Predicting the Probability of Default for Banks' Expected Credit Loss Provisions

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Banks can effectively utilise the internal credit-rating migration trend to predict the future risk of default for corporate loans. This will enable them to more proactively identify credit impairment and make necessary forward-looking loss provisions.

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Credit risk assessment plays an important role in ensuring the profitability, soundness, and stability of any financial institution. The large losses incurred by the banks during the global financial crisis urged the accounting standard setters the world over, including the International Accounting Standards Board (IASB) and Financial Accounting Standards Board (FASB), to re-examine the incurred loss models for provisioning that the banks and financial institutions were following and redesign the guidance for provisioning which would be forward-looking and the expected credit loss (ECL) based on the International Financial Reporting Standard (IFRS) 9. India, too, has adopted IFRS 9 as Ind AS 109 mainly in the non-banking financial company (NBFC) segment. The proactive approach to make provisions on the probable losses even for the standard assets is a globally accepted prudent norm set by IFRS 9 standard. Recently, Shaktikanta Das, the Governor of Reserve Bank of India (RBI), highlighted the importance of keeping the expected loss-based forward-looking provisions for the safety of commercial banks in India. Currently, the RBI (2023) has issued a discussion paper on ECL-based approach for loan loss provisioning by the banks. The governor had already indicated this after announcing the bimonthly policy review held on 30 September 2022.

International evidence suggests that the incurred loss approach favoured a belated recognition of the problem that led to an absence of prompt corrective action and forbearance. It allowed banks to avoid booking losses for non-performing loans that were existing on their balance sheets. In the worst scenario, it also encouraged to sustain zombie lending.[1] Adaptation of IFRS 9 would benefit Indian commercial banks by improving their internal credit risk management process.

Probability of default is the major element in measuring the expected credit loss in banks. IFRS 9 requires the probability of default weighted scenarios in estimating the future credit loss provisions. The measures of the probability of default are either credit ratings or historical statistics on defaults which can be used to estimate the default risk. There is a significant association between credit ratings and default frequencies. The transition matrix-based probabilities within the theory of Markov chains have been suitably employed by many researchers (for example, Altman and Kao 1992; Carty and Fons 1994; Gupton et al 1997; Jafry and Schuermann 2004; Engelmann and Ermakov 2011; Gunnvald 2014) for the estimation of credit risk in terms of the future probability of default. The probability of default modelling aspects for IFRS 9 are further detailed in Bellini (2019).

This article explains how banks in India can optimally utilise internal corporate credit-rating migration history to compute the stage 1 12-month probability of default and stage 2 lifetime probability of default estimates. These derived probabilities of default can be used for the derivation of 12-month ahead as well as lifetime credit losses required by the new accounting standard, IFRS 9.

Expected Credit Loss Model

Conceptual framework: Three stages have been specified under the new accounting standard to determine the amount of impairment to be recognised as ECL at each reporting date. If the credit risk has not been increased significantly, the assets would have to be recognised in the stage 1 category. At this stage, IFRS 9 requires loan loss provisions in the banks to be based on 12-month expected losses. However, if the credit risk has increased significantly, assets will go to stage 2 and allowances to be made based on the lifetime analysis of the expected loss. If the loan is credit impaired, it will be put under stage 3 and the standard requires provisions to be based on lifetime expected losses where the probability of default is to be considered as 100%. The impairment of the asset has to be identified on the basis of "default event" (objective, market/performance-based evidence of non-payment of dues).

ECL under Ind AS 109 is defined as losses anticipated on a credit exposure/credit portfolio due to defaults expected to occur during the normal course of business. The major inputs of ECL are: (i) probability of default (PD), (ii) exposure at default (EAD), and (iii) loss given default (LGD).

The ECL methodology also considers the discount rate, which is the rate used to discount the future expected losses to the present value at the reporting date. It is also termed as effective interest rate (EIR). The arithmetic behind ECL calculation for stages 1 and 2 has been summarised in equations 1, 1a, and 2.

$$\text{12-month ECL}_t = PV_{EIR}\{EAD_t * LGD_t * PD_t\} \quad \ldots (1)$$

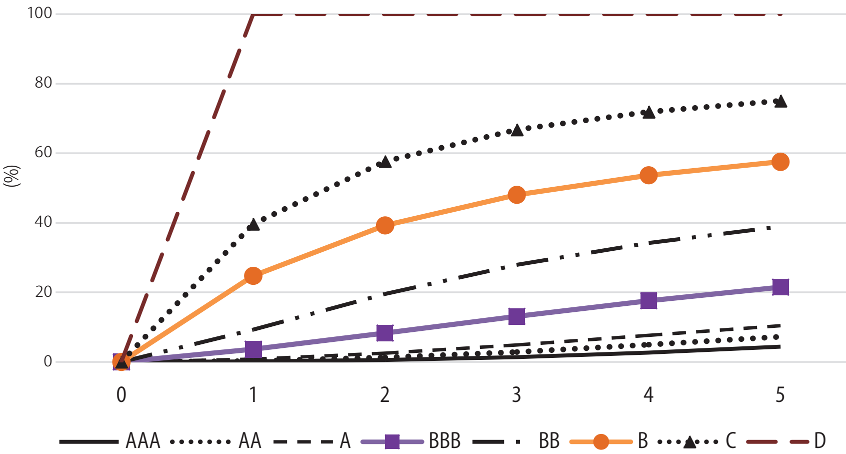
$$= PVEIR\{EAD_t * (1\text{- Economic Recovery Rate}_t) * PD_t\} \quad \ldots (1a)$$

$$\text{Lifetime ECL}_t = PV_{EIR}\{\Sigma(EAD_t * LGD_t * PD_t)\} \quad \ldots (2)$$

IFRS 9 ECL-based provisioning norms require institutions to use point-in-time (PIT) projections of probability of defaults, *LGDs*, and *EADs*. By accounting for the current state of the credit cycle at time *t*, PIT measures track closely the variations in default and loss rates over time. The term *PVEIR* is the present value at *EIR*. It captures the time value of money. The calculation of EIR includes all fees, transaction costs, and all other premiums or discounts that are directly related to the acquisition of financial assets on the book of an entity. For lifetime ECL estimation, the banks will have to predict the future probabilities of default over the lifetime of the loan. The summation (*Σ*) refers to the addition of all cashflows multiplied by the respective years' probability of defaults, LGDs, and EADs.

Figure 1: Projection of CPD

CPDs for the Bank



Source: Author's own estimates based on internal data of five public sector banks in India.

Estimation of borrower-level probability of default is the highlight of the ECL-based provisioning method mainly for stages 1 and 2 accounts. Banks need to derive forward-looking, more recent probability of default estimates. The lifetime probabilities of default are required for the estimation of stage 2 loss provisions.

Estimation of 12-month Probability of Default for ECL Purpose

By providing a probability of default for an obligor, one is providing a forecast of the likelihood of default over the specified horizon (for example, 12 months). We have followed discrete Markov-based transition matrix approach to derive the future probability of rating migrations to estimate the forward-looking probability of defaults. The Markov discrete stochastic property implies that the probability of an object (borrower account) occupying any given future state (future rating) depends only on its current state (current rating). A transition matrix describes a set of transition probabilities that fulfil this requirement. It acts as the indicator of the likely path of a given credit at a given time horizon.

As a first step, we start by mortality rate analysis of the yearly cohorts of companies for at least two years to find the number of firms, in each rating class in each cohort, moving towards default category (D). Each cohort comprises all the companies that have a rating outstanding at the start of the cohort year. From these cohorts, we calculate year-wise migration probabilities, including the default probabilities for different rating grades.

Say, there are $F_{i,j}$ number of firms migrating from *i*th rating to *j*th rating and N_i counts the number of firms rated at the start of period *t*. Thus, the one-year marginal probability that *i*th rated borrower will migrate to *j*th rating is estimatedby counting the frequencies $\left(\frac{F_{i,j}}{N_i}\right)$. These frequencies can be obtained from yearly cohort study (grade-to-grade movement).

The average one-year default probability for the *i*th rating grade will migrate to the *j*th rating grade (P_{ij}), obtained by the weighted average. The weights are the number of firms (*F*) in the *i*th rating class (or industry) in a particular year divided by the total number of firms (*N*) in all the years.

$$P_{ij} = \sum_{t=1}^{T} w_i^t \frac{F_{i,j}^t}{N_i^t} \quad \ldots (3)$$

where w_i is the weight representing the relative importance of a given year, that is, the relative number of accounts in each grade over time period (*t*). The weight

Table 1: Average One-year PIT-based Corporate Transition and Default Probability Matrix, 2015–21 (%)

		One-year Average Rating Transition Matrix, 2015–2021							
		T+1							
		AAA	AA	A	BBB	BB	B	C	D
	AAA	**65.00**	21.66	10.60	2.03	0.27	0.22	0.11	0.11
	AA	14.58	**55.15**	20.46	6.97	1.69	0.46	0.46	0.23
T	A	8.59	18.66	**52.76**	15.03	2.82	0.45	0.90	0.79
	BBB	6.07	10.03	14.92	**45.38**	14.83	3.60	1.57	3.60
	BB	0.58	4.62	9.83	13.01	**42.79**	14.14	5.78	9.25
	B	0.00	2.15	5.38	12.13	6.45	**40.58**	8.58	24.73
	C	0.00	0.54	1.50	3.54	7.69	10.15	**36.92**	39.66
	D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00

Source: Based on internal corporate rating data of five banks in India.

factor adjusts year-wise variability in default rates.

$$w_i = \frac{N_i^t}{\sum_{t=1}^{T} N_i^t} \quad \text{... (3a)}$$

Thus, one can estimate the probability of default for *i*th grade if *j* end grade is *D* or default. Using the above methodology, we have computed the average transition matrix for corporate loans based on the internal rating migration history of five public sector banks in India. For this, one can consider yearly cohorts: 2015–16, 2016–17, 2017–18, 2018–19, 2019–20, and 2020–21. Table 1 (p 16) reports the transition matrix for 2015–21 for all the borrower grades.

The probability figures reported in the default column are the grade-wise probability of defaults. One can look at the diagonal figures of the Table 1 matrix. These capture the probability of rating retention or rating stability. As can be seen, the rating stability declines as we move down the rating scale. Moreover, the probability of defaults monotonically goes up as we gradually move down from AAA to C. If the banks are using PIT ratings, these yearly probabilities of default can be used for the estimation of ECL.

The study by Perederiy (2015) advocates that the internal historical rating migration-based prediction of probability of default by the banks provides more reliable estimates of forward probabilities of default than the models based on macroeconomic forecasts. Stepankova (2021) empirically observes that bank-sourced credit transition matrices are more dynamic and PIT natured than those of credit-rating agencies (CRAs). Further, the data from banks provide a greater level of accuracy than the information provided by the CRAs.

Estimation of Stage 2 Probability of Default

The cumulative probability of default (CPD) gives us the default path for the entire lifetime of the loan. The CPD captures the incremental default probability of a borrower over a longer time horizon. CPD has uses in pricing the long-term loans and in studying the risk behaviour of the various grades over different maturity horizons. While the marginal probability of default (MPD) focuses on one-year estimate of risk, the CPD provides the lifetime (of the loan) estimate of risk.

The link between MPDs and CPDs is given in the following expression. The survival rate up to *n* years is:

$$(1 - cn) = (1 - cn{-}1)(1 - dn) \quad \text{... (4)}$$

where cn = cumulative default probability (CPD) dn = marginal default probability (MPD). The MPD: p1, p2,..., p10 can be estimated from the difference between two subsequent years' CPDs.

We have followed the matrix multiplication method to estimate the future probability of default that would be applicable for longer than one-year maturity for the ECL computation of stage 2 accounts. For this, we have used banks' transition matrix reported in Table 1.

Let us use the symbol *M* for the migration matrix given in Table 1 and define *G* to be a vector giving the probability of being in each grade, which is given in diagonal values of Table 1 (that is, rating retention). The probability distribution of ratings at the end of year *n* is given by *M* times *G*:

$$G_{T+n} = M^n G_T \quad \text{... (5)}$$

The estimated probabilities following equation 3 are the cumulative probabilities of default over the *n*th time horizon.

CPDs are important to find out the default probabilities over future horizon years for different rating buckets. This is crucial for the derivation of ECL for stage 2 accounts. Table 2 probability figures have been estimated by multiplying each row with its column of matrix 1 reported in Table 1.

The probability of default, given in the last column, is the two-year CPDs (CPD2). To better understand the CPD computation using algebra, let us take a numerical example. From Table 1, let us focus on A at the start of year T. The transition matrix forecasts that the borrower at A can retain as A with probability of 52.76%. However, it can upgrade to AAA with probability 8.59%, to AA with probability of 18.66%. The borrower can move down to BBB with probability 15.03%, to BB (prob=2.82%), to B (prob=0.45%) and to C with 0.90% migration probability. In the worst case, the borrower can go down to default with a 0.79% probability of migration. Assuming all these probable scenarios, the quest is: What would be the CPD (that is, movement from A to default or NPA) at the end of second year?

Thus, the CPD2 for an A rated borrower would be:

=8.59%×0%+18.69% × 0.23% + 52.76% × 0.79%+15.03%×3.60%+2.82%×9.25% +0.45%×24.75%+0.90%×39.66%+0.79% ×100%

=2.53% approximately.

This figure has been reported in Table 2, column D. Thus, it is obtained from the multiplication of row A with column default of Table 1 for the respective grades.

However, for estimating CPDs over three-, four-, and five-year horizons, we need to apply the matrix multiplication method. The estimated CPDs over longer horizons for all grades are given in Table 3.

Table 2: Two-year CPD Estimates Using Matrix Multiplication (%)

	AAA	AA	A	BBB	BB	B	C	D
AAA	46.44	28.22	17.26	5.41	1.28	0.50	0.37	0.51
AA	19.71	38.18	24.86	10.67	3.37	1.10	0.87	1.24
A	13.76	23.65	35.12	16.68	5.36	1.56	1.34	2.53
BBB	9.53	14.95	19.01	26.08	14.04	5.48	2.65	8.27
BB	2.93	8.12	13.19	15.20	21.95	12.91	6.14	19.55
B	1.55	4.62	8.03	12.53	8.02	18.72	7.27	39.25
C	0.47	1.71	3.29	5.41	7.36	9.09	15.02	57.66
D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00

Source: Author's own estimates using the banks' internal rating data.

Table 3: Banks' CPDs for Seven Standard Grades (%)

Time Horizon	AAA	AA	A	BBB	BB	B	C
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	0.110	0.230	0.790	3.600	9.250	24.730	39.660
2	0.511	1.238	2.529	8.266	19.555	39.249	57.664
3	1.349	2.857	4.889	13.102	27.884	48.031	66.774
4	2.644	4.915	7.591	17.556	34.158	53.663	71.885
5	4.344	7.258	10.430	21.479	38.882	57.521	75.035

Source: Author's own estimates using the banks' internal rating data.

It may be noted that the above probabilities of default are derived for each of the internal rating categories of the bank and would be applicable to credit facilities for which the latest bank ratings are available. Figure 1 (p 16) shows the CPD path over different time horizons as derived in Table 3.

Note that the above figures are CPDs, which give the probability of having fallen into the default grade. It shows the probability of default over five years. These CPDs can be used for stage 2 account ECL if the banks do not have yearly cash flows projections for various credit facilities.

However, if year-wise future cash flows are obtained, one can use the conditional MPD curve. We have estimated the conditional MPDs from the CPDs. The conditional marginal probability is the probability that the borrower will default in the given year, given that they did not default in any of the previous years. The conditional marginal probability for a given year is estimated using the following formula:

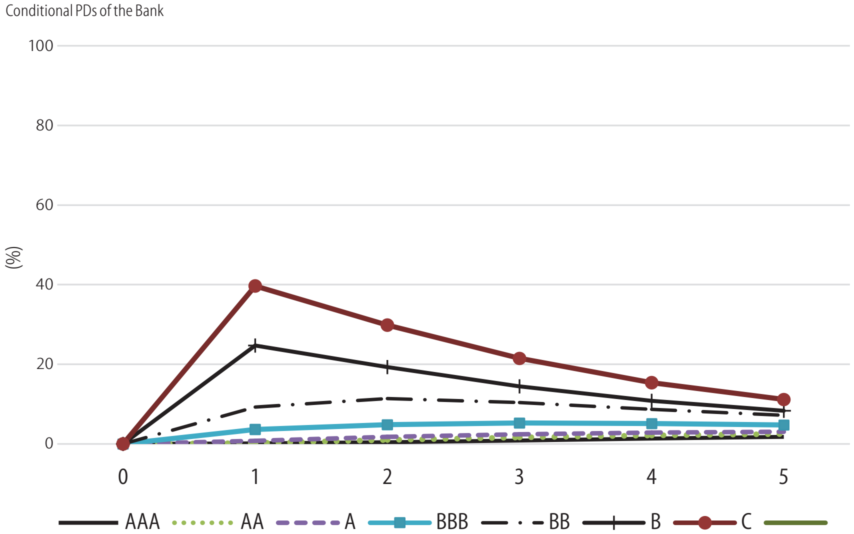
$$\text{PD-conditional at T} = \frac{\text{PDcum, T} - \text{PDcum, T} - 1}{1 - \text{PDcum, T} - 1} \quad \dots (6)$$

The figures reported in Table 4 show the conditional probability of default over five years.

These conditional marginal probabilities of default presented in Table 4 can be used to derive ECL estimates for stage 2 accounts that are having cash flows in different years up to their contractual maturity.

Figure 2 presents the conditional probability of default path over different time horizons. Note that conditional probability of default of any horizon is estimated assuming that the borrower has not defaulted in the previous horizon (or year). It is different from CPD which is more conservative since it does not pass the survival benefit to future years. Banks may end up with higher estimate of loss provision using ECL method if they use CPD instead of conditional probability of default. For this, they need to project future probabilities of default as well as track the yearly cash flows to be received from a loan through principal and interest payment.

Figure 2: Conditional Probabilities of Default Obtained from Cumulative Probabilities of Default



Source: Author's own computation based on internal rating data of five banks.

Banks need to assess, at each reporting date, whether credit risk on a corporate loan facility has increased significantly since the initial recognition. For significant increase in credit risk (SICR) among corporate loans, banks may consider slippage from high-grade or mid-grade category to the risky grade in a year as an additional indictor besides 30 days past due (as a backstop measure). This is due to the fact that both the probability of default as well as rating stability significantly change. These are considered as early detection measures.

Conclusions

Currently, the banks in India follow Income Recognition and Asset Classification (IRAC) norms given by the RBI which are based on incurred loss approach of provisioning, where money is set aside after an asset turns non-performing. They are yet to move to IFRS 9 standard to more proactively monitor and provide for impaired assets. The new financial-accounting norm moves away from the incurred credit loss estimation method to ECL model. It also considers trigger events and disincentivises a bank giving zombie loans.

Tracking the SICR is a novel addition in the new accounting norm since it will enable the banks to heighten the diligence to protect themselves from the risks of bad loans. The ECL calculates the expected present value of the loan losses that the bank may face if the borrowers default during the life cycle of the financial assets. The ECL methodology takes into account the historical probability of default trends as well as current and future economic scenarios and predictions. Thus, it significantly changes banks incentives by inclining them to manage and dispose-off bad loans much more actively than the existing process. The ECL method is expected to bring prudence in lending since banks will be able to better monitor their loan slippage and track rating movements.

Table 4: Bank's One-year Conditional Probabilities of Default for Different Time Horizons

Years	AAA	AA	A	BBB	BB	B	C
0	0.000	0.000	0.000	0	0	0	0
1	0.110	0.230	0.790	3.600	9.250	24.730	39.660
2	0.402	1.010	1.753	4.840	11.355	19.289	29.838
3	0.842	1.640	2.421	5.272	10.355	14.457	21.519
4	1.313	2.119	2.841	5.126	8.699	10.836	15.382
5	1.746	2.464	3.072	4.758	7.174	8.326	11.205

Source: Author's own estimates.

NOTE

1 Zombie lending refers to extending credit to entities that do not have the capability to repay.

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