

Optimising Credit Risk Management: An In-Depth Exploration of the Expected Credit Loss Framework for Effective Credit Loss Provisioning

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Abstract

The banking sector in India currently relies on the incurred loss approach (ILA) for provisioning non-performing assets (NPAs), wherein credit losses are recognised only upon the occurrence of a loss event. While widely adopted, this reactive approach suffers from significant limitations, including delayed recognition of losses, inadequate early warning indicators, procyclicality, and the absence of forward-looking insights. These shortcomings impede effective risk management and highlight disparities with globally accepted standards. To address these gaps, the Reserve Bank of India (RBI) has proposed a transformative shift to the expected credit loss (ECL) framework, as outlined in its discussion paper. The ECL approach introduces a forward-looking, proactive provisioning methodology based on a three-stage model for categorising loans and advances. By emphasising early loss recognition and aligning with international best practices, this framework aims to enhance the resilience and stability of the banking system. This paper critically examines the limitations of the ILA and provides a comprehensive analysis of the ECL framework. It underscores the potential of the ECL approach to revolutionise credit risk management (CRM) in India, offering insights into its benefits, implementation challenges, and implications for the financial ecosystem.

Keywords: Banking Resilience, Credit Risk Management, Expected Credit Loss (ECL) Framework, Incurred Loss Approach (ILA), Non-Performing Assets (NPAs), Proactive Provisioning

JEL Classification: E58, G21, G28

Introduction

As an integral part of the financial system, banking institutions play a crucial role in economic development by serving as intermediaries between entities/individuals with surplus investable funds and those in need of financing. Lending, a primary business activity for banks, constitutes an integral and important part of their operations, with loans and advances making up over 55% of their total assets. In addition, investments also form a substantial part of a bank's assets, accounting for 25–30% of the total assets. Moreover, interest income from loans and advances contributes to approximately 85% of their total income. Therefore, loans and advances represent a significant and vital segment of the asset portfolios of banks. It is noteworthy that loans and advances are regarded as bank assets since they generate interest income during the credit period.

However, the loans provided by banking institutions are inherently subject to various types of risks, with credit risk being a significant concern. Credit risk refers to the potential for banks to experience losses on their loans/exposures. These credit losses, intrinsic to the banking business, stem from the lending business and are impacted by forecasts of the future performance of borrower entities. Due to the inherent uncertainty and potential variability in these projections, losses are inevitable. Similarly, investments are vulnerable to changes in their realisable, recoverable, or maturity values, sometimes resulting in decreased recoverable values and subsequent impairment losses.

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How to cite: Madegowda, J. (2026). Optimising credit risk management: An in-depth exploration of the expected credit loss framework for effective credit loss provisioning. *International Journal of Banking, Risk and Insurance*, 14(1), 86-98.

To manage credit risk, standard approaches classify potential losses in a bank's credit portfolio into expected and unexpected losses. Expected losses are typically managed through pricing strategies and loan loss provisions (LLPs), while unexpected losses are mitigated by maintaining adequate capital. Any expected losses not covered by provisions must be absorbed by the bank's capital. This dual requirement leaves banks vulnerable to unexpected losses, consequently increasing the risk of failure (Cohen & Edwards, 2017), randomized, double-blind, placebo-controlled clinical trial. SETTING: Large, urban pediatric emergency department between March 2002 and November 2003. PATIENTS: Children aged 5 to 18 years with moderate to severe pharyngitis (odynophagia or dysphagia), moderate to severe pharyngeal erythema or swelling, and a McGrath Facial Affective Scale score of 0.75 or higher [scale 0.0-1.0]. A study by Prakash and Swayam (2024) examines how factors such as bank size, profitability, capital adequacy, liquidity, and diversification impact credit risk. The findings reveal that larger banks and those with higher income diversification tend to face higher credit risk, while stronger profitability, healthier capital buffers, and prudent lending practices mitigate it.

It is crucial to understand that LLPs are funds allocated as allowances for potential uncollected loans. Essentially, provisioning involves setting aside profits (of banking institutions) to cover potential losses from bad loans, commonly referred to as non-performing assets (NPAs). These provisions contribute to the loan loss reserves, a component in the statement of financial position (also known as the balance sheet), with the total reflecting the cumulative amount of loan losses subtracted from the loans and advances of banking entities. Thus, robust loan loss provisioning practices play a vital role in ensuring the safety and stability of any banking institution (Bank for International Settlements, 2017; Behn & Couaillier, 2003). We test the small molecule flexible ligand docking program Glide on a set of 19 non- α -helical peptides and systematically improve pose prediction accuracy by enhancing Glide sampling for flexible polypeptides. In addition, scoring of the poses was improved by post-processing with physics-based implicit solvent MM-GBSA calculations. Using the best RMSD among the top 10 scoring poses as a metric, the success rate (RMSD \leq 2.0 Å for the interface backbone atoms.

ILA – An Overview

There are two important methodologies for establishing LLPs: the incurred loss approach (ILA) and the expected credit loss approach (ECLA). Until recently, the ILA was the standard practice globally. However, several countries, including the United States, have transitioned to the ECLA. In India, the ECLA is mandated only for non-banking financial companies (NBFCs).

Therefore, banking companies in India, including the scheduled commercial banks (SCBs), currently adhere to the ILA for their loan loss provisioning. The Reserve Bank of India (RBI), the country's banking regulator, is now considering extending ECLA to all SCBs. In light of this, we aim to provide an overview of the developments in the ILA in India, followed by an analysis of the expected credit loss (ECL) framework.

Until the mid-1980s, India lacked standardised guidelines for assessing the quality of individual loans and making adequate provisions for bad loans. The management of such loans was left to the discretion of banking companies. However, following the recommendations of the *Pendharkar Working Group on the System of Inspection of Banks* (1985), which were reiterated by the *Committee to Consider Final Accounts of Banks* under the chairmanship of Shri A. Ghosh, the RBI introduced significant changes during 1985–86, effective from November 7, 1985.

Accordingly, the RBI advised all commercial banks (excluding branches of foreign banks in India, which already had similar mechanisms) to classify loans into eight categories under the Health Code System. This system was introduced to facilitate closer monitoring of credit quality. Furthermore, the Health Code System mandated all commercial banks to categorise their problematic loans into three distinct categories: (i) advances classified as 'bad and doubtful', (ii) advances where suits were filed and/or decrees were obtained, and (iii) advances with 'undesirable features'.

However, this system faced practical challenges due to a lack of transparency, objectivity, and uniformity in the criteria for assessing NPAs (Gowda, Inchara, 2020). Recognising these shortcomings and in line with the recommendations of the M. Narasimham *Committee*

on the Financial System, the central bank issued comprehensive prudential guidelines in 1992. The central bank mandated banks to classify loans into two main categories: standard assets and NPAs, further classifying the latter into substandard assets, doubtful assets, and loss assets based on the compression of health codes.

Subsequent revisions and modifications aimed to refine the definition of NPAs and enhance the mechanism

for provisioning against them. These revisions also prescribed rates for provisioning against loans in different categories and sub-categories. Currently, the *Master Circular on Income Recognition, Asset Classification, and Provisioning*, effective April 1, 2022, governs these provisions, outlining varying provisioning rates ranging from 0.25% to 100%. Some details are summarised in Table 1.

Table 1: Loan Categories and Rates of Provisions

Categories of Loan Assets			Rate of Provisioning (%)
Standard assets:			
(i)	Farm credit and SME sectors		0.25
(ii)	Advances to the commercial real estate (CRE) sector		1.00
(iii)	Advances to the commercial real estate (residential housing) sector		0.75
(iv)	Housing loans extended at teaser rates and restructured advances		2.00
(v)	In all other loans and advances [not included in (i) to (iii) above]		0.40
NPAs:			
Sub-standard assets:			
(i)	On total outstanding loan without making any allowance for securities available		15.00
(ii)	On the unsecured exposures		25.00
Doubtful assets:			
(i)	On the advance not covered by the realisable value of the security		100.00
(ii)	In the case of the secured portion of doubtful loans, and the period for which the advance has remained in the 'doubtful' category		
	(a)	Up to one year	25.00
	(b)	One to three years	40.00
	(c)	More than three years	100.00
Loss assets – it should be written-off fully; otherwise, the provision at,			100.00

Source: RBI (2022).

Extant ILA – Shortcomings

Per existing prudential guidelines, asset classification is intricately tied to recovery records, providing insight into banking companies' risk exposure only after the credit risk materialises. As a result, banks create provisions against loans using the ILA, which involves considering the asset classification of specific exposures and the corresponding provisioning rate.

Under this framework, banks recognise LLPs in response to borrower payment delays stemming from financial distress, thereby amplifying the credit risk faced by lenders. Notably, loan loss provisioning occurs after the escalation of credit risk to the lender banks, with loan classification as NPA serving as the prerequisite trigger

for provision creation. The ILA model recognises credit losses only after default or impairment (Frykström & Li, 2018). This backward-looking approach proved inadequate during the 2008 financial crisis, leading to significant delays in loss recognition and exacerbating the crisis's severity (Oreshkova, 2018; Joseph Mcphail & Lihong Mcphail, 2014). The incurred loss model's reliance on historical data and inability to anticipate future economic downturns were key weaknesses (Oreshkova, 2018).

This suggests that under the ILA, banking companies make provisions for actualised loan defaults/losses, thereby highlighting a temporal gap between the escalation of credit risk and the recognition of the provision. It is imperative to recognise that while

underlying default or credit risk may precede actual default events, mitigation efforts remain deferred until regulatory mandates for loan loss provisioning are activated upon exposure classification as NPA (Reserve Bank of India, 2023).

This delay in recognising expected losses under the ILA, coupled with a systemic increase in defaults, is compelling banks to bolster provisions to higher levels and poses a potential risk to their resilience. This trend erodes the capital maintained by banks precisely at a juncture where capital reinforcement is crucial, consequently impinging upon their resilience and posing systemic risks. Examining the impact of revised LLPs under International Financial Reporting Standards (IFRS) and generally accepted accounting principles (GAAPs) on Tier-1 capital reveals that these changes lead to a reduction in Tier-1 capital, particularly during economic downturns and for low-quality credit portfolios. The findings suggest that the provisioning rules exacerbate the procyclicality of bank capital requirements. Therefore, adjustments to significant increases in credit risk thresholds or capital buffers are recommended to mitigate the regulatory pressure resulting from the reduction of regulatory capital (Krüger et al., 2018).

Moreover, the delay in loan loss recognition inflates banks' reported income, exacerbated by dividend payouts, thereby diminishing internal accruals and further undermining banks' capital base, subsequently compromising their resilience. The ILA engenders provisioning shortfalls, necessitating adjustments in the calculation of capital requirements.

In addition, this practice leads to loans being presented on banks' balance sheets at inflated values relative to their realisable amounts. Such deviation from financial valuation principles, where asset value is determined by the present value of anticipated cash flows over the asset's lifespan, underscores the inconsistency of the ILA for LLPs. As a result, the traditional way of thinking about NPAs/non-performing loans (NPLs) and provision models is not working well. This is because different types of loans have different effects on how credit quality is judged (Beatty & Liao, 2020).

With empirical insights from 230 respondents (event management firms) in the Salem district, Krishnakumar &

Arul (2024) effectively demonstrated that access to bank credit significantly improves business outcomes such as profitability, capacity expansion, technology adoption, and competitive advantage.

IFRS 9/IND as 109: Financial Instruments

The situation described above, among others, prompted the G-20 and the Basel Committee on Banking Supervision (BCBS) to recommend that accounting standard setters (International Accounting Standards Board [IASB] and Financial Accounting Standards Board [FASB], among others) modify provisioning practices to adopt a more “forward-looking approach” rather than the ILA. Consequently, the standard setters have developed and issued accounting standards that incorporate methodologies for quantifying and including expected credit losses in provisioning. The relevant standards are:

- *IFRS 9: Financial Instruments* by IASB, effective from January 1, 2018.
- *Current Expected Credit Losses* by FASB, effective from January 1, 2020, and *Topic 326: Financial Instruments – Credit Losses*.
- *Ind AS 109: Financial Instruments* by the Institute of Chartered Accountants of India (ICAI) for NBFCs, effective January 16, 2023.

For India, IFRS 9 is particularly relevant, and it is noteworthy that Ind AS 109 closely mirrors IFRS 9. This standard (IFRS 9) specifies that the classification and measurement of an entity's financial assets should be based on the entity's business model for managing the financial assets and the contractual cash flow characteristics of these financial assets. The standard also provides detailed criteria for measuring financial assets at cost, fair value through other comprehensive income (OCI), and fair value through profit and loss. In addition, it outlines the effective interest rate method for computing interest income and the ECLA for impairment, measurement of loss allowance, and treatment of credit-impaired financial assets (Deloitte, 2016; PWC, 2014; Tayler & Zilberman, 2021). It is important to note that financial assets primarily include loans, advances, irrecoverable loan commitments, and investments categorised as held-to-maturity or available-for-sale. Moreover, the aggregate loan disbursed encompasses irrevocable loan commitments, including

sanctioned limits within revolving credit facilities. Against this backdrop, the RBI is making necessary preparations to transition commercial banks from the existing ILA to the ECLA for creating and maintaining credit loss provisions.

Literature Review – Global Experience

The ECL framework is a big change in how credit loss is calculated. It replaces the old ILA with a more forward-looking method that fits with new global accounting standards such as IFRS 9 and the current ECL standard in the US. This transition underscores the growing emphasis on proactive risk management and early recognition of potential credit losses to enhance the stability and resilience of the banking sector.

While the ECL framework is a relatively recent development, it has garnered significant academic and professional attention, particularly in the context of its implementation, challenges, and implications for financial institutions. Researchers have extensively explored its theoretical underpinnings, comparative effectiveness against the ILA, and practical application across jurisdictions.

This literature review, presented thematically, seeks to provide a comprehensive overview of existing research on the ILA and ECL framework, focusing on its operational mechanics, advantages over traditional models, and challenges in adoption. In addition, it highlights notable studies that examine the framework's impact on the banking sector, offering critical insights into its transformative potential in credit risk management (CRM).

A study on 10 Nigerian banks (2008–19) revealed that substandard and loss loans adversely affect financial performance, while doubtful loans do not. Strengthened risk assessment and loan repayment enforcement were recommended (Odeh et al., 2023). In Italian banks, LLPs are driven primarily by expected credit risk, with regional banks facing higher LLPs due to loan concentration and reduced competition. Income smoothing practices were also noted (Aristei & Gallo, 2019). An analysis of 15,931 European bank loan portfolio observations showed that provision reversals during recessions impacted reported income (Aggelopoulos et al., 2023).

Heightened economic policy uncertainty (EPU) led to increased LLPs in 6,384 US banks (2009–19), reflecting its use for income smoothing and capital management (Danisman et al., 2021). LLPs and bank lending significantly influenced business cycle fluctuations across 12 Organisation for Economic Co-operation and Development (OECD) countries (Pool et al., 2015). Fiscal measures during the COVID-19 pandemic, such as tax relief, reduced loan portfolio risks, while liquidity support had minimal impact (Degryse & Huylebroek, 2023).

Post-great financial crisis reforms improved stability through capital buffers, reducing domestic credit activity, especially in weaker institutional frameworks (Fratzscher et al., 2016). LLP regulations in Chile's mortgage market reduced loan-to-value ratios and highlighted the competition's role in lending standards (Calani & Paillacar, 2022). IFRS 9 increased Tier-1 capital in Spanish banks, benefiting larger institutions but with procyclical effects (López-Espinosa & Penalva, 2023).

Australian banks strategically increased LLPs for future growth, leveraging surplus capital and discretionary power (Cummings & Durrani, 2016). Simplified ECL models are advised to address procyclicality and ensure comparability (Jacobs, 2019). Dynamic provisioning, combined with credit gap-augmented Taylor rules, effectively curbs financial procyclicality (Agénor & Zilberman, 2015). Transitioning to ECL reduced stock price crash risks in banks with lower opportunistic incentives and opaque information environments (Jin & Wu, 2023). Md Nasim Ansari & Jamaluddeen (2025) assess bank performance with a focus on both interest and non-interest income efficiencies. While most public sector banks (PSBs) perform well in generating interest income, a notable efficiency gap exists in their ability to generate non-interest income, which adversely affects overall efficiency levels. The study underscores the need for PSBs to diversify income sources and improve internal financial management to remain viable in an increasingly competitive environment.

Adopting ECL under IFRS enhanced loss recognition timeliness, particularly in riskier institutions, with global influence seen in subsidiaries (Rakhaev, 2020). However, Portuguese banks reported procyclical tendencies and reduced capital adequacy under ECL (Resende et al.,

2024). Current ECL (CECL) adoption during COVID-19 slowed economic recovery in areas with high market share banks (Chen & Ryan, 2024). Forward-looking provisioning practices globally showed mixed effects on risk discipline, enhancing it through timely loss recognition but reducing transparency with earnings smoothing (Bushman & Williams, 2012).

ECL adoption increased loan loss allowances due to forward-looking assessments but challenged comparability due to modelling variations (Jacobs, 2020). This shift improved credit risk assessment timeliness and financial reporting accuracy while necessitating advanced forecasting models and technology investments (Kim et al., 2022; Gee et al., 2022). However, adoption varied due to preparedness, interpretations, and institutional risk appetites (Rafika Sari & Dwitayanti, 2023).

This literature review has examined the evolution of credit loss provisioning frameworks, with a particular focus on the ECL model and its implications for effective risk management in the banking sector. While existing studies have extensively analysed the theoretical foundations, comparative advantages, and practical challenges of transitioning from the ILA to ECL, most research has been centred on global or Western banking systems. This has resulted in limited insights into the operationalisation of ECL in the unique regulatory, economic, and credit environments of emerging markets, including India. This study seeks to address this gap by focusing on the application, challenges, and implications of the ECL framework within the Indian banking sector. By doing so, it aims to contribute to the broader discourse on optimising CRM and fostering resilience in emerging economies.

A Few Aspects of Methodology

The primary objective of this study is to evaluate the efficacy of the proposed ECL framework in facilitating effective credit loss provisioning. This includes a full review of the method, especially compared with the current incurred credit loss model, with the main goal of finding its flaws and ways to improve it. The primary source of literature for this study is the RBI, which offers authoritative information and insights into various aspects of credit loss provisioning. In addition, relevant details are collected from a range of secondary sources,

including scholarly articles, websites, industry reports, and specialised literature.

This study adopts a predominantly theoretical and qualitative approach, aiming to explore different dimensions of the proposed ECL model. Through rigorous analysis and synthesis of existing literature and regulatory frameworks, it seeks to provide a comprehensive understanding of the conceptual underpinnings and potential implications of the proposed framework.

Optimising CRM: Exploration of ECL Framework for Effective CI Provisioning

The ECL model fundamentally employs a forward-looking approach to estimating potential credit losses. Unlike its predecessor, the incurred loss model, it does not wait for defaults before recognising losses. Instead, it requires financial institutions to estimate expected losses over a loan's lifetime from its origination (Cohen, 2017; Frykström & Li, 2018). This forward-looking perspective is a key improvement over previous incurred loss methods, aiming to provide a more realistic and timely reflection of credit risk in financial statements, enhancing their predictive power and usefulness for investors (Gee & Neilson, Jed J., 2022).

The discussion paper of the RBI outlines the current ILA and the proposed ECL mechanism. The ECL model uses a forward-looking perspective, requiring institutions to estimate potential losses from loan inception (Cohen, 2017). This proactive approach aims to provide a more timely and accurate reflection of credit risk (Gee & Neilson, Jed J., 2022). The ECL model also incorporates a broader range of information, including macroeconomic forecasts and forward-looking assessments of creditworthiness (Frykström & Li, 2018). This forward-looking aspect aims to mitigate the procyclicality of loan loss provisioning – the tendency for LLPs to increase during economic downturns, exacerbating the cycle (Abad & Suarez, 2018; Michael Jacobs, 2020). Given the constraints in providing an exhaustive analysis of the discussion paper, this paper aims to highlight the key features of the proposed framework. Specifically, it delves into two critical components: the ECL mechanism and the classification of financial assets, offering a concise yet insightful examination of these aspects.

ECL refers to the probability-weighted estimate of the present value of all cash shortfalls arising from a financial instrument. Cash shortfalls occur when the actual cash receipts a bank expects from an instrument fall below the contractual cash flow expectations. As cash shortfalls are discounted, a delay in payment – even without an actual shortfall in the payment amount – can also contribute to an ECL.

Contractual cash flow receipts refer to the payments that a lender expects to receive from the borrower as outlined in the loan agreement. To correctly figure out the ECL of an asset or loan, banks have to look at a few variables. These include (i) a probability-weighted amount that comes from evaluating a range of possible outcomes; (ii) the time value of money, which means figuring out the present value of future cash flows – this is a basic idea in financial analysis; and (iii) information that is relevant at the time of reporting, such as events that have happened in the past, the current state of the economy, and predictions for the future.

The estimation of ECL involves considering three key components: (i) exposure at default, (ii) loss given default, and (iii) probability of default:

$$ECL = (EAD \times LGD \times PD) \quad (1)$$

EAD (exposure at default) represents the predicted outstanding loan amount at default. Estimating EAD requires forecasting future loan behaviour, such as prepayments or drawdowns, depending on the financial instrument (Engelmann, 2021). For revolving credit facilities, such as credit cards, estimating EAD is particularly challenging due to fluctuating outstanding balances (Canals-Cerdá, 2020). Accurate EAD estimation is important for determining the total amount of potential loss associated with a default. Accurate EAD forecasting also requires considering macroeconomic factors influencing borrower behaviour, such as changes in interest rates or economic growth (Lu & Nikolaev, 2019). In the context of a loan, EAD typically represents the difference between the disbursed loan amount and the repayments received. Therefore,

$$EAD = (\text{disbursed loan amount} - \text{repayment received}) \quad (2)$$

LGD (loss given default) refers to the percentage of exposure expected to be lost in the case of default.

Estimating LGD involves considering factors such as collateral value, recovery rates, and legal and administrative costs associated with debt recovery (Engelmann, 2021). Determining LGD can be complex, especially for loans with complex collateral or in jurisdictions with varying legal frameworks governing debt recovery. Accurate estimation often requires detailed historical data on defaults and recovery processes (Guamán-Chumaina & Vásquez-Acuña, 2024). The accuracy of LGD estimation is crucial for determining the severity of potential losses associated with a default. It is expressed as a percentage, calculated by dividing the net loss (that is, loan disbursed – repayment received – realisable value of collateral) by the outstanding loan amount (that is, amount of loan disbursed – repayment received). Therefore,

$$LGD = \left[\frac{\left\{ \begin{array}{l} \text{loan} \\ \text{disbursed} \end{array} \right\} - \left\{ \begin{array}{l} \text{repayment} \\ \text{received} \end{array} \right\} - \left\{ \begin{array}{l} \text{realisable value} \\ \text{of collateral} \end{array} \right\}}{\left\{ \begin{array}{l} \text{amount of} \\ \text{loan disbursed} \end{array} \right\} - \left\{ \begin{array}{l} \text{repayment} \\ \text{received} \end{array} \right\}} \right] \quad (3)$$

PD (probability of default) denotes the likelihood of a borrower failing to meet his contractual obligations. Its estimation often involves sophisticated statistical techniques and incorporates a few factors such as borrower credit history, macroeconomic conditions, and industry-specific risks (S. Drin, 2023; Xin Xu, 2016). The accuracy of PD estimation is paramount, as it directly impacts the overall ECL calculation. Different models exist, ranging from simple linear regressions to complex machine-learning algorithms (Chen, 2024). The model choice depends on available data, loan portfolio complexity, and the institution's risk appetite (S. Drin, 2023).

The discussion paper includes relevant parts of IFRS 9 and Ind AS 109 that specify to banks what they need to do about loss allowances for financial instruments:

- *Lifetime ECL*: If the credit risk of a financial asset has increased significantly since it was first recognised, banks must set the loss allowance for that asset at the same level as its lifetime ECLs. This mandate guarantees that the provisioning mirrors the heightened risk profile, thereby improving the precision of CRM and adhering to forward-looking accounting standards.
- *12-Month ECL*: If a financial asset's credit risk has not significantly increased since its initial

recognition, we should determine the loss allowance to match the 12-month ECLs. This method upholds a foundational level of provisioning that mirrors the credit risk of the asset for the upcoming 12 months, guaranteeing cautious risk management in line with accounting standards (IASB, 2022; Ministry of Corporate Affairs, 2015).

Another significant aspect of the discussion paper is the proposal to categorise financial assets (based on the evolution of credit risk relative to their initial recognition) into three groups, as outlined below:

- *Stage 1 – Financial Assets with Stable/Low Credit Risk:* This category includes financial assets that have minimal credit risk, have maintained their original quality since their recognition, or have been assessed as low risk at the reporting date. Under standards such as IFRS 9/Ind AS 109, banks are mandated to set aside provisions for ECLs over the next 12 months (12-month ECL). This proactive approach ensures that potential losses are anticipated and disclosed in financial statements, bolstering stability and investor confidence. Strategically, holding a significant portion of assets in Stage 1 supports a bank's steady income stream.
- *Stage 2 – Financial Instruments with Increased Credit Risk:* This category includes financial instruments that have shown a significant increase in credit risk since their initial recognition, but they do not meet the criteria for low credit risk at the reporting date, nor do they provide clear evidence of impairment. Mainly comprising loans or debt securities, this stage mandates banks to establish an allowance for credit losses representing ECLs over the asset's remaining lifetime, termed as Lifetime ECL. This framework makes sure that banks properly reflect the higher risk in these instruments, which accurately shows possible losses in their financial statements and makes financial reporting clearer and more reliable.
- *Stage 3 – Financial Instruments with Objective Evidence of Impairment:* This category pertains to financial instruments that demonstrate clear indicators of impairment at the reporting date. Specifically, all financial assets identified as being in a 'default' status fall under the classification of

Stage 3 assets. For these assets, financial institutions are obligated to acknowledge an allowance for credit losses that correspond to the anticipated credit losses throughout the entirety of the remaining lifespan of the asset (referred to as Lifetime ECL).

The proposed model represents a significant improvement over the current ILA for credit loss provisioning, which is known for its delayed recognition of impairment losses on financial assets. In contrast, the ECL model aims to promptly acknowledge credit losses by requiring banking entities to recognise allowances for anticipated lifetime credit losses. While ECL offers an integrated solution for IFRS 9 compliance and ECL-compatible estimation, its implementation may introduce procyclicality. This could have substantial effects on banks' regulatory capital ratios and lending practices during financial crises (Covas & Nelson, 2018). A study on the transition from the ILA to the ECL approach in European banks found that the ECL model outperforms the ILKA method in predicting future banking risk. Therefore, it is felt that adopting the ECL provisioning approach provides better insights for assessing bank risk, especially during periods of credit deterioration (Salazar et al., 2023).

Observations and Challenges in ECL Implementation

The transition to the ECL model presents a few significant challenges, as outlined below:

- *Methodological Challenges:* Implementing the ECL model requires sophisticated modelling techniques and substantial data. Key components such as PD, LGD, and EAD must be estimated using advanced statistical models. Incorporating macroeconomic factors and addressing uncertainties are critical yet complex tasks (Wolfgang Reitgruber, 2016; Joseph & Lihong McPhail, 2014). In addition, robust validation algorithms and techniques to separate risk costs into their primary components are necessary to ensure accuracy and reliability (Rathnakar, 2020). Furthermore, while macroeconomic factors are vital for capturing economic cycles' impact on credit risk, their inclusion introduces substantial uncertainty. Forecasting inaccuracies and subjective judgements by management regarding future

economic conditions can bias ECL estimates, reducing comparability and transparency (Lu & Nikolaev, 2019; Oreshkova, 2018; Jacobs, 2019). In addition, although the ECL framework aims to mitigate procyclicality, it can inadvertently exacerbate this phenomenon, especially for banks with low regulatory capital or heterogeneous loan portfolios (Jacobs, 2019; Chen et al., 2022). Robust monitoring and back-testing processes, alongside stress testing, are essential to counteract such risks (Reitgruber, 2015).

- *Data-Related Challenges:* Implementing ECL relies heavily on comprehensive and high-quality data, including historical defaults, recovery rates, and forward-looking information (Guamán-Chumaina & Vásconez-Acuña, 2024; Jacobs, 2019). Many institutions, particularly smaller ones, lack access to such datasets, leading to inaccurate model calibrations (Swanson et al., 2021). Besides, inconsistent reporting practices, potential biases in historical data, and variability in macroeconomic forecasts further complicate ECL estimations (Engelmann, 2021; Frykström & Li, 2018).
- *Governance and Operational Challenges:* Subjective judgements by management in estimating ECLs introduce potential biases and reduce transparency. Enhanced disclosure of assumptions, inputs, and methodologies is essential to improve accountability and comparability across institutions (Oreshkova, 2018; Jacobs, 2019). Furthermore, sophisticated ECL models demand significant computational resources and technical expertise, posing challenges for institutions with limited infrastructure (Gubareva & Silva, 2019). Smaller entities may struggle to align their internal risk management frameworks with the complexities of ECL estimation (Swanson et al., 2021).
- *Capital Management Implications:* The forward-looking nature of ECL provisioning increases banks' capital requirements, affecting their lending capacity and potentially amplifying procyclicality during economic downturns (Hsiang-Chieh Yang, 2024; Chen & Ryan, 2024). Institutions must refine capital allocation strategies and enhance risk

management frameworks to address these pressures (Resende et al., 2024). In addition, aligning ECL methodologies with regulatory frameworks such as Basel III is critical to avoid adverse impacts on banks' capital adequacy and lending behaviour. Greater collaboration between standard setters and regulators is necessary to optimise provisioning requirements (Mahieux et al., 2023; Rugilo, 2021).

Conclusion

Loan losses are an inherent and recurring aspect of banking operations, necessitating robust methodologies for credit loss provisioning. The transition from the ILA to ECL framework represents a paradigm shift in managing credit risk, offering more timely and forward-looking loss recognition.

The ECL framework provides superior insights into bank risk, particularly during periods of credit deterioration, compared with the ILA. Despite its merits, the ECL model poses significant challenges, including increased complexity in modelling, stringent data requirements, and heightened resource demands. Institutions must also navigate governance issues, procyclicality risks, and the interplay between accounting standards and regulatory frameworks.

To overcome these challenges, financial institutions must invest in data quality, enhance modelling techniques, adopt robust governance structures, and align strategic objectives with regulatory requirements. The RBI's proactive steps in promoting ECL implementation signal a positive direction, and with adequate support, scheduled commercial banks in India are well-positioned to navigate this transition. By addressing these challenges effectively, the banking sector can strengthen its risk management capabilities, build investor confidence, and foster long-term financial stability.

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