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# Insights into Credit Loss Rates: A Global Database

Li Lian Ong, Christian Schmieder, and Min Wei [1] [2] [3]

## Abstract

Credit risk has played a significant role in many financial crises, including the great financial crisis. The COVID-19 pandemic also highlighted 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 readily available to the public in any systematic manner. Building upon the work of Hardy and Schmieder (2020), we derive time series of actual as well as forward-looking market- and macro-implied credit loss rates for the majority of jurisdictions around the world. Our database, intended as a public good, is available through a user-friendly interactive dashboard, which allows downloads of credit loss rate time series for the desired jurisdiction(s). Users are also able to run simple scenario analyses based on their projected GDP paths. The data series will be updated on an ongoing basis as new information is published by the original sources.

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

JEL classification: G01, G21, G33, P52.

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# Abbreviations

| | |
|---|---|
| AE | advanced economy |
| BCBS | Basel Committee on Banking Supervision |
| CECL | current expected credit loss |
| COVID-19 | coronavirus disease of 2019 |
| EAD | exposure at default |
| ECL | expected credit loss |
| EME | emerging market economy |
| GFC | great financial crisis |
| GPPC | Global Public Policy Committee |
| IAS | International Accounting Standard |
| IRB | internal ratings-based (Basel II) |
| LGD | loss given default |
| LIDC | low income developing country |
| NPL | nonperforming loan |
| NUS-CRI | National University of Singapore Credit Research Initiative |
| PD | probability of default |

## Contents

*"If you don't have some bad loans, you are not in business."*

~ Paul Volcker
Chair of the US Federal Reserve, 1979–87

## 1. Introduction

Credit risk has played a central role in many financial crises, including the great financial crisis (GFC). It often contributes 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 the US 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. In other regions, 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. Importantly, corporate borrowing has expanded across several regions since the GFC (Abraham, Cortina, and Schmukler 2021). However, the COVID-19 pandemic has not (yet) resulted in the manifestation of massive credit losses, despite the severe disruptions to economic activity.

The COVID-19 pandemic has highlighted the importance of being able to properly assess the credit risk on bank balance sheets. The pandemic put substantial pressure on the balance sheets of firms and households worldwide, particularly in the most affected sectors (Mojon, Rees, and Schmieder 2021; Ho and Ong 2022), as widespread lockdowns and social distancing requirements crushed demand for goods and services, sharply increasing unemployment. Correspondingly, 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 requirements, as well as the treatment of classified and nonperforming loans (NPLs), amid highly accommodative monetary and fiscal policies. Consequently, corporate insolvencies have remained very low, particularly when juxtaposed against the depth of the recession, and even declined in many economies during 2020 (Banerjee, Cornelli, and Zakrajšek 2020; Djankov and Zhang 2021; Vandenberg 2021).

Although the unprecedented pandemic support measures appear to have been successful in avoiding mass bankruptcies, they may have disguised the amount of actual problem loans on bank balance sheets. Banerjee, Noss, and Vidal Pastor (2021) defines the gap between expected bankruptcy rates based on declining economic activity and actual realized bankruptcies as the "COVID-19 bankruptcy gap." The authors attribute the decoupling of bankruptcies from the sharp reduction in firm cash flows to the ample supply of credit that was facilitated by the monetary and fiscal support measures. However, they warn that the extension of credit – and hence increased indebtedness – may have only postponed firm insolvencies rather than canceled them. In this regard, Gourinchas and others (2021) observe that any subsequent contraction in credit to the corporate sector that reverses the results of the generous support policies poses significant risks of a potential spike in credit losses.

The sequence of concerted interest rate hikes globally in 2022, just as many economies were recovering from the pandemic, has increased debt service costs for borrowers, raising the likelihood of the bankruptcy gap closing and credit risks for lenders rising. At the same time, the extension or reintroduction of support measures, following the commodity price rises in some countries in the wake of the war, suggests that some future NPLs and potential insolvencies may remain "hidden" for some time to come. Indeed, the ultimate level of credit losses would depend on the evolution of economic activity, which, in turn, relies in part on fiscal policy support.

With risks to the growth outlook skewed to the downside (IMF 2023), reliable economy-level credit risk data – ideally categorized into economic sectors or asset classes – for financial stability analysis take on greater importance. However, no such information is readily available to the public, at least not systematically. The reasons are twofold: (1) a substantial share of credit risk relates to non-traded assets, for which the underlying information is scarce and opaque; and (2) the definition and/or format of the existing data is not easily accessible for credit risk analysis. Hence, there is a pressing need to address this gap.

This project aims to contribute toward closing the long-standing data gap on economy-level credit loss information, an important public good. Our analysis builds upon the work by Hardy and Schmieder (2020), combining time series of actual credit losses with forward-looking market- and macro-implied credit loss rates. Various definitions of credit loss data are estimated at the economy level for as many jurisdictions in the world as possible and published for public use. Our estimates, which will be updated as and when new source information is reported, are presented in a dashboard and downloads are readily accessible. Users may select datasets based on their desired jurisdiction(s), time period(s), and credit loss metrics, depending on the purpose of their analysis. We also offer a tool to run simple scenario analyses based on forecast GDP trajectories.

The rest of the paper is structured as follows: Section II discusses the relevant credit loss concepts, while Section III describes the proposed metrics and corresponding data sources. Section IV presents a worked example and Section V concludes. Readers who are primarily interested in the dashboard should focus on Sections III and IV.

## 2. Credit Loss Concepts

So, what is the best measure of credit loss? The answer to that very much depends on the purpose at hand. There are several concepts and metrics that have been proposed or adopted to date, for either micro- or macroprudential purposes or both. We distinguish between forward-looking credit loss rate estimates and backward-looking or actual/realized credit loss rates, as follows:

### *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 loss rate for the next 12 months (Equation 1). Expected losses are meant to be covered by credit pricing, eg spreads and maturity, and reflected in provisions, while unexpected losses exceeding the ex ante expected level will be deducted from bank regulatory capital. Post GFC, the regulatory framework was strengthened to take into account the lessons learned during the crisis (eg actual losses experienced in low default portfolios were often higher), but the basic approach – namely to compute PDs and LGDs for every credit exposure – remains the same (BCBS 2022):

(1) Expected credit loss (ECL) = PD x LGD x Exposure at default (EAD),

where, PD x LGD = Credit loss rate.

- The accounting standards complement the 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.[4] 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 (GPPC 2016). Any shortfall in covering expected losses from provisions is deducted from regulatory capital.
- Besides the approaches that are anchored in microprudential supervision and widely used by financial institutions, there have been several attempts to estimate system-wide credit risk:
  - Elizondo Flores and others (2010) proposes a method for estimating system-wide PDs and LGDs for a retail portfolio that is representative of the system, both cross-sectionally and for a particular stage of the economic cycle.
  - Hardy and Schmieder (2020) analyzes the time pattern of credit losses around crises for the universe of banking crises from the 1990s until the GFC. The authors find that credit losses are fairly symmetric with respect to macroeconomic downturns, and non-linear with respect to the severity of crises, which typically last between three to five years. Accordingly, they define two rules of thumb:
    - one for the level of credit losses to be expected for advanced economies (AEs) and emerging market economies (EMEs) for crises that occur once in 10–15, 20–30 and 50–100 years; and
    - another for the relationship between business cycles, ie GDP trajectories, and credit losses.

    We apply the latter rule in our estimations of macro-implied credit loss rates across jurisdictions, including to project future losses. Although there are other factors driving credit loss rates, GDP growth is key, and the concept is calibrated to implicitly also capture other relevant factors, such as interest rate levels based on historical relationships observed until the GFC.
  - Juselius and Tarashev (2020, 2021) propose another macro-anchored method to estimate credit losses. Based on their analytical framework, they posit that there may be value in projecting future corporate credit losses where the bankruptcy gap – as defined by Banerjee, Noss, and Vidal Pastor (2021) – could be followed by a delayed wave of insolvencies when it eventually closes

4 https://www.ifrs.org/issued-standards/list-of-standards/ifrs-9-financial-instruments/#about.

("A" and "B" in Figure 1). The authors draw on information on liquidity conditions and solvency risks to forecast losses on corporate loans. Specifically, two traditional financial cycle metrics are respectively used to forecast baseline (expected) and extreme but plausible deviations from the baseline (unexpected) losses on corporate loans ("B" and "C" in Figure 1):

  - private nonfinancial sector debt service ratio (DSR), which captures evolving cash flow strains; and
  - the credit gap, which signals the build-up of leverage in households and firms.

- Juselius and Tarashev (2022) subsequently considers how increased uncertainty in the imminence of the financial system's switch into a high-default phase could leave expected losses unchanged but raise unexpected losses. The authors argue that this decoupling could potentially result in shortfalls in banks' loss-absorbing resources ("C" in Figure 1).
- Market-implied credit loss rates are an alternative to establishing forward-looking metrics at various levels of aggregation. Their lead time in signaling credit losses is fairly short, reflecting the difficulty in predicting crises (eg Arsov and others 2013; IMF 2011). However, market-implied credit risk data are only available for public firms, ie those that are listed on the stock exchange.

*Contemporaneous realized credit loss rates*

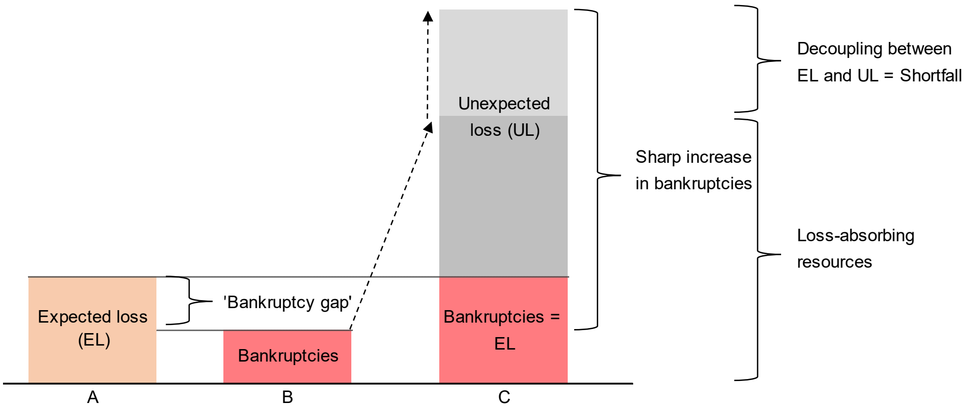
- Microprudential approaches:
  - Two popular methods of measuring credit loss are historical loss and migration (eg Ashbaugh 2015). The loss rate in the historical loss method uses losses incurred from the institution's own portfolio or those incurred by a peer bank or a pool of peer banks, while migration 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. A variant of these methods incorporates a loss discovery period in the outcomes, capturing borrower behavior and the time it takes to recognize default.
  - Under International Accounting Standard (IAS) 39, only past events and current conditions can be considered in measuring credit losses. However, one of the key weaknesses of IAS 39 impairment regulation is that it could lead to delayed recognition of credit losses (Black, Chinchalkar, and Licari 2016).
- 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 published by the IMF since 2009/10,[5] and the economy-level estimates for recovery rates last published by the World Bank in 2019.

In this project, we adopt the typology established by Schmieder, Puhr, and Hasan (2011) in the aftermath of the GFC. They posit that the "best" method for anticipating credit risk is to use forward-looking credit loss rate estimates, ie PDs and LGDs. Another possibility would be to use contemporaneous metrics of actual loss, including credit impairments and/or write-offs or NPL flows. A third alternative is the

[5] See IMF Financial Soundness Indicators.

use of NPL stocks translated into flows. The stock of NPLs is a cumulative metric of the level of losses, which can be a useful complement to flow metrics. We generally express loss rates as a fraction of credit exposures and aim for metrics that are, ideally, representative of country-wide credit losses across all assets classes.

## Figure 1. United States: Historical Credit Loss Rates for Bonds




Sources: Banerjee, Noss, and Vidal Pastor (2021); Juselius and Tarashev (2020, 2021, 2022); and authors' visualization.

# 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 consistently 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. Low default risk portfolios, which are subject to rare loss events, constitute a particular challenge. In terms of comparable publicly-available data, the IMF publishes economy-level NPL ratios, which are stock series. 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 are not readily compiled in one place. Moreover, although revised Pillar 3 disclosures are aimed at improving comparability and consistency across institutions, they also provide flexibility for bank management to comment on the specificities of a bank's risk profile (BCBS 2018), thereby limiting their comparability. There is a range of credit loss data compiled by vendors, but such information needs to be purchased.

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. Specifically, we distinguish between forward-looking credit loss rate estimates, contemporaneous realized credit loss rates, and implied credit loss rates from actual NPL stock data (Table 1).

We draw on credit risk information from multiple sources in both the public and private domains in deriving our database, omitting specific credit risk metrics that we are unable to reproduce for public consumption. The data series, which are standardized to annual frequency, comprise the following:

- 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.

We subsequently establish comparable time series of credit loss rates (Table 2):

*Forward-looking credit loss rate estimates*

- *Merton-model/market -implied credit loss estimates*. There are a number of approaches to inferring PDs and LGDs from the market price of credit risk using Merton-model type approaches, with a positive track record of projecting near-term loss rates.[6] For the purposes of this exercise, we compute average forward-looking credit loss estimates at the economy level by (1) multiplying NUS-CRI PDs with World Bank LGDs; and (2) adjusting the resulting output for public firms to the aggregate level of credit losses observed in a specific jurisdiction.[7] Our rationale for the latter is as follows: The representativeness of our economy-level loss estimates depends on the composition of non-financial firms in a particular jurisdiction, which are typically larger in size in this case because the firms covered in the NUS-CRI database are listed and thus likely to have comparably lower default rates than the economy-level average. Hence, we adjust the levels of the Merton-model/market implied loss rates to those of the realized credit loss rates reported by banks from 2007–21, obtained from BankFocus.
- *Macro-implied credit loss estimates based on projected GDP trajectory*. We project banks' economy-level credit loss estimates based on their empirical relationships with real GDP growth, as established in Hardy and Schmieder (2020). The five-year outlook of the series is anchored on the latest actual credit loss rates reported by banks (for example, end-2021 loss rates that were published during 2022 or more recent 2022 loss rates published in early 2023), sourced from BankFocus. The increase in the loss rate estimates is non-linear with respect to the changes in macroeconomic conditions, that is, the marginal increase (and subsequent decrease) of the estimated credit loss rates would depend on the severity of a particular crisis, as observed during previous stress events.[8] Another important dimension is the degree of public sector backstop, a key driver that helped lower actual credit losses relative to the severity of the macroeconomic

6 See, for example, NUS-CRI (2022).

7 The NUS-CRI credit loss metric corresponds to that of the Moody's Analytics Expected Default Frequency (Moody´s Analytics 2011). A comparison of the two series (NUS-CRI and EDF) suggests that the former sample is wider and that the levels between the two are somewhat different, but their respective trends appear to correspond over time.

8 For example, we assume an AE reporting a credit loss rate of 1 percent in year t is expecting a drop in real GDP growth of 1 percentage point in the next year, resulting in the projection of a loss rate of 1.2 percent at t+1 (= 1% + (–1 x –0.2%)). If GDP growth were to drop by 5 percentage points then the projected loss rate for the AE might not be 2 percent (= 1% + (–5 x –0.2%)) but rather, it could be 3 percent (= 1% + (–5 x –0.4%)). For an EME, the loss rate might be greater at 1.4 percent (= 1% + (–1 x 0.4%)) in the first instance and 5 percent in the second case (=1% + (–5 x –0.8%)).

dip during the COVID-19 pandemic, thereby reducing the GDP-elasticity of credit losses. Hence, the concept may over- or underestimate actual credit losses relative to the calibration period covering banking crises during the 1990s and 2000s.

*Contemporaneous realized credit loss rates / default rates /LGDs*

- 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, going back to the early 2000s.[9] We also provide series of estimated macro-implied credit loss rates based on observed GDP trajectories, to complement the corresponding forward-looking series. Realized LGDs are reported by the World Bank for 2019 and simulated based on macroeconomic conditions for the previous and future years.

*Implied credit loss rates from NPL stock data*

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

The original data series are adjusted for incorrect information and missing entries. The output is then subjected to further quality checks to address outliers – in very extreme cases, we cap the level of reported losses or remove the data from the sample (Box 1).

[9] Loss rates reported by rating agencies for bonds and other credit at the economy level are valuable, but not publicly available. The same holds true for supervisory data.

[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%)).

## Table 1: Typology of Credit Risk Metrics *(the series available to users are referenced)*

| Type of Data | Source | Rationale for Inclusion/Exclusion | Reference (See Table 2) |
|---|---|---|---|
| Forward-looking credit loss estimates | • Credit risk parameters established by IRB banks (Pillar 3) | • No, given high collection costs and inconsistencies in publication format and information (may be added at later stage) | – |
| | • Merton model/market -implied credit loss rate estimates | • Yes, NUS-CRI corporate PD data at the economy level, multiplied by macro-implied LGDs from the World Bank | 1a |
| | • IFRS / CECL impairment rates | • No, not readily available | – |
| | • Macro-implied credit loss rate estimates based on projected GDP trajectory | • Yes, based on Hardy and Schmieder (2020) | 1b |
| | • Supervisory data at the economy level | • No, unavailable because of confidentiality laws and competition sensitivities | – |
| Contemporaneous realized credit losses/ LGDs | • Vendor data (credit loss rates) | • Yes, actual bank credit loss rates from BankFocus (bank-level) loan impairment rate (metrics 2a, 2b) and charge-off rates (metric 2c) | 2a, 2b,2c |
| | • Macro-implied credit loss rates based on observed GDP trajectory | • Yes, macro-implied credit loss rates applied to observed 2017 credit loss rates from BankFocus (based on Hardy and Schmieder 2020) | 2d |
| | • Data from rating agencies (Figure 1) | • No, not consistently available for many jurisdictions and part of core commercial undertaking | – |
| | • Realized LGDs (World Bank) | • Yes, survey-based LGDs from the World Bank (actuals for 2020 (latest data); implied from macroeconomic conditions for other years, both in the past and going forward | 5 |
| | • Supervisory data at the economy level | • No, unavailable because of confidentiality laws and competition sensitivities | – |
| Implied credit losses from NPL stocks | • Vendor data | • Implied credit loss rates from NPL stocks (BankFocus) | 3a |
| | • IMF economy-level statistics | • Implied default rates from IMF Financial Soundness Indicators (Nonperforming Loans to Total Gross Loans, percent), multiplied by realized LGDs | 3b |
| | • Data from rating agencies | • No, not consistently available for a wide set of jurisdictions and part of core commercial undertaking | – |
| Stock of credit losses | • Vendor data | • NPL stocks (BankFocus) | 4a |
| | • IMF economy-level statistics | • Stock of defaulted loans from IMF Financial Soundness Indicators (Nonperforming Loans to Total Gross Loans, percent), multiplied by realized LGDs | 4b |
| | • Data from rating agencies | • No, not consistently available for a wide set of jurisdictions and part of core commercial undertaking | – |

## Table 2: List of Available Credit Risk Metrics and Corresponding Economy-Level Calculations

| Reference (From Table 1) | Description and Purpose | Formula |
|---|---|---|
| **Forward-looking credit loss estimates** | | |
| 1a-1 | Original forward-looking Merton model/market - implied credit loss rate<br>(NUS-CRI PDs, World Bank LGDs)<br>• Purpose: Anticipate losses<br>• Period covered: From 2002<br>• Exposure type: Nonfinancial corporates (loans and securities) | • Take firm-level monthly 1-year forward-looking PDs and aggregate to economy level[1/]<br>• Average economy-level series over calendar year to obtain the annual economy-level PDs<br>• Multiply series by economy-level LGDs in year t+1 (LGD metric 5, see below) |
| 1a-2 | Forward-looking Merton model/market -implied credit loss rate level adjusted to economy-specific level of bank loan losses<br>(NUS-CRI PDs, World Bank LGDs)<br>• Purpose: Anticipate losses<br>• Period covered: From 2002<br>• Exposure type: Nonfinancial corporates (loans and securities) | • Take metric 1a-1 and multiply by scaling factor X<br>  o X: Ratio between time series average of metrics in row 2b below (ie economy level of bank loan losses) and 1a-1 above |
| 1b | Forward-looking credit loss rate implied from GDP<br>(BankFocus, IMF IFS)<br>• Purpose: Anticipate losses<br>• Period covered: Next 7 years from latest<br>• Exposure type: All sectors (loans and securities) | • Take economy-level metric 2a[2/]<br>• Start estimations from latest year (2022), using a linear function for the GDP elasticity of credit losses established by Hardy and Schmieder (2020), per the parameters below<br>  o GDP deflator = GDP[t] – GDP[t-1]<br>    – GDP: real GDP year-over-year percentage change<br>    – Exception: For 2023, GDP[t-1], i.e., actual real GDP growth in 2022, is substituted with the average of the IMF's real GDP growth forecasts over the 2024–28 period to avoid distortions arising from the COVID-19 pandemic<br>  o GDP elasticity of credit losses<br>    – AEs: –0.0302* $\lvert \text{GDP deflator (t)} \rvert$ – 0.1746 (min: –0.5)<br>    – EMEs: –0.0402* $\lvert \text{GDP deflator (t)} \rvert$ – 0.492 (min: –0.8)<br>• $1\text{b}[\text{t}] = \text{a}[\text{t}-1] + \frac{\text{GDP deflator} * \text{GDP elasticity}}{100}$<br>• Threshold: Min: 0.1 percent<br>• In the event that metric 2a is unavailable, use metric 2a average of AEs or EMEs in the latest year |

| Reference (From Table 1) | Description and Purpose | Formula |
|---|---|---|
| **Contemporaneous realized credit losses** | | |
| 2a | Realized credit loss (impairment) rate (BankFocus)<br>• Purpose: Nowcast losses<br>• Period covered: From 2005<br>• Exposure type: All sectors (loans and securities) | • $2a = \frac{\text{Net impairment charges on loans \& advances+ Net impairment charges on other assets}}{\text{Gross loans \& advances to customers+ Total financial assets: securities}}$<br>o Thresholds: Min: 0.05 percent; max: 30 percent<br>• Aggregate bank-level metric 2a to economy level [1/] |
| 2b | Realized loan loss (impairment) rate (BankFocus)<br>• Purpose: Nowcast losses<br>• Period covered: From 2005<br>• Exposure type: All sectors (loans only) | • $2b = \frac{\text{Net impairment charges on loans \& advances}}{\text{Gross loans \& advances to customers}}$<br>o Threshold: Min: 0.05 percent; max: 30 percent<br>• Aggregate bank-level metric 2b to economy level [1/] |
| 2c | Realized loan loss (charge-off) rate (BankFocus)<br>• Purpose: Actual losses<br>• Period covered: From 2005<br>• Exposure type: All sectors (loans only) | • $2c = \frac{\text{Gross loans charged / written off}}{\text{Gross loans \& advances to customers}}$<br>o Maximum threshold: 30 percent<br>• Aggregate bank-level metric 2c to economy level [1/] |
| 2d | Realized credit loss rate implied from GDP (BankFocus, IMF IFS)<br>• Purpose: Macro-implied losses<br>• Period covered: From 2001<br>• Exposure type: All sectors (loans and securities) | • Take economy-level metric 2a:[2/]<br>o GDP deflator = GDP[t] – GDP[t+1]<br>o GDP: real GDP year-over-year percentage change<br>• In the event that metric 2a is unavailable, use metric 2a average of AEs or EMEs in the latest year and estimate end of current period (for forward-looking ratio see metric 1b)<br>• *See metric 1b for concept and parameters; we anchor the projected GDP-implied credit loss estimates in the realized credit loss rates in 2017, a year with fairly "normal" relationships between loss rates and GDP growth and prior to the COVID-19 pandemic, where the unprecedented policy support measures to the economy resulted in unusual relationship trends between GDP growth rates and credit loss rates.* |
| **Implied credit losses from NPL stocks** | | |

| Reference (From Table 1) | Description and Purpose | Formula |
|---|---|---|
| 3a | Loan loss rate implied from (bank-level) NPLs (BankFocus)<br>• Purpose: Loan losses capturing write-off process at individual bank level<br>• Period covered: From 2006<br>• Exposure type: All sectors (loans only) | • Take bank-level metric 4a<br>$3\mathrm{a}[\mathrm{t}] = 4\mathrm{a}[\mathrm{t}] - \left(1 - \frac{1}{T}\right) * 4\mathrm{a}[\mathrm{t}-1)$<br>○ T: Time to resolve insolvency (years) from World Bank (economy level)<br>○ Minimum threshold: 0.1 percent<br>• Aggregate bank-level metric 3a to economy level [1/] |
| 3b | Loan loss rate implied from (economy-level) NPLs<br>(IMF FSI, World Bank LGDs)<br>• Purpose: Capture loss write-off process at economy level<br>• Period covered: From 2006<br>• Exposure type: All sectors (loans only) | • Take economy-level metric 4b<br>$3\mathrm{b}[\mathrm{t}] = 4\mathrm{b}[\mathrm{t}] - \left(1 - \frac{1}{T}\right) * 4\mathrm{b}[\mathrm{t}-1]$<br>○ T: Time to resolve insolvency (years) from World Bank (economy level)<br>○ Minimum threshold: 0.1 percent |
| **Stock of credit losses** | | |
| 4a | Stock of loan losses implied from NPLs (BankFocus)<br>• Purpose: Capture cumulative level of losses<br>• Period covered: From 2005<br>• Exposure type: All sectors (loans only) | • $4\mathrm{a} = \frac{\text{Total impaired/ Non Performing loans}}{\textit{Gross loans \& advances to customers}} * LGD$<br>○ LGD metric 5 (economy level)<br>○ Maximum threshold: 75 percent<br>• Aggregate bank-level metric 4a to economy level [1/] |
| 4b | Stock of loan losses implied from NPLs<br>(IMF FSI, World Bank LGDs)<br>• Purpose: Capture cumulative level of losses<br>• Period covered: From 2005<br>• Exposure type: All sectors (loans only) | • $4\mathrm{b} = \mathrm{x} * LGD$<br>○ x: NPL to Total Gross Loan Rate (percent) from IMF (economy level)<br>○ LGD metric 5 (economy level) |
| **LGDs** | | |

| Reference (From Table 1) | Description and Purpose | Formula |
|---|---|---|
| 5 | LGDs implied from GDP<br>(World Bank LGDs; IMF IFS)<br>• Purpose: Capture anticipated relative level of losses for representative businesses across countries.<br>• Period covered: From 2003<br>• Exposure type: Nonfinancial corporates (loans only) | • Real values (up to current year): $Y[t] = \frac{100-X[t]}{100}$<br>○ X: Recovery rate (cents on the US dollar) from World Bank (economy level)<br>○ Y: Metric 5<br>– Estimations (from current year onwards): Y[t] = $\mathrm{X[t-1] - 2.5 * GDP\ Deflator[t] * 0.01}$<br>– GDP deflator = GDP[t] – GDP[t-1]<br>○ GDP: Real GDP year-over-year percentage change from IMF<br>○ Thresholds: min: 15 percent; max: 100 percent |

Source: Authors' estimates.

*Note: Period covered depends on data availability by jurisdiction and is indicative of the majority only.*

*1/ For metrics 1a-1, 1a-2, 2a, 2b, 2c, 3a, and 4a, aggregation to economy level comprises the following options: (1) simple average, (2) simple average with consistent sample (including only banks or firms constantly reporting since year 2007), (3) weighted average (by asset), (4) weighted average (by asset) with consistent sample (including only banks or firms constantly reporting since year 2007), (5) median within the economy, (6) 75th percentile within the economy, and (7) 90th percentile within the economy.*

*2/ For metrics 1b and 2d, the simple average series of metric 2a is used for estimations.*

Box 1

## Adjusting Data for Missing Values, Outliers and Comparability

Several steps are taken in the data adjustment process. They are applied to each data source as follows:

- BankFocus financial statement data
    - We generally use annual consolidated financial statement data, unless those are not available, in which case we use unconsolidated data.
    - Only commercial banks with time series of at least five years are included.
    - To account for differences in reporting periods across banks, the data are processed by calendar year, such that:
        - For banks whose reporting year ends in Q1 (between January and March), data are stitched to those of the previous year (for example, a reporting year that runs from February 2021 to January 2022 is defined as calendar year 2021).
        - For banks whose reporting year ends between April and November, data are stitched to those of the following year (for example, a reporting year that runs from November 2021 to October 2022 October is defined as calendar year 2022).
        - For banks whose reporting year is the same as the calendar year (that is, January to December), no action is required.
    - Missing single time-series data points are removed using linear interpolation, ie the average between the previous and following years.
- NUS-CRI PD data
    - Data are obtained on a monthly frequency and averaged to aggregate up to annual frequency.
    - Firms in the financial and government sectors are excluded.
    - Qatar's 2009 data and Madagascar's 2016 data are removed as outliers because they appear to be reporting errors.
- World Bank data
    - For the credit recovery rate (in cents on the dollar), collected from the Doing Business database, zeros are replaced with N/A;
    - For time-to-resolve-insolvency (in number of years), also collected from the Doing Business database, we compute the fraction of debt that is being written off; values less than 1 are replaced with 1, that is, all debt is assumed to have been written off in the previous year.

Separately, the following adjustments and assumptions are made during the analytical process:

- When calculating the weighted average from the micro to the macro levels (that is, from bank/firm up to the economy level), total assets are used to estimate the weights for each reporting year, conditional on data available for the economy-specific banks in that very year.
- When calculating simple and weighted averages with consistent samples, only banks/firms that start reporting data on or before 2007 and continually do so until the current year are included in the aggregation.

Finally, the following rules are applied to the output data:

- Minimum and maximum value thresholds are applied to each credit loss rate to eliminate outliers. A minimum threshold of 0.05 percent is used to avoid negative loss rates (which are possible for impairments, for example), while maximum thresholds set at 30 percent are meant to remove outliers on the upper end of the scale (Table 2).
- To ensure that the credit loss rates are comparable, metric 1a sourced from NUS-CRI is rescaled to match the mean of the whole time series (metric 2b from BankFocus).

## 4. Illustration of Data Use: Example

The possible uses of the estimated data series are illustrated with a variety of examples, covering the majority of jurisdictions worldwide (https://www.amro-asia.org/credit-loss-rates/). Specifically, we examine the various credit loss rates – which have different uses for financial stability analysis purposes – for selected AEs, EMEs, and low income developing countries (LIDCs).[11] The estimates that are presented for a select set of economies (Annex 1) suggest the following:

- The pandemic was an unusual event, with fairly low credit loss rates across financial systems – at least to date – despite many countries suffering very deep economic recessions. This phenomenon is likely attributable to the unprecedented policy support measures afforded to the financial, business, and household sectors across many economies. In the US, for example, credit losses for securities were slightly more pronounced during the pandemic, but have levelled out more recently (Figure 2). The corresponding realized macro-implied credit loss rates (Figure 3, metric 2d) spiked while the other actual loss rates (Figure 3, metrics 2a, 2b, 2c) remained contained. However, the forward-looking market-implied credit loss rates (metrics 1a-1, 1a-2) signaled potential increases in loss rates for 2023, albeit less pronounced compared to the initial phase of the pandemic.
- AEs tend to realize lower loss rates, on average, compared to EMEs and LIDCs (Figures 3–6), consistent with Hardy and Schmieder (2020). A number of factors have been identified to explain this trend: (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. Generally, the jumps in loss rates over time differ across countries, reflecting idiosyncratic, economy-specific developments. However, they tend to rise concurrently during major stress events – notably, the GFC – affecting a wide range of countries.
- Following the GFC period (2007–11), the forward-looking market-implied credit loss rates (metrics 1a-1, 1a-2) led realized loss rates (metrics 2a, 2b) by half of a year on average, while loan impairments (metrics 2a, 2b) further led actual charge-offs (metric 2c) by one quarter. However, the forward-looking metrics (ie 1a-1 and 1a-2) also did not anticipate the jumps well ahead of time given the sudden shock nature of crises. The same is true for forward-looking macro-implied credit losses (metric 1b) – the limited success in forecasting GDP trajectories ahead of time is well documented. There have been some improvements in forecasting in recent years but without any fundamental breakthrough.
- Ultimately, all metrics have their usefulness, given their different purposes. Aside from the attempt to anticipate (metrics 1a-1, 1a-2, 1b) or nowcast (metrics 2a, 2b) losses, the stock of NPLs characterizes 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 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.

[11] Development groups as defined by the IMF.

Our framework also allows for multi-year projections based on **anticipated** GDP trends, that is, simplified scenario analyses, which may be useful for simulating the impact of adverse macroeconomic conditions (Box 2).

## 5. Conclusion

The COVID-19 pandemic exposed a blind spot in assessing the credit risk on bank balance sheets. Unfortunately, significant data gaps remain in terms of reliable credit risk information for estimating time series credit losses at the economy level, which is a key element in financial stability analysis. This paper attempts to close that gap, especially for countries with less available information on credit risks, such as EMEs and LIDCs, by applying a myriad of macro- and credit-related information, including at the individual bank level. Furthermore, it facilitates comparisons with peer countries, which – despite the underlying caveat that economy-specific conditions may differ – could be useful benchmarks given that not all countries have experienced severe crises associated with high(er) levels of credit loss rates.

Drawing on several sources, the paper estimates a suite of credit loss rate metrics, which have different purposes and are useful in their own right. Given the difficulty in anticipating peaks in credit loss rates, the paper also makes the case for GDP-implied loss rate simulations, as is regularly adopted in stress tests. Ideally, one would run these stimulations using granular data – eg at the sectoral level – to establish precise loss estimates, but such data remain scarce.

The data series generated in this exercise can help facilitate credit loss analyses and predictions. Yet, more work is needed. The availability of comparable bank-level Pillar 3 could facilitate economy-level analysis, but there is little consistency given the flexibility allowed in how the information is reported across banks and countries. Meanwhile, forward-looking market-based estimates are only available for a subset of firms and typically signal crises only shortly before they actually materialize. A promising avenue may be to use concepts anchored in a consistent analytical framing of various macro-financial variables (such as those applied in Juselius and Tarashev 2020, 2021), but that is left for future research.

Box 2

## Scenario Analysis Using Economy-Level GDP Trajectories

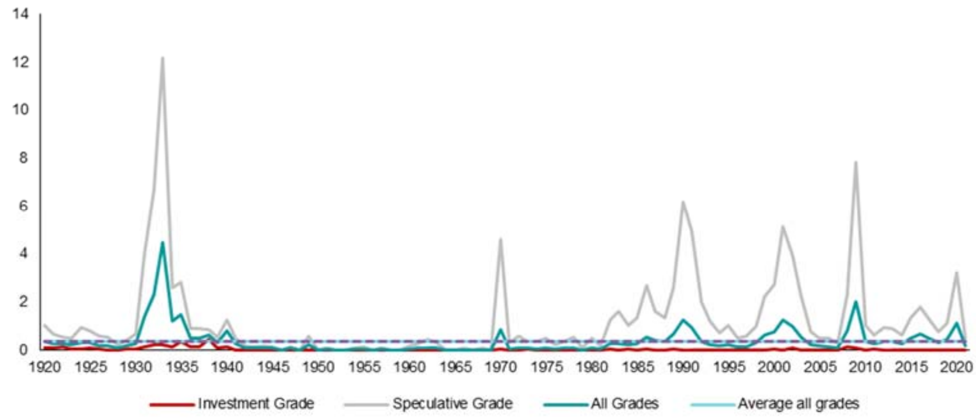
We offer an interactive dashboard (Link: https://www.amro-asia.org/credit-loss-rates/scenario-analysis-based-on-gdp-growth/) to run simplified scenario analyses for future credit loss rates based on projected real GDP growth paths. As documented in Hardy and Schmieder (2020), credit loss rates have followed typical patterns around crisis periods, captured in rules of thumb for GDP semi-elasticities of credit loss rates:

- The association between GDP growth paths and credit losses reflects historical relationships up until the GFC, when extraordinary levels of public support were provided to the economy in many instances. At the same time, public support measures implemented during the COVID-19 pandemic have been even more substantial, mitigating any substantial increase anticipated for GDP-implied credit loss rates. We generally project the concurrent effects of GDP growth on credit loss rates (which may not be entirely reflective for some use cases, eg in economies with long workout periods):
    - Metric 1b captures the projected GDP-implied credit loss rates using IMF forecasts of economy-specific real GDP growth rates through 2028. However, 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 in 2022 with the average of the IMF's real GDP growth trend forecast over the 2024–28 period.
    - We also provide separate historical series for the realized GDP-implied credit loss rates (metric 2d) anchored in the realized credit loss rates in 2017, a year with fairly "normal" relationships between those loss rates and GDP growth.
- Users can select a specific economy and timeframe, and then use the "submit" button. For past periods, the actual real GDP growth trajectories are displayed in a table, as well as the corresponding GDP-implied loss rates along with the realized loss rates. A comparison of the two series offers the users a perspective on the "in-sample" calibration of the tool, established for average patterns observed in advanced and emerging market economies, respectively.
- If the selected timeframe includes future years, then users have the option of defining alternative GDP growth paths for up to three scenarios, in addition to IMF baseline projections (labeled "actuals"). Using the "refresh" button will display the resulting loss rates in the chart, to provide users with perspectives on the implications for credit losses from more adverse or benign outlooks.

# Annex 1: Economy-Specific Credit Loss Rates

## Figure 2. United States: Historical Credit Loss Rates for Bonds

(Percent)




Source: Moody´s.

*Note: Loss rates (in percent) are computed as issuer-weighted corporate default rate series multiplied by LGDs based on historical relationships (Hardy and Schmieder 2020). The sample is pre-dominantly for the United States.*

## Figure 3. United States: Credit Loss Rates during GFC and COVID-19 Pandemic

(Percent)

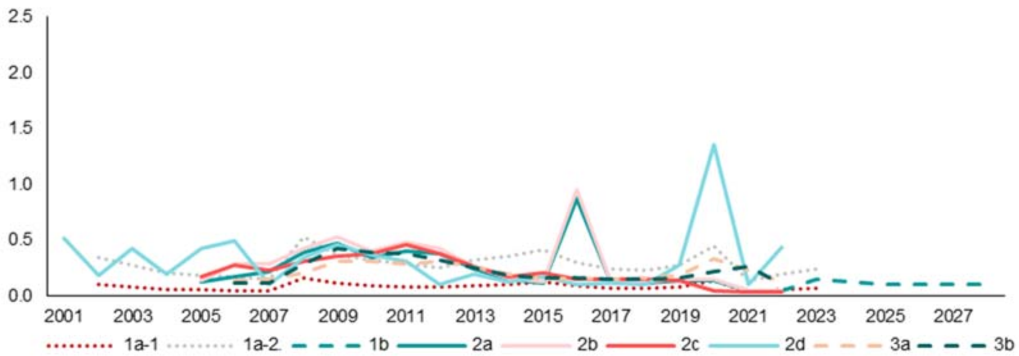

Source: Authors' estimates.

*Note: 1a-1: Merton-model/market -implied credit loss rate, original series; 1a-2: Merton-model/market -implied credit loss rate, adjusted to economy-average; 1b: Forward-looking credit loss rate implied from GDP; 2a–c: Realized credit loss (impairment) rate / Realized loan loss (impairment) rate / 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.*

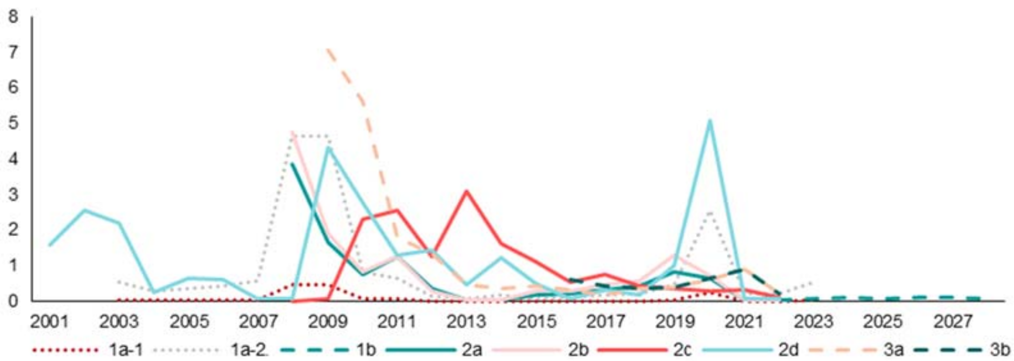
Figure 4. Credit Loss Rates: Selected Advanced Economies

(Percent)

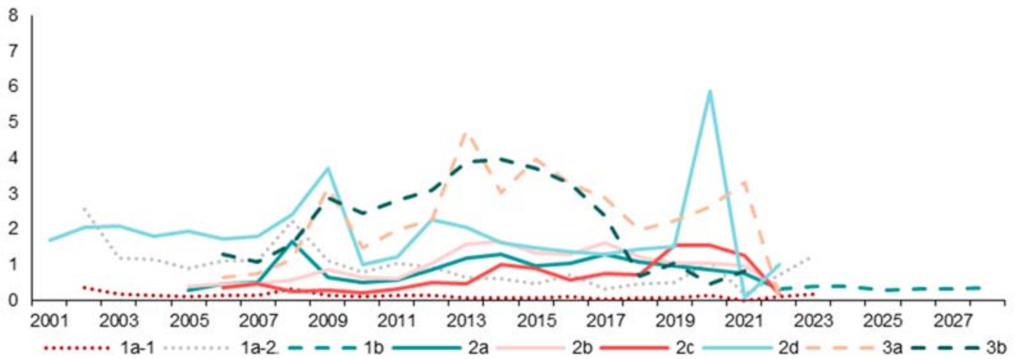
**Australia**




**Iceland**




**Italy**




Source: Authors' estimates.

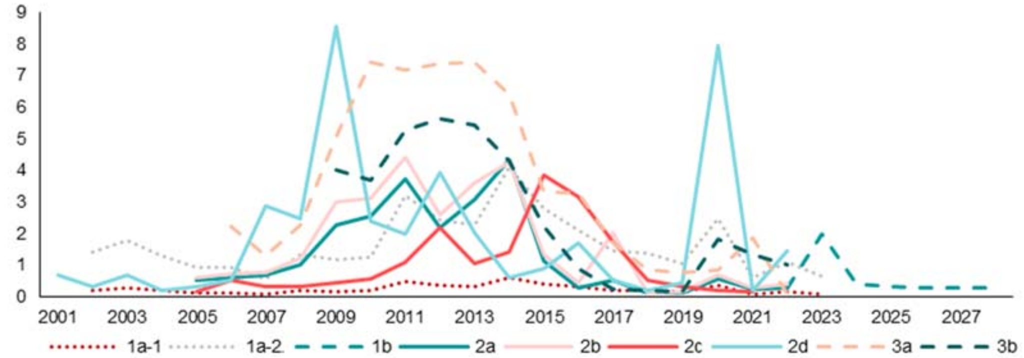
*Note: 1a-1: Merton-model/market -implied credit loss rate, original series; 1a-2: Merton-model/market -implied credit loss rate, adjusted to economy-average; 1b: Forward-looking credit loss rate implied from GDP; 2a–c: Realized credit loss (impairment) rate / Realized loan loss (impairment) rate / Realized 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 5. Credit Loss Rates: Selected Emerging Market Economies

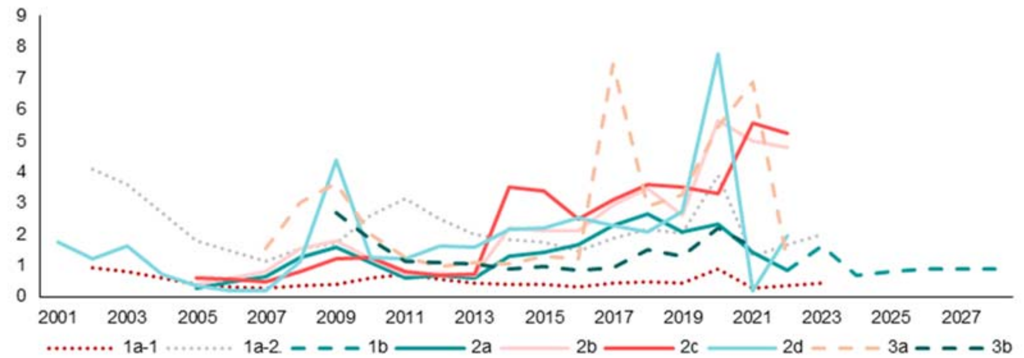
(Percent)

**Brazil**


**Hungary**




**South Africa**



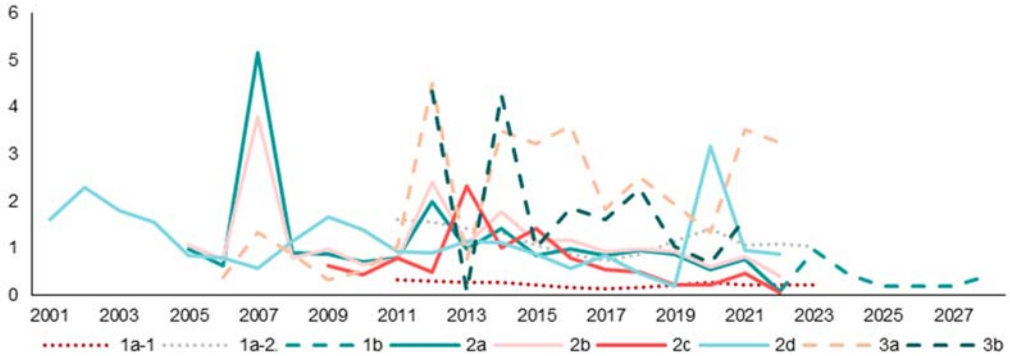

Source: Authors' estimates.

*Note: 1a-1: Merton-model/market -implied credit loss rate, original series; 1a-2: Merton-model/market -implied credit loss rate, adjusted to economy-average; 1b: Forward-looking credit loss rate implied from GDP; 2a–c: Realized credit loss (impairment) rate / Realized loan loss (impairment) rate / 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.*

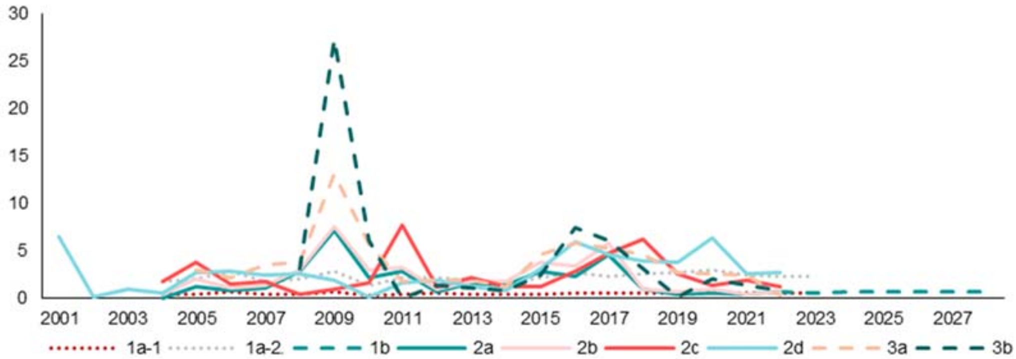
## Figure 6. Credit Loss Rates: Selected Low Income Developing Countries

(Percent)

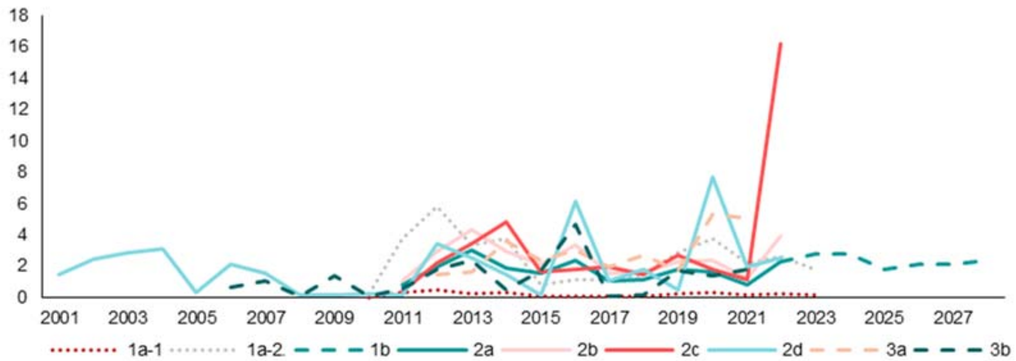
### Bangladesh




### Nigeria




### Uganda




Source: Authors' estimates.

*Note: 1a-1: Merton-model/market -implied credit loss rate, original series; 1a-2: Merton-model/market -implied credit loss rate, adjusted to economy-average; 1b: Forward-looking credit loss rate implied from GDP; 2a–c: Realized credit loss (impairment) rate / Realized loan loss (impairment) rate / 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.*

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