SUERF Policy Brief
No 620, June 2023

Insights into Credit Loss Rates: A Global Database*

  

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Keywords: credit risk, credit loss rates, data gap, forward-looking, loss given default (LGD), macro-implied, probability of default (PD), stress test.

JEL codes: G01, G21, G33, P52.

Credit risk has played a significant role as a catalyst or key factor in many financial crises, including the great financial crisis. More recently, the COVID-19 pandemic highlighted the importance of potential bank credit losses to the private sector. However, there remains a significant gap in terms of reliable economy-level credit risk data for financial stability analysis, given that such information is not publicly available in any systematic manner. We discuss the various credit loss concepts and estimate a time series database of actual as well as forward-looking market- and macro-implied credit loss rates for the majority of jurisdictions around the world, intended as a public good that is freely accessible.

*This policy brief draws heavily on the fuller BIS and AMRO working papers. The views expressed in this paper are solely those of the authors and do not necessarily represent the views of the ASEAN+3 Macroeconomic Research Office or the Bank for International Settlements. We would like to thank Irina Barakova, Stijn Claessens, Renzo Corrias, and Nikola Tarashev for helpful comments and feedback.

1. Introduction

Credit risk has played a central role in many financial crises, including the great financial crisis (GFC). It has contributed to the bulk of banks´ overall crises-related losses, which tend to spike suddenly from the very low levels typically observed during "peacetime." Major credit-related crises in history include the Great Depression of the 1930s, the Savings and Loan crisis in the late 1980s and early 1990s, and the subprime crisis in 2007 that triggered the GFC, all in the US. Elsewhere, the Latin American debt crisis of the 1980s, Asia's twin banking and currency crises during the latter part of the 1990s, and Europe's bank-sovereign debt crisis in 2011–12 stand out. Globally, corporate borrowing has expanded since the GFC. Interestingly, however, the COVID-19 pandemic—followed by the sharp rise in interest rates around the world to address inflationary pressures arising from pent up demand and supply chain disruptions—has not (yet) resulted in the manifestation of massive credit losses.

The COVID-19 pandemic highlighted the importance of being able to properly assess the credit risks on banks' books. The pandemic put substantial pressure on the balance sheets of firms and households, particularly in the most affected sectors, as widespread lockdowns and social distancing requirements crushed demand for goods and services and sharply increased unemployment. Consequently, banks were faced with deteriorating asset quality in their loan portfolios. In recognition of this threat to financial stability, policymakers introduced wide-ranging measures that included moratoria on debt payments and regulatory forbearance on bank capital and liquidity requirement, as well as their treatment of classified and nonperforming loans (NPLs), amid highly accommodative monetary and fiscal policies. Consequently, corporate and private insolvencies have remained very low—even declined in many economies during 2020[1]—particularly when juxtaposed against the depth of the recession, an outcome referred to as the "COVID-19 bankruptcy gap."[2] However, the concern is that the expansive public support measures may have only postponed firm insolvencies rather than canceled them altogether.[3]

Our aim is to close the long-standing gap in economy-level credit loss information. Our analysis builds upon the work by Daniel Hardy and Christian Schmieder[4], combining time series of actual credit losses with forward-looking market- and macro-implied credit loss rates to develop various credit loss datasets at the economy level, covering as many jurisdictions in the world as possible. Importantly, we make this database freely available for public use, in an effort to extend the reach and improve the transparency of financial stability analysis.[5]

2. Credit Loss Concepts

So, what is the best measure of credit loss? There are several concepts and metrics that have been proposed or adopted to date, for either micro- or macroprudential purposes or both. In this project, we adopt the typology established by Schmieder, Puhr, and Hasan (2011) in the aftermath of the GFC. We express loss rates as a fraction of credit exposures and aim for metrics that are, ideally, representative of economy-wide credit losses across all assets classes.

[1] Banerjee, Cornelli, and Zakrajšek (2020), Djankov and Zhang (2021), and Vandenberg (2021).

[2] Banerjee, Noss, and Vidal Pastor (2021).

[3] Gourinchas and others (2021).

[4] Hardy and Schmieder (2020).

[5] A detailed exposition of the CLR estimations may be found in the respective BIS and AMRO working papers, and the associated dashboard and database are publicly available.

Forward-looking credit loss rate estimates

- Following the introduction of Basel II in 2006 (BCBS, 2006), financial institutions are allowed to use their own internal measures of key drivers of credit risk under the internal rating-based (IRB) approach, as primary inputs to determine capital requirements. Those measures include estimates of the probability of default (PD) and loss given default (LGD), the multiplication of which is the forward-looking expected credit loss rate for the next 12 months. Expected losses are meant to be covered by credit pricing, e.g., spreads and maturity, and reflected in provisions, while unexpected losses exceeding the ex ante expected level will be deducted from bank regulatory capital.
- The accounting standards complement the regulatory BCBS standards. In July 2014, the International Accounting Standards Board introduced an ECL framework for the recognition of impairments. The International Financial Reporting Standard 9—Financial Instruments (IFRS 9) requires that forecasts of future conditions be used in measuring ECL to capture cumulative losses that may occur, in addition to taking into account past events and current conditions. IFRS 9 does not prescribe any specific method for estimating ECL, only that it reflects an unbiased and probability-weighted amount that covers a range of possible outcomes, and that it considers all reasonable and supportable information that is available without undue cost or effort. It also requires that the metric captures the time value of money. Any shortfall in covering expected losses from provisions is deducted from regulatory capital.
- There have also been several attempts to estimate system-wide credit risk, for example(1) estimating system-wide PDs and LGDs for specific asset classes;[6] (2) applying rules of thumb for the projected credit losses for advanced and emerging market economies based on the expected GDP trajectories;[7] (3) projecting future corporate credit losses drawing on firms' liquidity conditions and solvency risk information;[8] and (4) establishing forward-looking metrics at various levels of aggregation using market-implied credit risk data.

Contemporaneous realized credit loss rates

- Two popular microprudential approaches to measuring credit loss are historical loss and migration.[9] The former uses losses incurred from the institution's own portfolio or those incurred by a peer bank or a pool of peer banks, while the latter tracks how a cohort of loans in a portfolio move to loss over a particular single or multi-period, without the addition of new loans to diffuse the losses.
- The macroprudential approaches are anchored in the establishment of economy-level credit loss estimates. Prime examples are the economy-level time series for system-wide NPL ratios and economy-level estimates for recovery rates. Realized credit loss rates can be nowcast based on actual impairments and measured using charge-off rates reported by banks in their Profit & Loss accounts. Macro-implied credit loss rates can be estimated based.

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[6] Elizondo Flores and others (2010).

[7] Hardy and Schmieder (2020).

[8] Juselius and Tarashev (2020, 2021) use metrics such as debt service ratios and credit gaps to forecast baseline (expected) and extreme but plausible deviations from the baseline (unexpected) losses on corporate loans.

[9] Ashbaugh (2015).

Implied credit loss rates from NPL stock data

- NPL ratios reported by banks and national authorities are used to compute the corresponding flow of loss rates. These rates are estimated using the time-to-resolution of losses in the respective jurisdictions multiplied with the corresponding economy-level LGDs for a particular year.[10]

3. Data and Metrics

Unlike many other types of financial data, real-time contemporaneous and forward-looking credit risk statistics are scarce, and even if available, not regularly published. An important reason for this lack of information is that the nature of credit risk is complex to capture and tends to be relatively sticky. Forward-looking credit risk flow data, such as the Basel III IRB parameters, are typically published in banks' Pillar 3 reports. However, Pillar 3 information across individual banks is not readily compiled in one place and the flexibility for bank management to comment on the specificities of a bank's risk profile limits comparability. Then there is a range of credit loss data compiled by vendors, but such information needs to be purchased, typically at very high costs.

In an effort to address the gaps in and shortcomings of existing data, we estimate three different series of economy-level loss rates, with different purposes: we distinguish between forward-looking credit loss rate estimates, contemporaneous realized credit loss rates, and implied credit loss rates from actual NPL stock data. We distinguish between eight different metrics (Figure 1), which are standardized to annual frequency and, as much as possible, in their definitions. We draw on credit risk information from multiple sources in both the public and private domains in deriving our database:

- individual PDs from the National University of Singapore Credit Research Initiative (NUS-CRI) for a global sample of 70,000 listed non-financial corporates (Duan and others 2012; Chan-Lau and others 2018), available from 2002;
- bank balance sheet information reported by BankFocus, available from 2001;
- economy-level NPL ratios published in the IMF Financial Soundness Indicators (FSI) database, available from 2009; and
- country-level LGDs and time to resolve insolvencies published by the World Bank up to 2019, with GDP-implied LGDs available from the early 2000s.

4. Illustration of the Use of the Data

The data confirm that the impact of the pandemic was unusual, with fairly low credit loss rates across financial systems—at least to date—despite many countries suffering very deep economic recessions. In general and on average, AEs tend to realize lower loss rates compared to EMEs and LIDCs (Figure 1), attributable to: (1) generally more stable economic conditions; (2) stronger corporate governance; (3) better supervision and regulation of banks; (4) more established crisis management capacity and tools; and last but not least, (5) more developed legal systems and efficient bankruptcy laws.

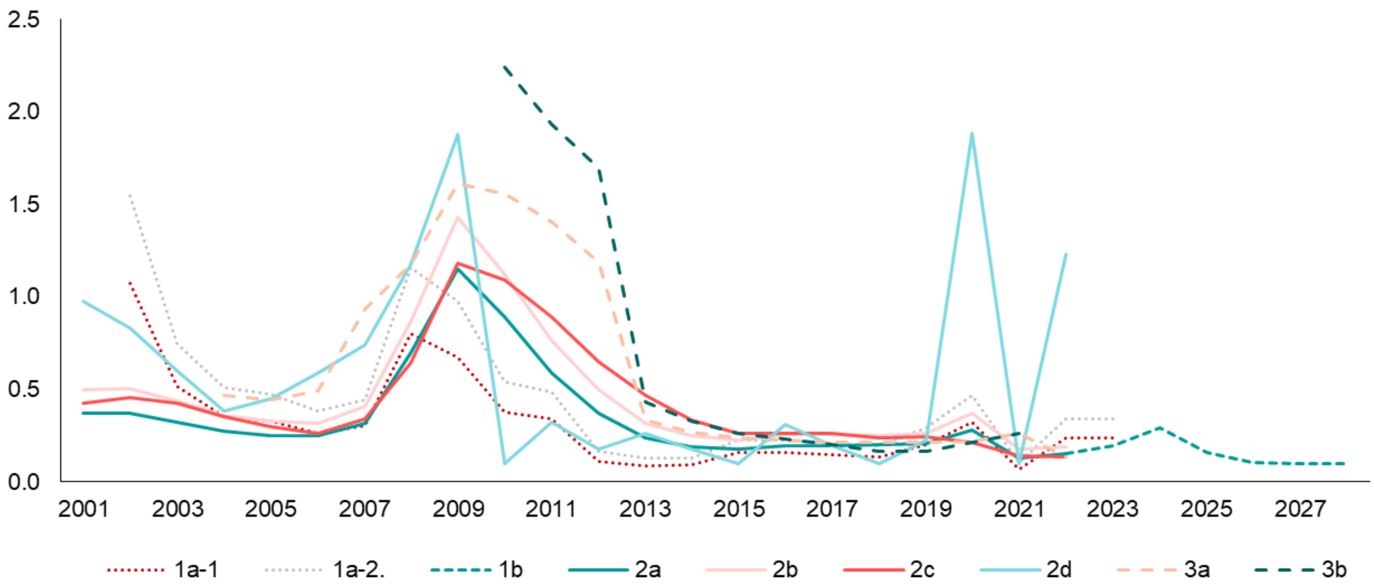
[10] For example, if a jurisdiction reported an NPL stock ratio of 2 percent in year t-1 and 3 percent in year t, and the time to resolution is 2 years, then the implied NPL flow ratio (default rate) at year t would be 2 percent (= 3% – 2% + (50% x 2%)).

Each metric has its usefulness, given its purpose and country-specific factors. We present two countries—the United States Brazil and Nigeria—to highlight the differences (Figure 1). Aside from the attempt to anticipate (metrics 1a-1, 1a-2, 1b) or nowcast (metrics 2a, 2b) losses, the stock of NPLs and implied NPL flow metrics (metrics 3a, b) characterize the process of writing off losses, which can be fairly swift in some countries, or fairly lengthy in others where bankruptcy processes may be protracted. Moreover, comparisons from using different sources—aggregated information based on bank-specific information and data reported by national authorities—are useful and could potentially reveal the clustering of risks, including at the institution level.

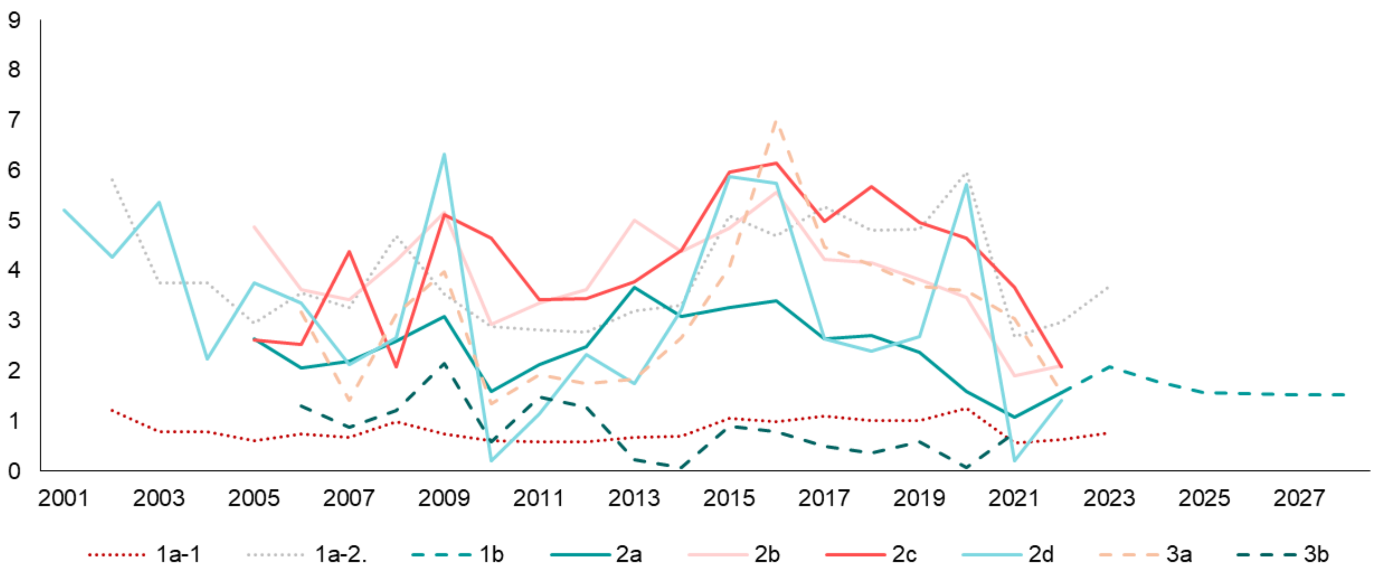
Our framework also allows for [multi-year projections based on anticipated GDP trends](). Specifically, simplified scenario analyses are possible, to simulate the impact of adverse macroeconomic conditions (Figure 2). As a caveat, users should recognize the limitations of using one macroeconomic variable only, which keeps the framework simple but does not necessarily translate one-to-one into reality, especially if substantial policy support is being provided to mitigate the impact of recessions.

Figure 1: Credit loss Rates (Percent)

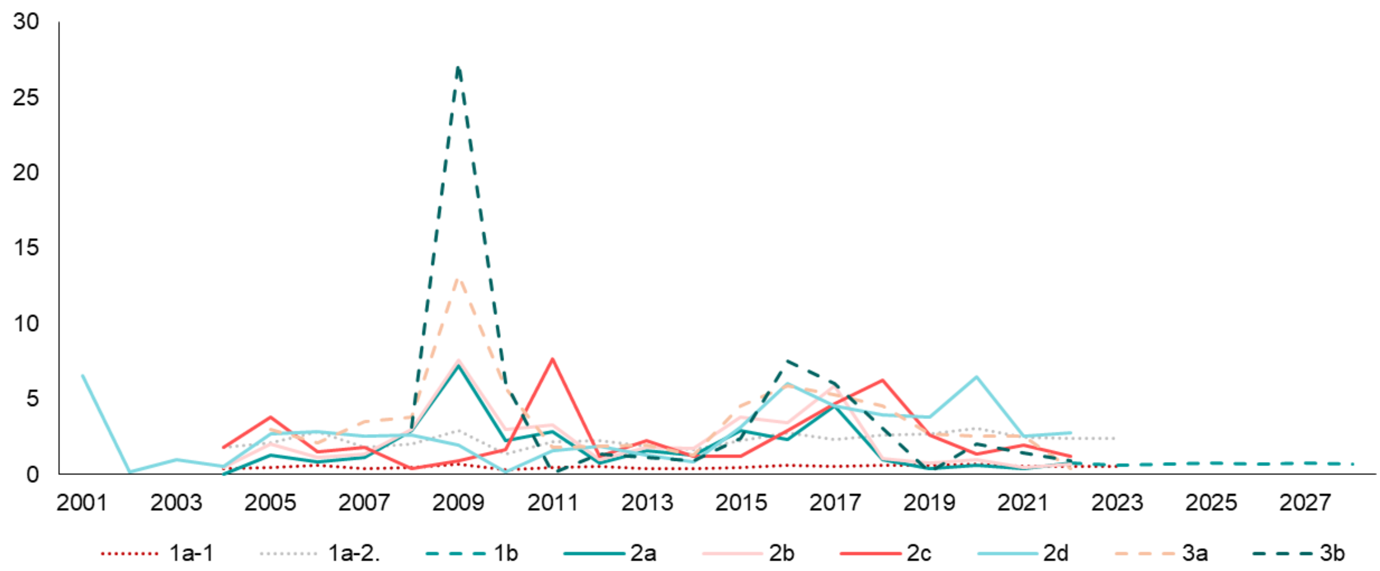
Advanced Economy: United States



Emerging Market Economy: Brazil



Low Income Developing Country: Nigeria



Source: Authors' estimates.
Note: 1a-1: Market -implied credit loss rate, original series; 1a-2: Market -implied credit loss rate, adjusted to economy-average; 1b: Forward-looking credit loss rate implied from GDP; 2a: Realized credit loss (impairment) rate; 2b: Realized loan loss (impairment) rate; 2c: Realized loan loss (charge-off) rate; 2d: Realized credit loss rate implied from GDP; 3a: Loan loss rate implied from (bank-level) NPLs; 3b: Loss rate implied from (economy-level) NPLs.

Figure 2: Credit Loss Simulations of Very Adverse Recessions Scenarios for the US

United States: Real GDP Growth Rate (Percent)

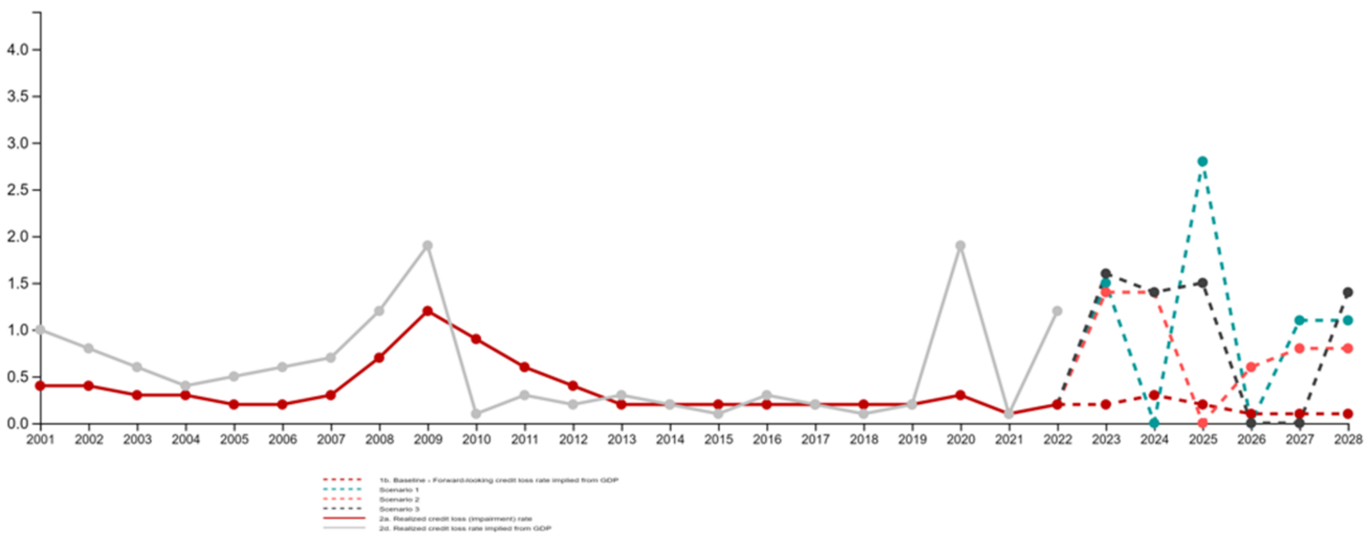
(Insert own forecasts in Scenarios below)

United States	2019	2020	2021	2022*	2023	2024	2025	2026	2027	2028
Baseline	2.3	-2.8	5.9	2.1	1.6	1.1	1.8	2.1	2.1	2.1
Scenario 1	2.3	-2.8	5.9	2.1	-2.4	2.8	-4.3	3.8	0.1	0
Scenario 2	2.3	-2.8	5.9	2.1	-2.2	-2.4	3.5	1.0	0.1	0
Scenario 3	2.3	-2.8	5.9	2.1	-2.6	-1.5	-2.0	3.5	3.5	-0.9

* To avoid distortions to credit loss rate projections arising from the unprecedented policy support measures during the COVID-19 pandemic, we anchor them by substituting actual real GDP growth trend in 2022 with the average of the IMF's real GDP growth forecasts over the 2024–28 period.

Refresh

United States: GDP-Implied and Realized Credit Loss Rates (Percent)



5. Conclusion

The COVID-19 pandemic exposed a blind spot in the assessment of credit risk on bank balance sheets. Unfortunately, significant gaps in credit risk information for estimating credit losses at the economy level—a key element in financial stability analysis—persists. We attempt to close that gap, especially for countries with less available information on credit risks, such as EMEs and LIDCs, by applying a myriad of macroeconomic, as well as economy-level and institution specific credit-related information. In particular, we estimate a suite of credit loss rate metrics with useful applications in their own right. We also propose GDP-implied loss rate simulations, as is regularly adopted in stress tests, in an effort to anticipate peaks in credit loss rates. Our database can help facilitate credit loss analyses and predictions, but can be continuously improved. Going forward, a promising avenue may be to use concepts anchored in a consistent analytical framework of macro-financial variables.

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