Expected Credit Losses

WORLD BANK GROUP

AABE

Accounting and Audit Board of Ethiopia
የኢትዮጵያ የሂሳብ አያያዝ እና ኦዲት ቦርድ
Established under proclamation no 847/2006

Disclaimer

» The sponsors, the authors, the presenters and the publishers do not accept responsibility for loss caused to any person who acts or refrains from acting in reliance on the material in this PowerPoint presentation, whether such loss is caused by negligence or otherwise.

» Unless specified otherwise, the accounting requirements that are the subject matter of this presentation are International Financial Reporting Standards (IFRS) as issued by the International Accounting Standards Board (IASB) that are applicable for annual period beginning on or after 1 January 2023 without early applying new and amended IFRS Accounting Standards that have a later mandatory application date.

Common Methodologies for Measuring ECL

Discounted Cash Flow Methodology

A discounted cash flow analysis is based on the present value of expected future cash flows discounted at the loan's effective interest rate. The allowance for credit losses is the difference between the amortized cost basis and the present value of the expected cash flows.

Loss-Rate Methodology

Under a loss rate approach, loss rate statistics are developed on the basis of the historical rate of loss of the financial assets. When computing its loss rates, an entity should segment its portfolio into appropriate groupings or sub-portfolios based on shared credit risk characteristics. These historical credit loss trends should then be adjusted for current conditions and expectations about the future. Credit losses are calculated using the estimated loss rate and multiplying it by the amortized cost of the asset at the balance sheet date.

Roll-Rate Methodology

The roll-rate method is often referred to as "migration analysis". Roll rates are determined by predicting credit losses by segmentation (for example, by delinquency or risk rating) of a portfolio of financial assets. An assessment of the roll rate is made (the percentage of balances of the number of accounts which move from one delinquency stage to the next). Once a roll rate is determined for each segment, it is applied to the balance in each category to estimate the amount that will migrate to the next category. The total migrations across all categories are aggregated to determine the estimate of credit losses.

Measurement of expected credit losses (ECL)

Estimates of expected credit losses should reflect an entity's *own* expectations of credit losses; entities should be able to explain how they have arrived at their estimate and how it is based on reasonable and supportable information.

Consider market information.

Expected credit losses are estimates, which will be updated as more reasonable and supportable information becomes available over time.

THE NEED FOR MODELS

What is a Model?

- A model is a representation containing the essential structure of some object or event in the real world.
- They are as ancient as our understanding of the physical world – the model of the atomic structure for example.
- Have been used in a number of areas from Physics, Engineering and Social Sciences.
- Finance since the birth of the Black Scholes Merton formula which lead to the birth of Quantitative Finance.

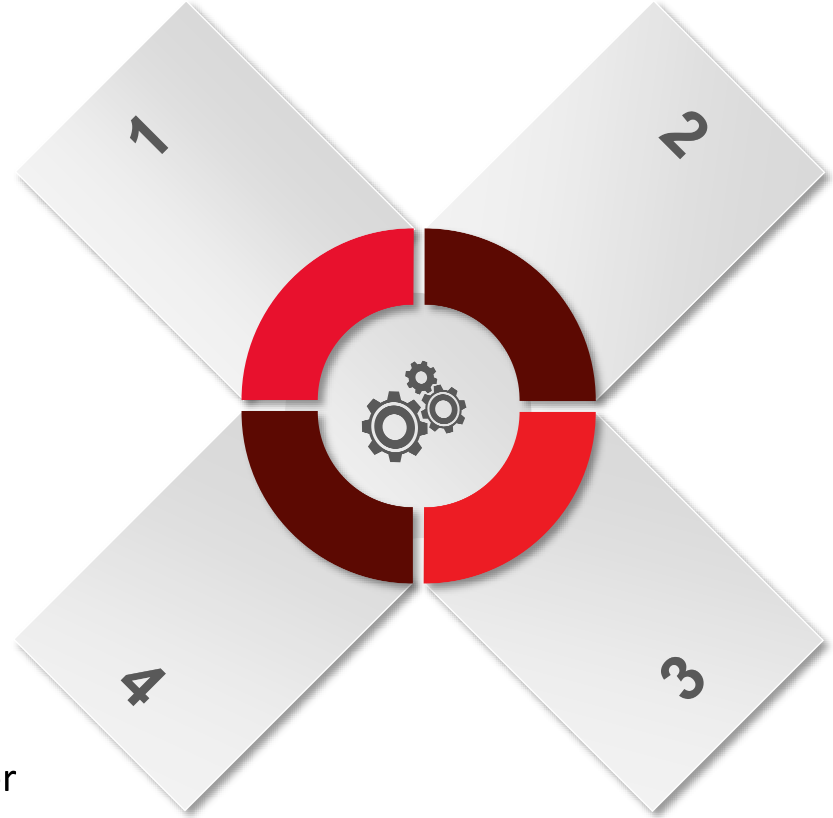
Why Use Models?

1

We need to use Models as we are trying to PREDICT the future losses and NOT current losses.

2

So any ECL model has to be designed to meet the measurement objectives of IFRS 9.



3

The Models therefore have a VERY specific PURPOSE.

4

All Models should be evaluated keeping this purpose in mind:

- New models developed for ECL;
- Regulatory models adapted for ECL; or
- Vendor or Consultant developed models.

Consequences of Using Models

Measurement Uncertainty

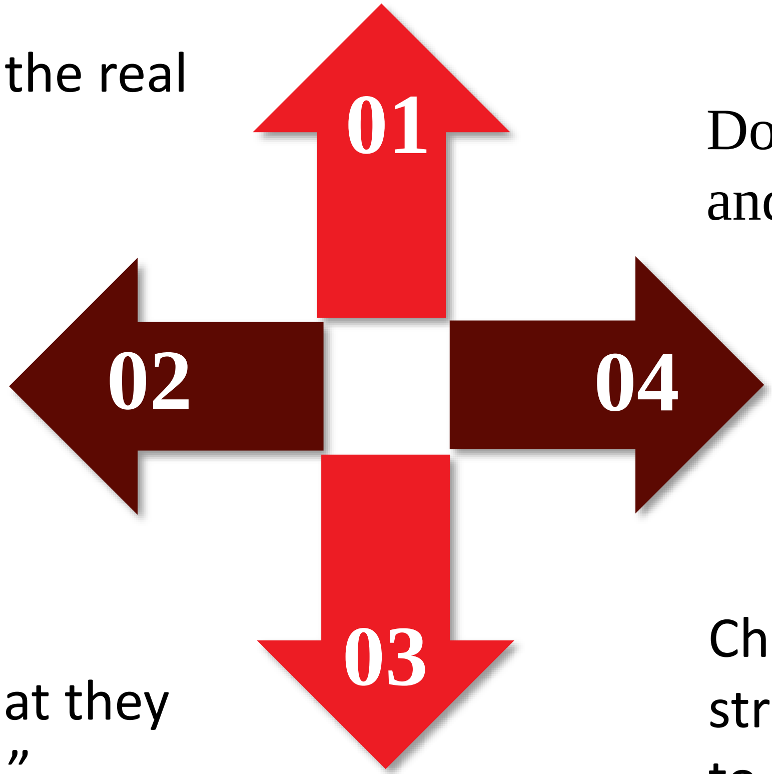
(BC 5.85) Expected credit losses, in isolation, are not directly observable. ……..
But, because expected credit losses are not directly observable, their measurement is inherently based on judgement and any model that attempts to depict expected credit losses will be subject to measurement uncertainty.

Any review of ECL therefore has to focus on measurement uncertainty and the challenges they pose.

Models: Limitations

It is only a representation of the real world; Not Reality.

Does not obviate human intervention and critically judgement.



Consequently one inherent characteristic of models is that they “are necessarily incomplete. ”

Challenge is to capture the essential structure of the object we are trying to model be it credit risk, market risk or operational risk.

Models: Why do we need them?

01 Provides a "Logical structure or framework" for measuring and quantifying essentially an illusive concept 'Risk'.

02 Has the ability to quantify impact under various scenarios.

03 Provides a flexible tool for understanding the exposures and risks carried by an institution.

04 Combined with judgement can be a very powerful tool to aid decision making and managing the chameleon of Risk.

05 As of date the best method we know to handle such concepts and I do not see them going away soon.

Features of a good quantitative model

01 Reasonable, understandable risk drivers

02 Uncorrelated risk drivers

03 Limited number of risk drivers in the model

04 Risk drivers with high predictive power

05 All important information covered

06 High and stable predictive power of the model

07 Credit Department acceptance

CREDIT RISK MODELS: A PRIMER

Credit Risk Models

Two primary types of models:

01

Structural Models

02

Reduced Form Models
(Statistical Models)

Credit Risk Models: Structural Models of Credit Risk

Structural models in use:

- Merton's Model
- KMV
- Z Metrics

Structural models use the evolution of firms' structural variables, such as asset and debt values, to determine the time of default.

Defaults are endogenously generated.

The value of the firm's assets and liabilities at default determine recovery rate.

PD MODELS

Parametric and Non-Parametric models

Parametric Methods

» Linear Regression
» Discriminant Analysis
» Binary Response (Logit / Probit)
» Panel Data
» Hazard

Non-Parametric Methods

» Neural Networks
» Decision Tree

Univariate Analysis: Linear Regression

Linear relationship between borrower's characteristics and default variable

$$Y_i = bX_i + u_i$$

Y indicates whether borrower has defaulted (Y = 1) or not (Y = 0)
X is a column vector of the borrower's characteristics
b is a column vector of parameters which captures the impact of change in characteristics on default variable
u is residual variable which contains variation not captured by X
Easy to understand and compute
However if the u_i i.e. the residuals are heteroscedastic and therefore fails the BLUE conditions as the variance of u_i is not constant.
Consequently the estimate of b is inefficient and more critically biased.

Multi-Variate / Multi-factor Analysis

Such analysis encompasses:

- Optimal factor selection to select best single factors
- Correlation analysis to prevent multi-collinearity
- Generation of long-list of potential factor combinations to reflect common sense (based on factor categories) besides correlation analysis
- Primary validation to reduce long list based on statistical performance
- Regression optimization analysis to assign weights to factors
- Final analysis to study performance of best combination in great detail

Logit / Probit Models

Aim is to estimate default probabilities

For groups of borrowers the default frequency can be observed and interpreted as default probabilities.

Consider the simple regression equation: $Y_i = bX_i + u_i$

The outcome is not bounded between zero and one and therefore cannot be interpreted as default probabilities.

So we need to transform bX_i using a non-linear function and it is done as follows: $p_i = F(bX_i)$

Where F is a non-linear function which transforms the values of bX_i to a scale within the interval [0,1].

Logit / Probit Models - Motivation

- It is the choice of F that determines the model i.e. Logit or Probit
- With a logistic link function it becomes a Logit Model and
- With a normal distribution results in the Probit Model.
- Differences between the model results can often be negligible..
- However the Logit model has some advantages.

Logit / Probit Models

Designed for analysing binary dependent variables

$$Y^*_i = bX_i + u_i$$

Latent variable approach assumes an unobservable (latent) variable Y^*_i which is related to the borrower's characteristics

Y^*_i triggers the value of binary default variable Y_i such that $Y_i = 1$ if $Y^*_i > 0$, else $Y_i = 0$.

Probit model: Normal distribution for residuals (u_i)

Logit model: Logistic distribution for residuals (u_i)

Results can be interpreted directly as probability using the transform:

$$P_i/1-P_i = e^{bXi}$$

Theoretically sound

Significance of the model and individual ratios can be tested.

Logit / Probit Models Example

We perform the following steps to estimate the model:

To estimate the model, we need a set of independent variables and data for sample firms.

Next, we select a large sample of firms as our data set and divide it into estimation sample (for estimating the model) and validation sample (for validating / testing the model). Both samples would contain both defaulting and non-defaulting firms

The final model should contain few, significant variables, hence, we begin with all variables and eliminate those which are not significant in explaining default till we are left with a model with few variables all of them significant (this final model is shown in previous slide)

Do not underestimate the challenge of selecting the right ratios (We will come back to this in more detail later)

Logit / Probit Models Example

Consider the case of a firm whose probability of default is dependent on a set of financial ratios (the significant variables) such as equity / total assets, bank debt / total assets, short term debt / total assets and accounts payable / net sales

We can write the model as:

Prob. of default = constant + b1 * (equity / total assets) + b2* (bank debt / total assets) + b3*(short term debt / total assets) + b4*(accounts payable / net sales)

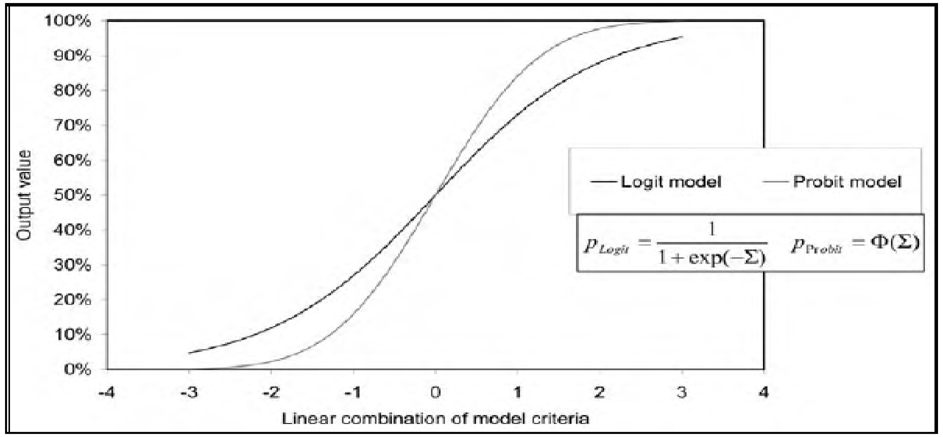
Now, using the firm data in estimation sample, we estimate the coefficients for the model

Logit / Probit Models Example

Parameters	Hypothesis
Equity/ Total Assets	-ve
Bank debt / Total Assets	+ve
Short term debt / Total Assets	+ve
Accounts payable / Net Sales	+ve

- We need to formulate a clear hypothesis for the input variable about its impact on the PDs estimated by the model.
- For example as equity/total assets increase the PD should decrease and vice versa for the other parameters.
- This is not always that simple. Consider Net Sales/ Net Sales last year:
- Although sales growth is good, unrestrained growth can lead to default.
- So the hypothesis can at times be +/-

Logistic Regression Model



01

Could include qualitative factors in the analysis

02

Generates the outcome between 0 and 1, and therefore can be interpreted as probability of default

03

Has no normality assumption for input indicators

04

Response variable is assumed to be linearly related to the explanatory variables

OTHER APPROACHES

IFRS 9

IFRS 9 does NOT mandate the use of PD, LGD models.

It is not prescriptive about the method used for measuring credit risk as long as the objectives of the measurement are met.

Expected Credit Losses – What is IFRS 9 aiming for?

Objective (5.5.17)

An entity shall measure expected credit losses of a financial instrument in a way that reflects:

a) An unbiased and probability-weighted amount that is determined by evaluating a range of possible outcomes;
b) The time value of money; and
c) Reasonable and supportable information that is available without undue cost or effort at the reporting date about past events, current conditions and forecasts of future economic conditions.

Principal Based Approach to Measurement (BC 5.242)

The 2013 Impairment Exposure Draft and 2009 Impairment Exposure Draft proposed to define expected credit losses as the expected present value of all cash shortfalls over the remaining life of the financial instrument. The IASB decided to retain the emphasis on the objective of the measurement of expected credit losses, and to keep the requirements principle-based instead of specifying techniques to measure expected credit losses.

Expected Credit Losses – What is IFRS 9 aiming for?

(BC 5.266) The IASB also acknowledged that an entity may use various techniques to measure expected credit losses, including, for the 12-month expected credit losses measurement, techniques that do not include an explicit 12-month probability of default as an input, such as a loss rate methodology. The requirements in Section 5.5 of IFRS 9 do not list acceptable techniques or methods for measuring the loss allowance. The IASB was concerned that listing acceptable methods might rule out other appropriate methods for measuring expected credit losses, or be interpreted as providing unconditional acceptance of a particular method even when such a measurement would result in an amount that is not consistent with the required attributes of an expected credit loss measurement. Instead, Section 5.5 of IFRS 9 sets out the objectives for the measurement of expected credit losses, allowing entities to decide the most appropriate techniques to satisfy those objectives.

Expected Credit Losses – What is IFRS 9 aiming for?

(B 5.5.12) An entity may apply various approaches when assessing whether the credit risk on a financial instrument has increased significantly since initial recognition or when measuring expected credit losses. An entity may apply different approaches for different financial instruments.

Measurement Objective and Requirements

(B 5.5.28) Expected credit losses are a probability-weighted estimate of credit losses (i.e. the present value of all cash shortfalls) over the expected life of the financial instrument. A cash shortfall is the difference between the cash flows that are due to an entity in accordance with the contract and the cash flows that the entity expects to receive. Because expected credit losses consider the amount and timing of payments, a credit loss arises even if the entity expects to be paid in full but later than when contractually due.

IFRS 9 DOES NOT stipulate any particular type of Model.

Different models can therefore be used depending on nature of asset, data availability and preparer and used sophistication.

What IFRS 9 *doesn't require* and the ITG *didn't* say

You must always use multiple scenarios

You must use three scenarios

You must use 'PD'

Application to a non-PD based approach

- Illustration of one of the possible approaches

Illustrative scorecards inputs

Retail	Wholesale
Customer age	Profitability
Employment status	Size
Customer income	Gearing

Some inputs may have a non-linear relationship to changes in macroeconomic parameter. Consideration of multiple scenarios may be required for such inputs.

Adjusted scorecard

Credit scores & credit rating

ECL

Global Experience

Even the largest banks will use the simplest model if that model:

- Provides the best estimate of credit losses;
- Is the best model to use given systems limitations;
- Most critically is the best model to use given data availability and limitations.

Loss Rate Approach

Loss-Rate Methodology

Under a loss rate approach, loss rate statistics are developed on the basis of the historical rate of loss of the financial assets. When computing its loss rates, an entity should segment its portfolio into appropriate groupings or sub-portfolios based on shared credit risk characteristics. These historical credit loss trends should then be adjusted for current conditions and expectations about the future. Credit losses are calculated using the estimated loss rate and multiplying it by the amortised cost of the asset at the balance sheet date.

Sometimes also called the WARM or Weighted Average Remaining Maturity Method or some other nomenclature.

Loss Rate Approach

Uses observed loss rates on portfolios with qualitative adjustments to determine ECL.

Works for both IFRS and US GAAP.

But approach different under each GAAP.

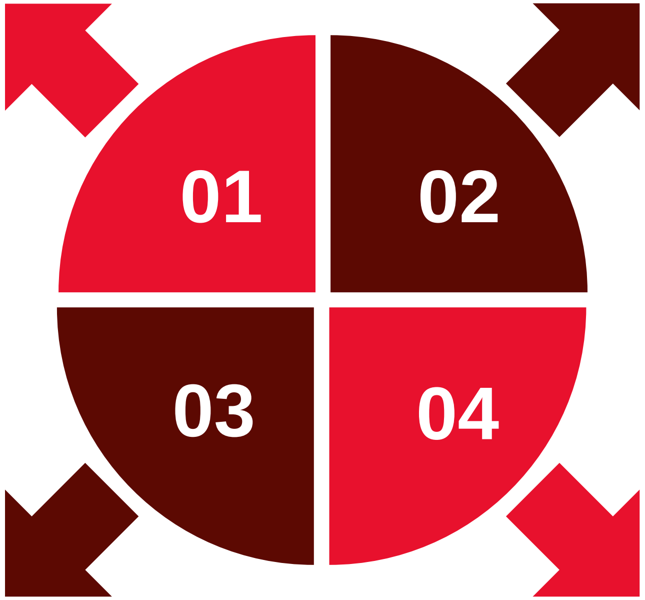
Best illustrated through an example.

TESTING OF MODELS / BACK TESTING

Outcome Analysis / Back Testing of models

Comparison of model outputs to actual outcomes.

Evaluates model performance by establishing expected ranges and key reasons for any variation.



Typically relies on statistical tests or other quantitative measures.

Outlines procedures for dealing with results of the outcome analysis.

Outcome Analysis / Back Testing of models – Regulatory Expectations

The performance of models and the models that input into the calculation should be backtested. The backtesting framework should be able to identify poor performance in EPE model components.

The backtesting of models and all the relevant risk factors that input into the calculation should be performed separately for a number of distinct time horizons. The time horizons considered must include those that reflect typical margin periods of risk.

The validation of models and all the relevant models that input into the calculation should be made using forecasts initialised on a number of historical dates.

Validation of Vendor Models

- Appropriate processes in place for selecting vendor models.
- Require the vendor to provide developmental evidence explaining the product components, design, and intended use, to determine whether the model is appropriate for the bank's products, exposures, and risks.
- Vendors should provide appropriate testing results that show their product works as expected. They should also clearly indicate the model's limitations and assumptions and where the product's use may be problematic.
- Expect vendors to conduct ongoing performance monitoring and outcomes analysis, with disclosure to their clients, and to make appropriate modifications and updates over time.
- Validate their own use of vendor products as external models may not allow full access to computer coding and implementation details.

Validation of Vendor Models (contd.)

- Rely more on sensitivity analysis and benchmarking.
- Customization choices should be documented and justified as part of validation. Should conduct ongoing monitoring and outcomes analysis of vendor model performance using the bank’s own outcomes.
- Detailed knowledge is necessary for basic control operations in case the vendor or the bank terminates the contract for any reason, or if the vendor is no longer in business. Should have contingency plans for instances when the vendor model is no longer available or cannot be supported by the vendor.

APPENDIX

Financial ratios selection for multivariate analysis

1. Take only ratios with sufficient GINI values (ex 5%, 10%, 15% etc.)
2. Get rid of unstable ratios
3. Take only uncorrelated ratios
4. Take ratios from every financial category (make sure you covered all risky aspects)

Logit / Probit Models Example (Contd.)

A word on financial ratios:

Please note what goes in there and then adapt accordingly

What GAAP is being used for financial reporting – comparing local GAAP numbers with USGAAP or IFRS may not yield good results

Consistency is of critical importance

Logit / Probit Models – Linearity Test

Remember we said that the transformation in a Logit model is as follows:

$$\mathbf{P_i/1\text{-}P_i = e^{bXi}}$$

Where $Pi/1\text{-}P_i$ is the odds ratio.

$$\mathbf{Log\ odd = \ln(P_i/1\text{-}P_i\ ) = bX_i}$$

This can be tested as follows:

Subdivide the indicators into groups containing the same number of observations

Calculate empirical log odd within each group and estimate a linear regression of the log odds

Review the results for linearity

Logit / Probit Models Example (Contd.)

Even with a small sample of say 12 indicators or financial ratios we have to build $2^{12} = 4{,}096$ models in order to determine the best econometric model.

A bit difficult!

So following Hosmer and Lemeshow we use the forward / backward selection method.

Start by building the full model with all parameters

Eliminate the worst covariates or parameters one by one until the significance level of all remaining explanatory variables is below the chosen critical level

Usable model with limited input parameters

Logit / Probit Models Example (Contd.)

The Hosmer-Lemenshow test statistic can be used for goodness of fit as it measures how well a Logit model represents the actual probability of default.

It derives the expected number of defaults per group using the average estimated default probability.

This is compared with the realised defaults in each group.

The test statistic then summarises the results for all groups.

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	1217.774	1033.797
SC	1224.812	1090.099
-2 Log L	1215.774	1017.797

- The Model Fit Statistics table contains the Akaike Information Criterion (AIC), and the Schwarz Criterion (SC)
- Both are goodness-of-fit measures that can be used to compare one model to another.
- Both depend on the number of parameters in the model.
- Lower values of the statistics indicate a more desirable model.

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
rd_liq _4	13.4666	2.444	74.191
rd_ pro _33	2.631	0.986	7.021
rd_deb_28	11.872	1.688	83.483
rd_eff_00	2.643	1.335	5.233
rd_ pro_01	5.759	1.979	16.765
rd_deb_02	21.749	4.325	109.376
rd_deb_29	3.003	1.419	6.355

The odds ratio measures the effect of the input variable on the target adjusted for the effect of the other input variables.