least 20% of banking system assets.<sup>10</sup> We use total assets to break DBP ties.

Next, for the “Banks at Risk” we compute the consolidated values at the country level for the Consolidated Break Point (CBP) and the Consolidated Distance from Break Point (CDBP). The weight of each bank is proportional to its gross loans. The CDBP summarizes a country’s vulnerability to an increase in NPLs focusing on the weakest banks. Higher values indicate that a banking system is more resilient.

Table 1 summarizes the steps followed using an illustrative example. Note that the CBP (17.4%) minus the CDBP (13.6%) does not correspond to the weighted NPL ratio (4.0%) for “Banks at Risk” reported in Table 1. This is because the value of the DBP is 0 for one bank (Bank A) which is already undercapitalized.

**Table 1. Illustration of the computation of CBP and CDBP**

Column “Bank ID” shows the “Banks at Risk”. These banks have the smallest DBP values (Column C) and jointly represent at least 20 percent of banking assets (in fact they cover 30%, see Column E). The consolidated Bank’s Break Point (CBP) of “Banks at Risk” is 17.4% (of gross loans) (Column G). The consolidated Distance from Break Point (CDBP) is 13.6 percentage points (Column H).

Bank ID	Bank-level analyses					Country-level analyses		
	NPL ratio (% gross loans)	Bank’s Break Point (BP) (% of gross loans)	Distance from Break Point (DBP) (% points)	Total assets (\$ millions)	Cumulative banking assets (% of total banking system assets)	Gross loans (\$ millions)	Consolidated Break Point (CBP) (% of gross loans)	Consolidated Distance to Break Point (CDBP) (% points)
	(A)	(B)	(C)=(B)-(A)	(D)	(E)	(F)	(G) = [sum(B×F) / sum(F)]	(H) = [sum(C×F) / sum(F)]
A	19.3	1.8	0.0	2699.6	0.38	1,793.7		
B	4.1	10.2	6.1	41321.3	6.24	40,282.5		
C	3.5	11.4	7.9	2456.5	6.58	1,987.3		
D	2.4	18.4	16.0	74323.6	17.11	53,387.0		
E	4.9	21.5	16.6	94968.7	<b>30.57</b>	69,889.1	<b>17.4</b>	<b>13.6</b>

The results of the bank-level reverse stress testing are computed under the following assumptions, some of which can be relaxed:

- **Negative impact from increased provisioning.** The decrease in total regulatory capital is generated by an increase in loan loss provisioning associated with the increase in NPLs. The increase in NPLs occurs because of a re-balancing of the loan portfolio, where performing loans turn to NPLs due to a credit shock.
- **No profits.** We make the conservative assumption that banks have no profits. Hence provisions are fully absorbed by capital. This assumption can be relaxed by adjusting Equation (1) as follows:

$$BP_i = \frac{TRC_i + Profit_i - MCR_c \times RWA_i}{[(55\% \times Gross\ Loans_i) + MCR_c \times (55\% \times Gross\ Loans_i) - MCR_c \times RWATerms_i]} + NPL\ ratio_i \quad (6)$$

where *Profit* could be current profits or a hypothetical value (for example the average or minimum value of a bank’s profit over a 10-year period). In a robustness test presented below, we compute the BP as per equation (6) and then the consolidated values (CBP and CDBP) as described above.

<sup>10</sup> As discussed in Laeven and Valencia (2013), a systemic banking crisis could be defined as the collapse of a relevant fraction of the banking system. Among several other criteria, the authors identify the collapse of banks representing 20% of banking system assets as a sufficient condition to classify a crisis episode as “systemic”.

We do not consider tax implications. Even without profit, tax credits can significantly contribute to mitigating the impact on capital.

- **NPL composition and provisioning.** A key assumption is that the NPL portfolio is equally divided among substandard, doubtful, and loss loans. We further assume that the corresponding provisioning rates are 20, 50, and 100 percent. As a result, we hypothesize an overall provision rate of 55 percent for all banks. This assumption could be relaxed using the information at the country level on provisions to nonperforming loans or using granular bank-level data on provisioning or on the ratio of the difference between gross loans and net loans over gross loans.
- **No collateral.** We assume that loans are not collateralized or that collateral cannot be liquidated sufficiently quickly.
- **Minimum capital requirements.** Data on country minimum regulatory capital requirements refer to year-end 2016 and are taken from the World Bank's Bank Regulation and Supervision Survey. The minimum capital requirement is applied equally to all banks and does not take into account specific capital buffers (e.g., capital conservation buffer and capital buffers for systemically important institutions). Effective capital requirements may be also higher due to, for example, leverage ratio requirements (i.e., requirements on bank capital to unweighted assets ratio) or additions following supervisory stress test exercises.

Further, the empirical approach presents the following limitations:

- **Interdependence structure.** The CDBP does not capture non-linear distress dependencies among the banks in the banking system (Goodhart & Segoviano, 2009). For example, it does not incorporate knock-on effects and balance sheet interlinkages that may lead to contagion.
- **Type of shock.** The system-wide bank instability measure accounts for increases in credit risk. Other important sources of risk in EMDEs could be the sovereign-bank nexus (Feyen & Zuccardi, 2019), foreign exchange rate risk (Demirgüç-Kunt & Detragiache, 1998), a sudden stop of capital inflows and sharp depreciation (Reinhart & Rogoff, 2013), and volatility in commodity prices (Eberhardt & Presbitero, 2021; Kinda et al., 2018).
- **Likelihood of the increase in NPLs.** The approach says little about the likelihood of occurrence of the potential increase in non-performing loans due to the credit shock (or recognition of the true performance of the actual portfolio). The reverse stress test mechanically computes the NPL breaking point without attaching an estimate of the likelihood for a bank of such occurrence. It is also silent on the time horizon over which the increase in NPLs materializes.
- **Quality of NPL data.** NPL data are backward-looking and come with a lag. NPL data may be underreported, particularly in countries with weaker supervisory practices.
- **Sample coverage.** The bank sample may be incomplete, especially in some countries and for specific bank types such as unlisted banks (including mutual banks or state-owned banks), smaller banks, rural credit institutions, and other credit institutions.

### 3. Application to the COVID-19 pandemic

The macro-financial shock caused by the COVID-19 pandemic precipitated a global economic recession in 2020 and put severe pressure on financial markets and institutions around the world. After the initial shock, many economies have (partially) recovered but the COVID-19 health crisis may produce long-lasting negative effects on banking systems, especially in EMDEs. Uncertainty in the development of the health crisis and its negative spillovers are likely to weigh heavily on banking sectors and are expected to lead to

an increase in non-performing loans (NPLs), which may weaken both financial stability as well as the sector's capacity to contribute to the post-pandemic economic recovery. Asset quality could deteriorate significantly in the wake of the pandemic outbreak, especially in countries where firms and households exhibit high levels of debt (Reinhart, 2021b).

Financial sector authorities undertook a wide-ranging set of measures to preserve the stability and resilience of the banking system and bolster its capacity to support economic activity (Demirgüç-Kunt et al., 2020; Feyen et al., 2020; Casanova et al., 2021). Some of these measures may have reduced the transparency of bank balance sheets.

To explore the value added of CDBP in environments where financial data are limited or opaque such as it is the case for many economies during the COVID-19 pandemic, we collect balance-sheet information for Q3 2020 for approximately 1,500 commercial banks headquartered in 59 EMDEs<sup>11</sup> using Fitch data. If balance-sheet information is not available for the third quarter of the year 2020, we use the latest balance sheet information available, although not older than 2019.<sup>12</sup> The key variables needed to compute the Consolidated Distance to Breakpoint (CDBP) are:

- NPL ratio (as % gross loans);
- Total Regulatory Capital (in USD millions);
- Risk-weighted Assets (in USD millions);
- Minimum Capital Requirement (as % of RWA);
- Gross Loans (in USD millions);
- Total Assets (in USD millions).

Figure 2 summarizes the country distribution of the CDBP across World Bank regions. In line with recent assessments (see for example Yuuki et al., 2021), the data suggest that EMDE banks are resilient in the short-term to credit shocks, although there is wide variation across regions and countries. The country median CDBP is 9.8 percentage points (pp). This percentage-point increase in the consolidated NPL ratio of “Banks at Risk” would render these banks undercapitalized in the median country. In 10 countries, a 5 percentage point increase in current NPL ratios is sufficient to deplete capital buffers of “Banks at Risk”. Two countries have “Banks at Risk” that are already undercapitalized. There is wide variation across regions. The interquartile range is larger for Sub-Saharan Africa (SSA), which exhibits the highest median CDBP. South Asia (SAR) has the lowest median CDBP at 3.8 percentage points, while Latin America and the Caribbean (LAC) has the most dispersed distribution (Figure 2, Panel A). East Asia and Pacific (EAP) countries show a tighter interquartile range and the tightest distribution.

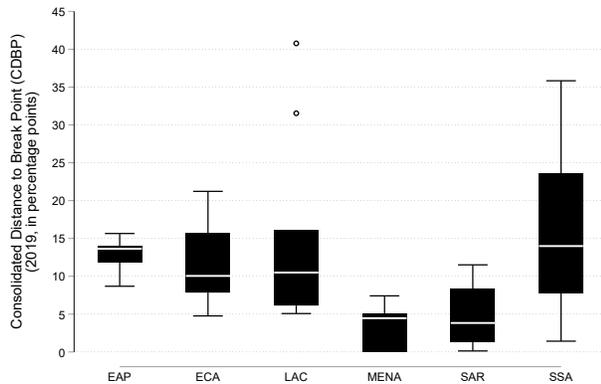
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<sup>11</sup> In this paper, EMDEs are defined as non-high income countries, according to the 2021 World Bank classification available at: <https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups>.

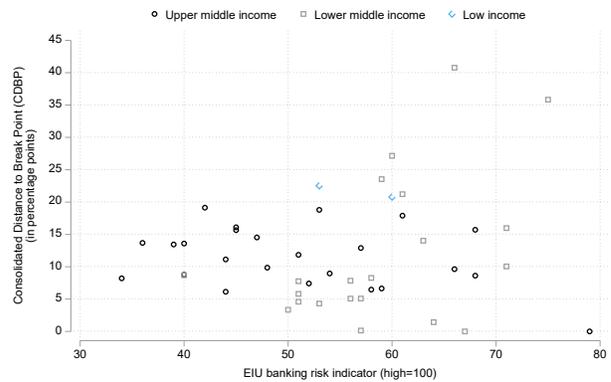
<sup>12</sup> For approximately a third of our sample, we use information from year 2019.

**Figure 2: CDBP vs. bank risks, GDP growth outlook, and fiscal space**

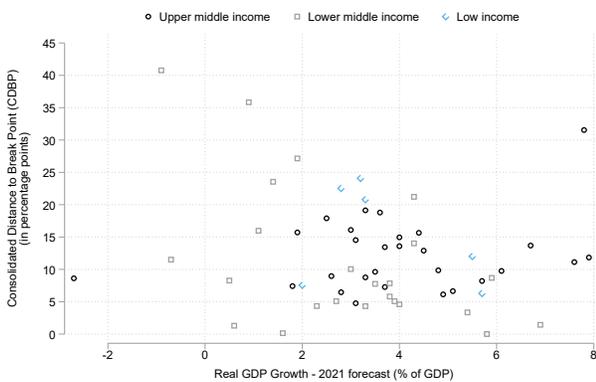
**Panel A: Increase in NPLs that will wipe out capital buffers for at least 20% of total banking system assets (in percentage points)**



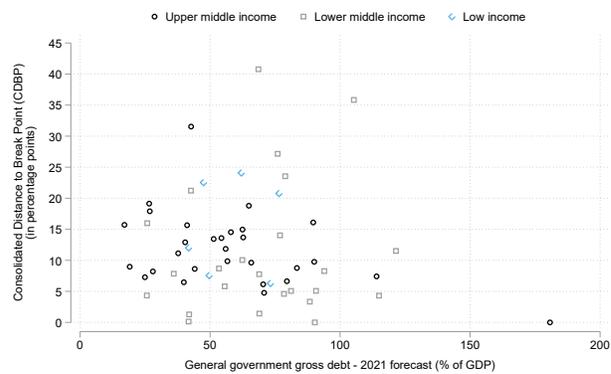
**Panel B: Increase in NPLs that will wipe out capital buffers for at least 20% of total banking system assets (in percentage points) vs. EIU banking risk index**



**Panel C: Increase in NPLs that will wipe out capital buffers for at least 20% of total banking system assets (in percentage points) vs. real GDP growth (2021 forecast)**



**Panel D: Increase in NPLs that will wipe out capital buffers for at least 20% of total banking system assets (in percentage points) vs. general government gross debt**



Source: Own calculations using data from Fitch (up to third quarter 2020), the Global Economic Prospects (2021), and the World Bank Macro-Fiscal Model Data Base available at <https://mtimodelling.worldbank.org/highfreqmonitor/dashboard.html>.

Note: All figures report the percentage point increase in the non-performing loan ratio at the country level (the Consolidated Distance from Break Point - CDBP) that wipes out capital buffers for banks representing at least 20 percent of the banking system assets (Y axes). Higher values denote higher capacity to absorb NPLs increases. Panel A shows the country distribution of the CDBP across World Bank developing regions (EAP: East-Asia Pacific; ECA: Europe and Central Asia; LAC: Latin America and the Caribbean; MENA: Middle East and North Africa; SAR: South Asia; SSA: Sub-Saharan Africa). Panel B plots the CDBP against the Economist Intelligence Unit (EIU) banking risk indicator. Panel C plots CDB against the real GDP growth. Lebanon is not included in the graph because of a too-low value for the 2021 real GDP growth. Panel D plots CDP against the general government gross debt.

To evaluate how the CDBP could be used in country-monitoring exercises, we plot it against a measure of banking sector risk computed by the Economist Intelligence Unit (EIU). The two indicators appear to be weakly related, suggesting that information conveyed by CDBP could complement the EIU banking sector risk indicator as the CDBP focuses on the weakest tail of the distribution of banks according to their exposure to a credit shock.

Banking sector vulnerabilities could be compounded by a sluggish economy. Some countries have a negative forecasted real GDP growth for year 2021 of more than 5 percent which may have repercussions for bank resilience (Figure 2, Panel C). A weak macroeconomy may weigh negatively on the banking sector, setting off a negative feedback loop between lackluster financial sector performance and a weakening real economy.

The government fiscal position also has implications for the stability of banking systems, and vice versa. Economies with weak public balance sheets may find it difficult to provide policy support and maintain a credible backstop for the banking sector, which could also increase funding costs. In turn, weak banks may put sovereign debt sustainability in doubt and contribute to the bank-sovereign “doom loop” (Feyen & Zuccardi, 2019). Some countries are forecasted to approach 100 percent general gross government debt to GDP (Figure 2, Panel D), suggesting potential future vulnerabilities arising from the bank-sovereign nexus.

To assess whether the CDBP correlates with other indicators of banking systems' stability, we run cross-sectional regressions and relate the CDBP with a set of core financial soundness indicators (FSIs).<sup>13</sup> A summary of the values of CDBP and FSIs across regions appears in Table 2. The Sub-Saharan Africa region (SSA) shows the highest un-weighted values of the CDBP, the regulatory Tier1 capital ratio, and liquid assets to short-term liabilities. South Asia (SAR) is the worst performing in terms of CDBP, non-performing loans ratio and exposure to changes in foreign exchange. Latin America and the Caribbean (LAC) has the lowest capital ratios, and MENA has the lowest liquidity ratios.

**Table 2. Consolidated distance to breakpoint and selected FSI indicators (2020; unweighted median and median weighted by GDP at market prices)**

Region	Consolidated Distance to Break Point (CDBP) (% points)		Regulatory Tier 1 Capital to Risk-Weighted Assets (%)		Non-performing Loans to Total Gross Loans (%)		Net Open Position in Foreign Exchange to Capital (%)		Liquid Assets to Short Term Liabilities (%)		Interest Margin to Gross Income (%)	
	Un-weighted	GDP weighted	Un-weighted	GDP weighted	Un-weighted	GDP weighted	Un-weighted	GDP weighted	Un-weighted	GDP weighted	Un-weighted	GDP weighted
EAP	13.6	11.8	15.3	11.7	2.8	1.8	3.5	2.4	24.0	24.1	64.4	77.9
ECA	10.0	9.0	16.1	10.4	5.9	8.8	2.0	4.0	27.7	22.3	58.5	76.1
LAC	10.5	13.4	12.0	14.3	3.1	2.4	0.9	0.5	28.5	19.5	70.5	56.5
MENA	4.5	5.1	15.3	15.3			2.1	2.1	20.5	12.6	121.5	169.1
SAR	3.8	3.3	13.0	14.3	7.7	7.9	5.9	12.7	24.2	7.8	74.1	66.9
SSA	14.0	16.0	16.9	15.3	6.0	6.0	2.5	3.8	34.1	18.5	59.5	55.1

Source: Authors' calculations using data from Fitch and IMF Financial Soundness Indicators

Note: EAP: East-Asia and Pacific; ECA: Europe and Central Asia; LAC: Latin America and the Caribbean; MENA: Middle East and North Africa; SAR: South Asia; SSA: Sub-Saharan Africa. Data for non-performing loans to total gross loans for year 2020 is not available for the MENA countries in the sample.

The results in Table 3 indicate that CDBP correlates positively with liquidity risk (Table 3, Column 4) and negatively with the cost of intermediation (Table 3, Column 5) – a higher relative lending spread is negatively correlated with CDBP. When we condition on all FSIs at the same time, the non-performing loans ratio is negatively associated with CDBP, while the sign on the coefficient for the liquidity risk ratio is still positive and statistically significant (Table 3, Column 6). Overall, the associations are relatively weak and the variation in the CDBP explained by FSIs is low, suggesting that the CDBP may capture information that is not already encapsulated in alternative financial stability indicators.

<sup>13</sup> For an overview of the FSIs, see <https://data.imf.org/?sk=51B096FA-2CD2-40C2-8D09-0699CC1764DA>.

**Table 3. Cross-sectional regression of CDBP on selected Financial Soundness Indicators**

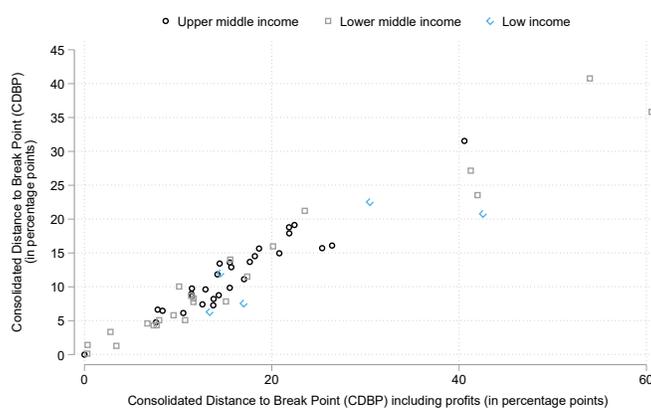
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Consolidated Distance to Break Point (CDBP) (% points)					
Regulatory Tier 1 Capital to Risk-Weighted Assets (%)	0.517 (0.354)					0.525 (0.396)
Non-performing Loans to Total Gross Loans (%)		-0.050 (0.121)				-0.577** (0.228)
Net Open Position in Foreign Exchange to Capital (%)			0.118 (0.105)			0.154 (0.122)
Liquid Assets to Short Term Liabilities (%)				0.156* (0.083)		0.213* (0.114)
Interest Margin to Gross Income (%)					-0.087** (0.034)	-0.028 (0.076)
Constant	3.710 (5.800)	12.000*** (1.466)	10.276*** (1.139)	7.100*** (2.305)	17.078*** (2.550)	1.698 (7.090)
Observations	43	42	40	44	44	35
R-squared	0.060	0.002	0.113	0.073	0.053	0.311

Source: Own calculations using data from Fitch (up to third quarter 2020), and IMF Financial Soundness Indicators available at <https://data.imf.org/?sk=51B096FA-2CD2-40C2-8D09-0699CC1764DA>.

Note: Data on the selected core FSI indicators is as per the third quarter of 2020. Robust standard errors appear in parentheses.

Figure 3 provides information on the relevance of considering bank profits as a first absorbing buffer for increases in loan provisioning. Overall, the two approaches provide a similar assessment as denoted by the large pairwise correlation coefficient between the two indicators (0.953).

**Figure 3: Testing for the inclusion of profits in the computation of the Distance from Break Point (CDBP)**



Source: Own calculations using data from Fitch (up to third quarter 2020).

Note: The figures report the percentage point increase in the non-performing loan ratio at the country level (the Consolidated Distance from Break Point - CDBP) that wipes out capital buffers for banks representing at least 20 percent of banking system assets (Y axis). Higher values denote higher capacity to absorb NPLs increases. The X axis reports the CDBP adjusted using equation (6) to incorporate bank profits as a buffer to absorb increases in loan provisioning. For each bank, we plug in the minimum value of a bank profit over a 10-year period to take into consideration that profitability may be low when a bank is hit by a credit shock.

## 4. Conclusions

A reverse stress test can be a useful (off-site) surveillance tool to evaluate a bank's resilience to a credit shock, particularly in an environment where reliable and complete financial data is limited, such as in countries with weak supervisory, accounting, auditing, and reporting practices or when temporary regulatory forbearance measures are in place such as during the COVID-19 pandemic.

Leveraging individual bank-level reverse stress test results, we introduce a novel banking sector resilience metric at the country level, the Consolidated Distance to Breakpoint (CDBP). The CDBP is a simple measure based on a set of transparent assumptions that could be adjusted to accommodate country-specific conditions. Specifically, the CDBP is defined as the percentage-point increase in non-performing loans that would deplete capital buffers for a subset of the most vulnerable banks which collectively represent at least 20 percent of the banking system assets, a level commonly associated with a systemic banking crisis -- a higher CDBP suggests a banking system is more resilient.

To empirically test the CDBP's value added, we compute it for 59 EMDEs during the pandemic and assess its association with a set of widely-used country-level financial stability indicators and macroeconomic and fiscal factors. The results show that these associations are modest, suggesting that the CDBP reflects additional information that is not already encapsulated in traditional measures, perhaps since these measures may obscure challenges in individual banks. As such, the CDBP could complement traditional country-level indicators and could be used as part of a first step to establish a basic understanding of a banking sector's resilience.

It is important to note that the CDBP has several important limitations and should be interpreted as a very rough approximation of systemic banking resilience. Ideally, the CDBP should be used in conjunction with additional stress tests and complemented with supervisory information and data. The CDBP could also be used to flag the need for more in-depth supervisory risk reviews (including through on-site inspections or asset quality reviews).

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