

Private and Confidential

IFRS 9 Training

April 2019

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Introduction

- IFRS 9 Financial Instruments has been a significant change to the accounting for financial instruments, in particular for financial institutions.

- This two-day workshop is to familiarize the participants with modeling techniques for IFRS 9 ECL computations from an implementation perspective. This will cover the underlying concepts, data requirement, key decision points as well as challenges with regard to various modeling techniques

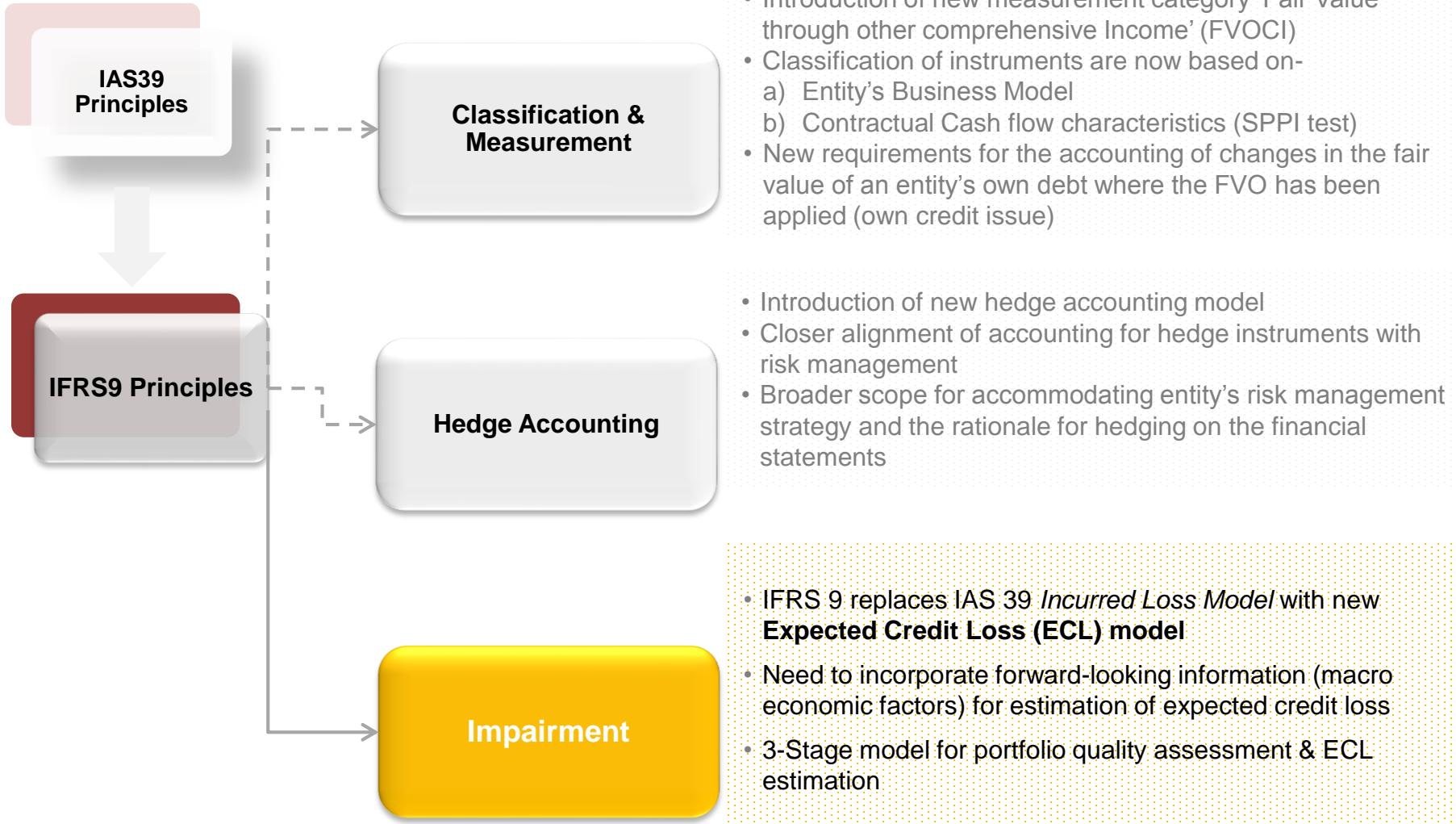
- **Key Learning Outcomes**
 - ▶ Analyze the requirements of expected credit loss impairment model
 - ▶ Understand different modeling techniques available to estimate forward-looking PD, LGD, and EAD
 - ▶ Understand the limitations and usage of various approaches for risk components estimation
 - ▶ Analyze the model maintenance requirement due to IFRS 9 compliance

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Our vast risk management experience with 100+ banks over the last thirteen years separates us as a clear regional frontrunner. We have worked with 4 of the top 10 leading banks in US, 8 of the top 10 banks in Saudi Arabia, 5 of the top 8 banks in UAE, 4 of the top 8 banks in Bahrain, Top 3 banks in Jordan, 2 of the top 3 banks in Lebanon, 4 of the top 10 banks in India and 6 of the top 10 banks in Sri Lanka.



ECL ingredients and Building Blocks



Simpler Approaches

Term to maturity approach

- Does not estimate PD, EAD and LGD for separate time intervals
- Instead, uses a single measure of each for the remaining term in order to measure lifetime ECL
- More suited to exposures that are non-amortizing and cannot be prepaid and shorter term

Loss rate approach

- PD and LGD are assessed as a single combined measure, based on past losses, adjusted for current conditions and forecasts of future condition
- Use when the data is insufficient to measure the components separately

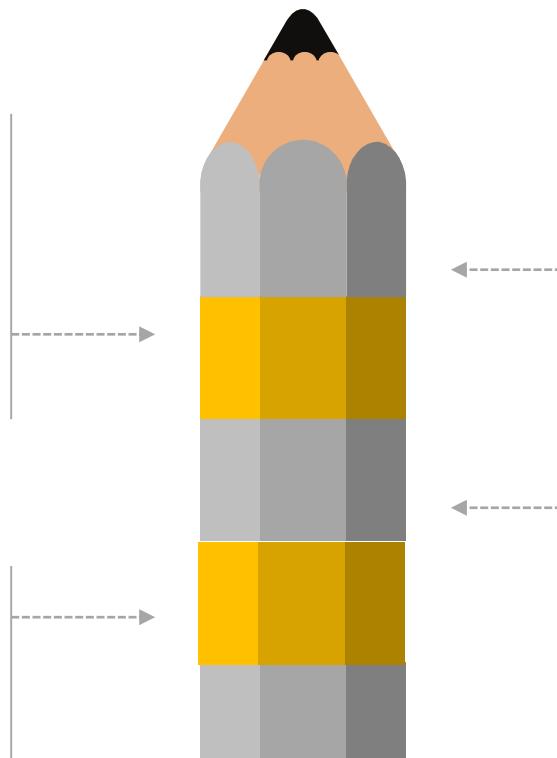
Sophisticated Approaches

PD^*LGD^*EAD - Collective

- Assessment of staging and PD, LGD & EAD measures on a collective basis
- Grouping of exposures into segments on the basis of shared credit risk characteristics
- Suitable for retail and SME exposures

PD^*LGD^*EAD - Individual

- Assessment of staging and PD, LGD & EAD measures on an individual basis
- Calculating each component for a series of time intervals over the period of exposure (such as monthly, quarterly or annually)
- Mandatory for large exposures



ECL

- PD*LGD*EAD Approach
- 12 month ECL for Stage 1 assets
- Lifetime ECL for Stage 2 assets



Probability of Default (PD)

- TTC PD
- PIT PD Calibration
- 12 month and Lifetime PD estimation



Definitions and Data Requirements

- The degree of likelihood that the borrower will not be able to repay
- Data Required: Historical Observed Default Rates (ODR), Macroeconomic Variables etc.

Loss Given Default (LGD)

- Workout LGD (historical average recovery)
- Or Regulatory LGD as proxy
- Or FIRB LGD



Definitions and Data Requirements

- LGD is defined as the loss amount when a borrow defaults on a loan
- Data Required: Date of Default, Discount Rate, Recovery Amount & Date etc.

Exposure at Default (EAD)

- Outstanding Balance as of reporting date for stage 1
- Repayment schedule for stage 2 assets
- CCF for Off-BS items

Definitions and Data Requirements

- Total outstanding on the reporting date (including off-balance sheet portion after CCF)
- Data Required: Amortization Schedule, Prepayment Rates, Credit Conversion Factor estimates etc.

An entity shall measure the expected credit losses in a way that reflects the time value of money. Expected credit losses shall be discounted to the reporting date using the effective interest rate determined at initial recognition or an approximation thereof.

Model Landscape for IFRS

Portfolio Type	Model Type	Model Sub Type	Development Complexity					
			Data Sufficiency	Methodology Soundness Study	Quantitative Validation	Qualitative Validation	Documentation	Validation Overall Complexity
Wholesale	Credit Rating Model/ Scorecards	Pure Expert Opinion (Judgment Based Scorecards)	Low	Medium	Low	Medium	Medium	Low
		Complex Hybrid Model (Judgment + Statistical Model)	High	High	High	Medium	High	High
		Pure Vended Models (Moody's MRA, S&P etc.)	High	High	High	Medium	High	High
	PD	External Benchmarking	Approaches for Calibrated TTC PD	Low	Medium	Medium	Medium	Medium
		Judgement Based		Low	Medium	Low	Low	Medium
		Curve adjustment (based on historical default data)		High	High	High	Medium	High
		Vasicek Formula (for LDP)	Approaches for Macro adjusted and Calibrated PIT PD	Medium	High	High	Low	High
	LGD	External Benchmarking (for LDP)		Medium	Medium	Low	Low	High
		Regression (for HDP)		High	High	Low	Low	High
		Z Score (for HDP)		High	High	High	Medium	High
	EAD	Haircut Based LGD	Fyre Jacobs Transformation to Macro adjust the instrument level LGDs	Medium	Medium	Low	Medium	Medium
		Regression		High	High	High	Low	High
		Decision Tree		High	High	High	Low	High
	EAD	Regression Model – CCF Model (for revolving line)	Medium	Medium	High	Low	High	Medium
		Direct Value – CCF Model (for revolving line)	Medium	Medium	Medium	Medium	High	Medium
ECL	PD*LGD*EAD (Basel Loss Equation)		High	High	High	Medium	High	High

Portfolio Type	Model Type	Model Sub Type	Development Complexity					
			Data Sufficiency	Methodology Soundness Study	Quantitative Validation	Qualitative Validation	Documentation	Overall Complexity
Retail	Segmentation Models	Expert Judgment	Low	Medium	Low	Medium	Low	Low
		Statistical Techniques (CART, CHAID etc.)	High	High	High	Low	High	High
	PD	Vasicek Formula (for LDP)	<i>Approaches for Macro adjusted and Calibrated PIT PD, taking the historical default rates as input</i>	Medium	High	High	Low	High
		External Benchmarking (for LDP)		Medium	Medium	Low	High	Medium
		Regression (for non-LDP)		High	High	High	Medium	High
	LGD	Haircut Based LGD	<i>Fyre Jacobs Transformation</i>	Low	High	Low	Medium	Low
		Pool Based LGD (Empirical estimate based on historical data)		High	High	High	Medium	High
		Macro Regression		High	High	High	Medium	High
	EAD	Regression Model – CCF Model (for revolving line)	Medium	Medium	High	Low	High	Medium
		Direct Value – CCF Model (for revolving line)	Medium	Medium	Medium	Medium	High	Medium
	ECL	Collective Loan Loss Assessment (Historical Exposure vs Default/Loss Measurements)	<i>Loss rate Approach (Collective measurements)</i>	Medium	Medium	Medium	Medium	Medium
		Pool Level Grouping (Pool Level PD, LGD, EAD Assessment)		Medium	High	High	Low	High
		Individual Assessment (PD*LGD*EAD)	<i>PD/LGD/EAD Approach</i>	High	High	High	Low	High
		Discounted Cashflow Assessment		Medium	High	Medium	Medium	Medium

PD Modeling – Corporate and SME Portfolios

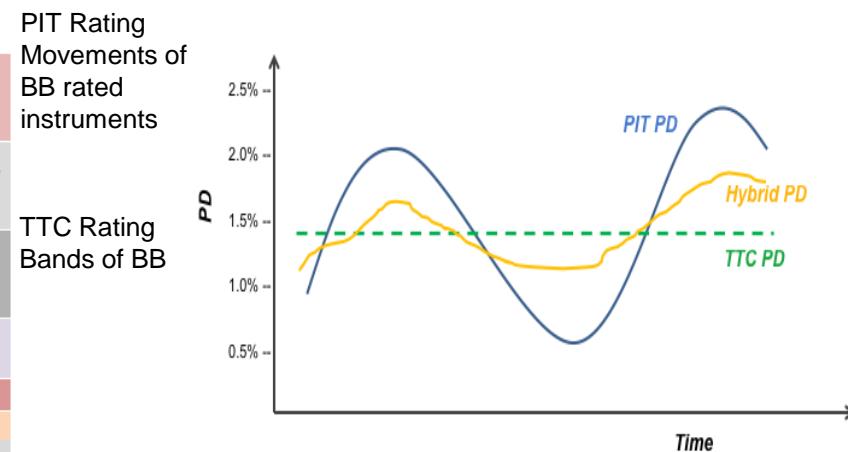
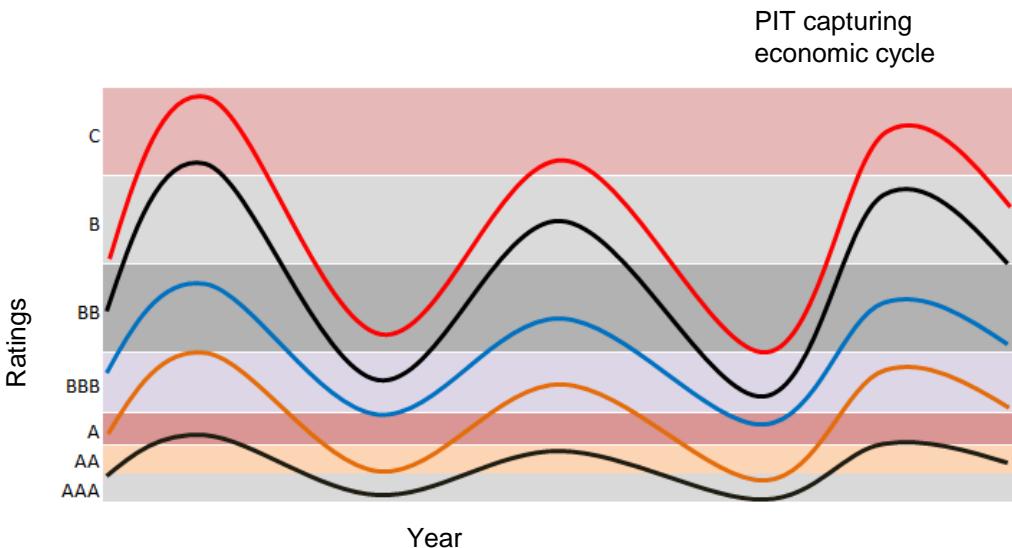
Observed Default Rates (ODR)

- For any calculation associated to PDs, the ODRs forms a critical input
- The ODRs are calculated for each of the pool using the default definition as mentioned below.
 - ▶ **Default Category** – A performance period of 12 months is considered for tagging of defaults. Account level DPDs are tagged through the performance period. For cases where the DPD is above 90 (or 3 Months past due) during the performance period, then these are tagged as default.

Note: *The default rates are computed post applying the curing period criteria. As per the curing period criteria, if a customer has defaulted any time in 12 months prior to the snapshot date, then that customer would be removed from the base. Basically, ‘bad’ or ‘near-bad’ cases on start date are removed from the base for computation of ODR.*

- The following steps have been followed in the process of default rate computation:
 - Calculate the number of performing customer at the start of the year post applying the probationary period concept. (In curing period concept, the customers that have been in the “Default Category” as described above, in any of the 12 months prior to the snapshot date are excluded from the base)
 - The defaulted customers which get self cured (back to <90DPD) maybe excluded from the default count
 - The default rate is calculated as number of new defaults in the next 12 months from the observation date, as a percentage of performing customers at the observation date
 - Calculate historical observed default rates (ODR) on quarterly basis for each pool
 - Take a count-weighted average across time for portfolio/grades/pools (depending on data granularity)

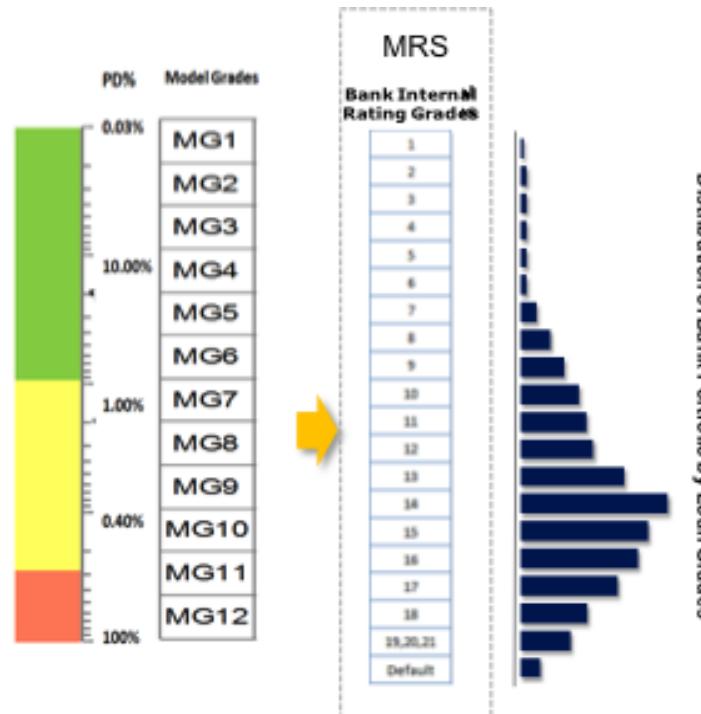
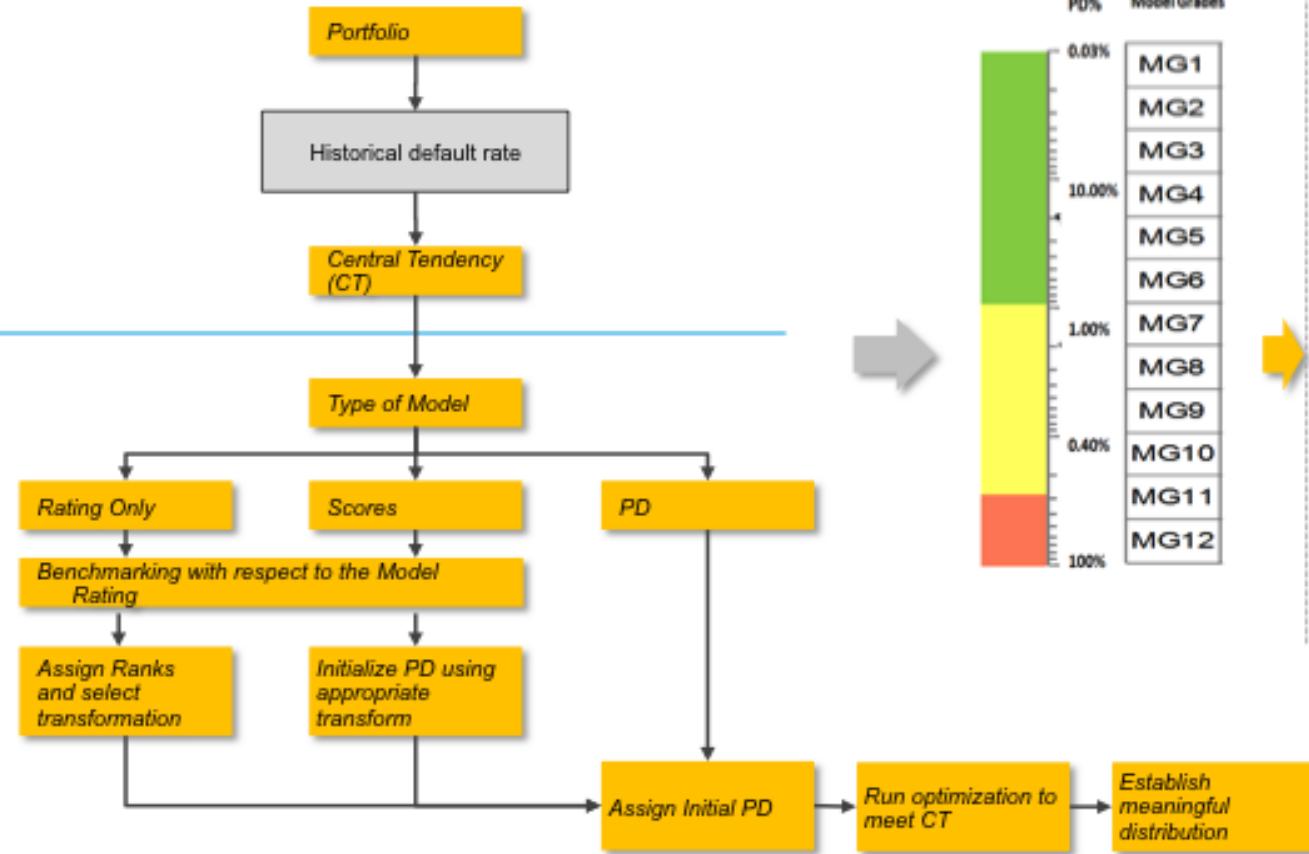
- A rating model that includes both idiosyncratic and macroeconomic factors is said to follow PIT rating philosophy.
- Due to presence of macro economic factors, score/grade generated by PIT rating model will be pro-cyclical in nature and will closely mimic observed default rates with correlation closing in to 100 percentage under ideal conditions.
- If a rating model includes only idiosyncratic factors, the model is said to follow TTC philosophy. The score/grade generated by TTC rating model will show little or no variation over the economic cycle and will closely mimic long term average observed default rate.
- PD predicted by PIT Rating model is called PIT PD and PD predicted by TTC Rating Model is called TTC PD.
- In reality, it is difficult to develop a pure PIT or TTC Model. Hence PIT and TTC ness of the rating model needs to be tested before calibrating them to either PIT or TTC PD.



TTC Calibration to grades/pools

- The bank can leverage the existing TTC PDs from the Internal Rating Model, as may be provided by the vendor or internally computed by the bank
- However, these PDs need to be recalibrated before being put to use in any calculations

Approach
Model Type Dependency



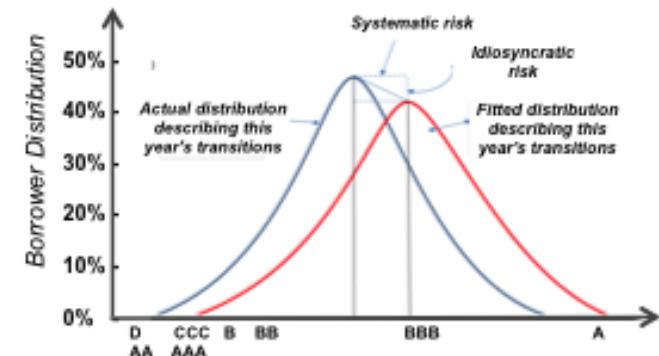
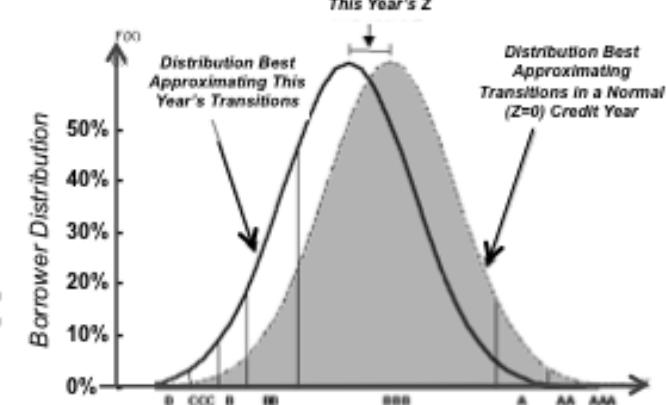
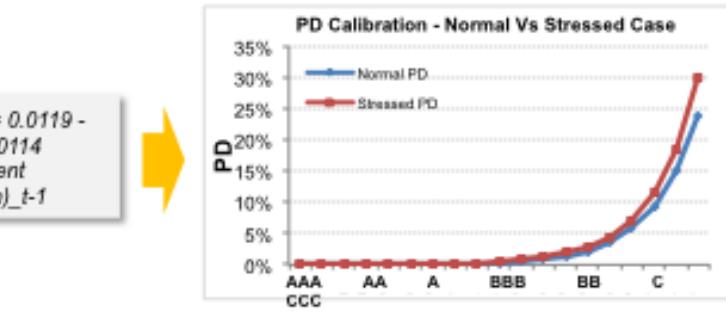
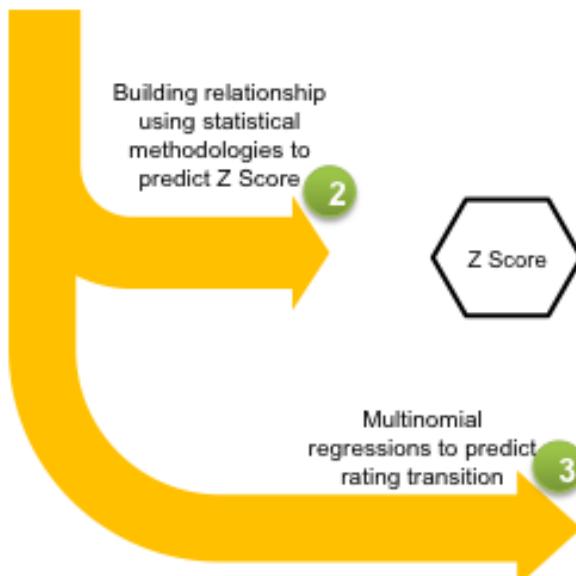
- Optimization options:
 - ▶ Calibrate PD to individual grades by matching average calibrated PD with Long-term ODR
 - ▶ Optimize Mean Squared Error (MSE)
 - ▶ Optimize Mean Average Percentage Error (MAPE)
 - ▶ Optimize weighted MSE
 - ▶ Optimize weighted MAPE
 - ▶ Optimize HL Chi-square distance
 - ▶ Optimize piece-wise curves
- This step is very critical, as it will drive provisioning requirement for exposures within specific grades. For instance, high historical ODR may not lead to high ECL if:
 - ▶ Historical default rates have been very low in high rating grades and therefore, calibrated PD is low for these grades; and
 - ▶ Most of the portfolio on reporting date falls under these high rating grades
 - ▶ Converse is also True

PIT PD Estimation

Macroeconomic Modelling



*(Change in Default Rates)*_t = 0.0119 -
0.00142 * (Stock Index)_{t-1} - 0.00114
*(GDP)_{t-1} - 0.000211 *(Employment
Indicator)_{t-1} - 0.000152 *(Inflation)_{t-1}



- The Vasicek framework (theoretical model underpinning the Basel II IRB capital formula) is used to find PIT PD conditional on a state of single systematic factor. As per Vasicek framework, asset value of a borrower is impacted by systematic risks (risk impacting all borrowers in a portfolio such as domestic economy) and idiosyncratic risk (risk 'specific' to the borrower such as management risk).
- The degree to which the systematic factor impacts a borrower is denoted by asset correlation 'R'. In Basel II framework, it is assumed that asset correlation with the systematic factors is high for high credit quality borrowers (as investment grade and high credit quality asset typically default because of systematic factors and not idiosyncratic factors) and lower for poor credit quality borrowers (as speculative grade and poor credit quality exposures default typically because of high idiosyncratic risk). The model further assumes that all systematic factors impacting a borrower can be summarized by a single factor, thus simplifying the model.

- PIT PD can be derived as follows:

$$PITPD = N \left(\frac{(N^{-1}(TTCPD) + \sqrt{R} * (SRF))}{\sqrt{1 - R}} \right)$$

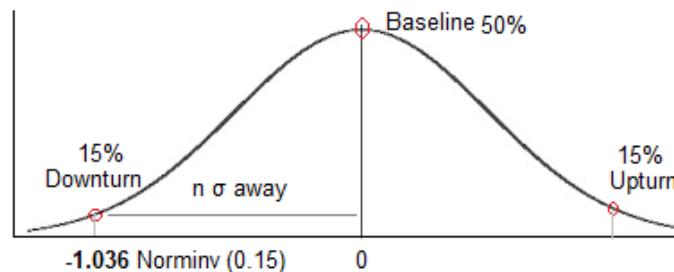
- ✓ TTC PD is the through-the-cycle unconditional PD
- ✓ PIT PD is the conditional PD, conditional on specific state of the macro factor
- ✓ N is the cumulative distribution function for normal distribution
- ✓ N^{-1} is the inverse cumulative distribution function
- ✓ R is the asset correlation and $(1-R)$ is the idiosyncratic risk for an exposure
- ✓ SRF is the state of the risk factor summarizing the systemic risk impacting an exposure



- Vasicek technique maybe used to develop PIT PD estimates. In this process, the dependent variable is the default rate and the independent variables are the macro variables. The macro variable (Oil price) maybe selected on the basis of business intuition and statistical analysis. The following steps are involved in deriving PIT PDs using Vasicek framework:
- Step 1 – Long Term TTC PD
 - ▶ The TTC PD is computed by error optimization method
 - ▶ In this method the implied PIT PD for each quarter historically, is compared with the ODRs (considered as actual PIT PD pertaining to that quarter)
 - ▶ The difference in the two is termed as the error
 - ▶ The long term TTC PD is an input in the Vasicek framework equation (given below) to attain the quarter wise Implied PD (used in the 1st step)
 - ▶ This long term TTC PD is optimized (by solver) in such a manner that the error is minimum
- Step 2 – Forecasted PIT PD
 - ▶ The Vasicek framework equation is used to generate the forecasted PIT PDs for the upcoming quarters, based on the forecasted macroeconomic data and the long term TTC PD

Illustrative Scenarios

- IFRS 9 regulations require use of macroeconomic forecast to generate forward looking ECL estimate and assign probability weights to possible outcomes. The guidelines do not require generation of all possible as it states "In practice, this may not need to be a complex analysis. In some cases, relatively simple modeling may be sufficient, without the need for a large number of detailed simulations of scenarios."
- Following are the three illustrative scenarios for PD estimation:
 - ▶ 15% upside scenario: Upside scenario has 15% upside tail probability associated with itself i.e. there is a 15% probability that actual outcome might even be better than upside scenario and 85% probability that actual outcome will be worse. PIT PD for the upside scenario are generated using Vasicek framework
 - ▶ 15% downside scenario: Downside scenario has 15% downside tail probability associated with itself i.e. there is a 15% probability that actual outcome might even be worse than downside scenario and 90% probability that actual outcome will be better. PIT PD for the downside scenario are generated using Vasicek framework
 - ▶ Probability weights: Probability associated with baseline, upside and downside scenarios are thus 50%, 15% and 15% respectively. These are normalized to add up to 100%



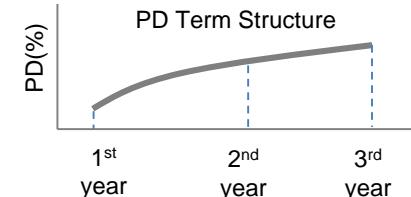
1

Binomial Movement Approach:

Binomial movement approach assumes that the borrower will either default or will remain in its current credit quality. This approach assumes no transition in credit quality. The PD Term Structure under this approach is developed based on 1 year PD rate.

PD in next 3 years =

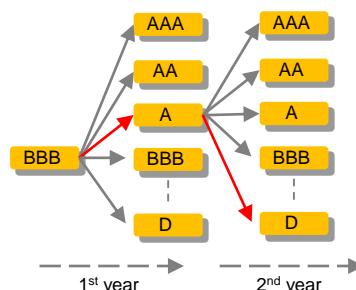
$$\text{PD}_1 + (1 - \text{PD}_1) * \text{PD}_1 + (1 - \text{PD}_1) * (1 - \text{PD}_1) * \text{PD}_1$$



2

Credit Deterioration Approach:

Under this approach, it is assumed that in addition to default, borrower also has probability of moving to other credit rating grades (typically represented in the form of Transition Matrix). PD Term structure under this approach is developed through transition matrix multiplication.



One Year average PD

	AAA	AA	A	BBB	BB	B	CCC	D
AAA	92.94%	4.71%	2.35%	0.00%	0.00%	0.00%	0.00%	0.00%
AA	0.46%	92.52%	6.08%	0.47%	0.47%	0.00%	0.00%	0.00%
A	0.00%	4.45%	84.95%	9.54%	0.64%	0.00%	0.00%	0.42%
BBB	0.73%	0.37%	3.26%	85.52%	5.78%	0.37%	0.00%	0.34%
BB	0.00%	0.68%	0.00%	2.68%	82.42%	10.05%	0.00%	4.17%
B	0.00%	0.00%	0.72%	0.72%	2.89%	87.50%	5.06%	3.11%
CCC	0.00%	0.00%	0.00%	0.00%	0.00%	7.39%	73.88%	18.75%

3

BASEL Maturity adjustment Approach:

Basel III capital calculation formula (ASRF) uses a maturity adjustment formula to convert 12 month PD to Lifetime PD based on maturity of the exposure.

$$\text{Maturity Adjustment} = \frac{1 + (M - 2.5) * b(\text{PD})}{1 - 1.5 * (b(\text{PD}))}$$

Where , $b(\text{PD}) = (0.11852 - 0.05478 * \log(\text{PD}))^2$

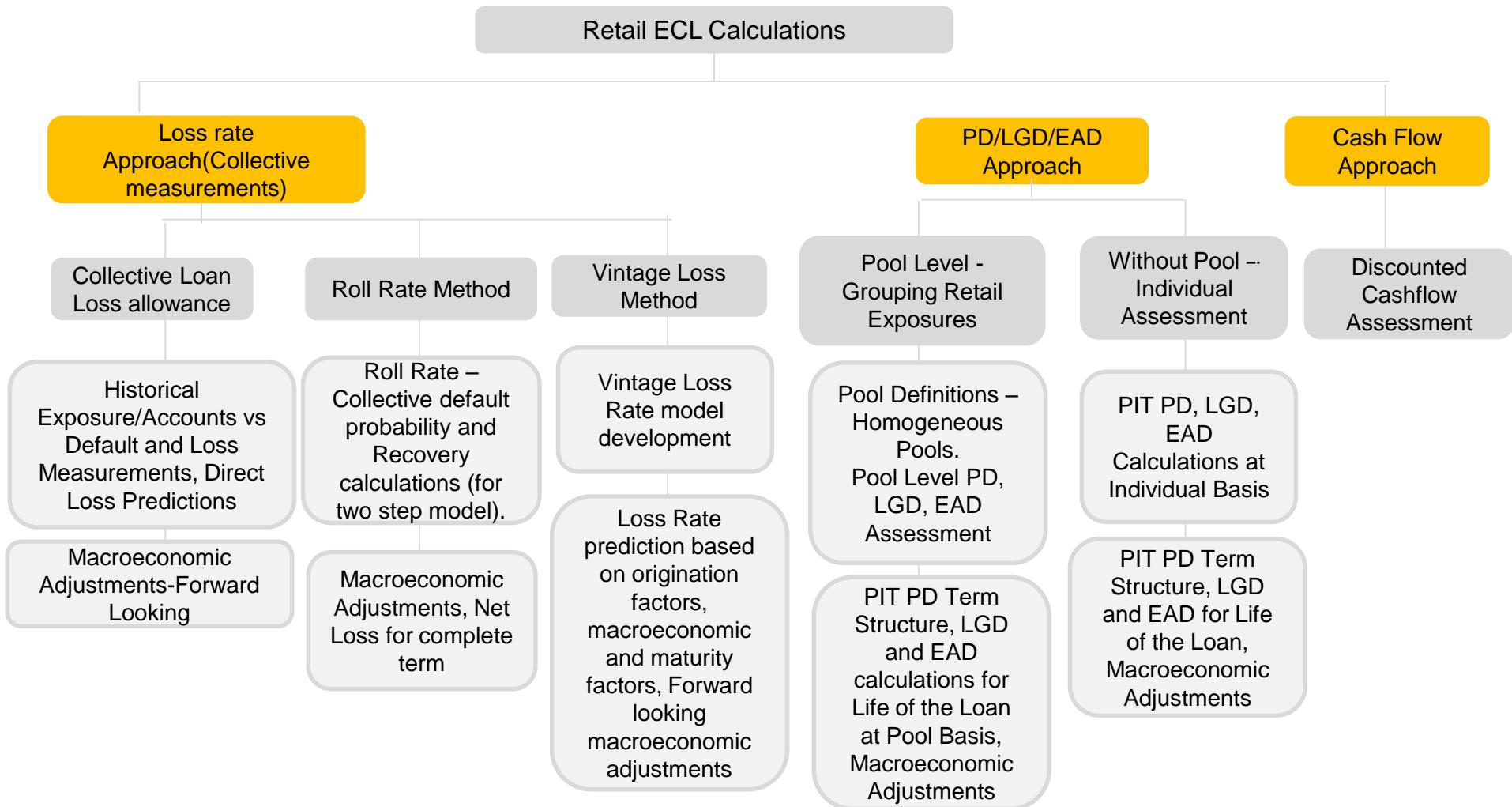
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Multi year Transition Matrix Approach

Under this approach, Banks needs to develop Transition Matrices for multiple years (1,2,3...). PD Term Strcuture can be developed directly by taking PD from these multi year Transition Matrices.

PD Modeling – Retail Portfolios

- There are multiple methodologies that could be used for calculating Expected Credit Loss (ECL) mentioned below:



- For PD estimation scorecard based approach is used widely across banks to determine PD. For IFRS9 calculations, PIT PD (Point in time) PD is calculated for loss calculations.
- For New customers, Application scorecards can be developed for PD estimation. Below equation presents typical scorecard for retail portfolio :

Application Score = f(Income, Credit Bureau factors (number of enquiries/ defaults), Repayment method)

This application score is mapped to PD by PD calibration methodologies

- For existing customers, Behavioral scorecard is developed by taking behavioral factors. Below equation presents typical behavioral scorecard for retail portfolio (for example credit card portfolio):

Behavioral Score = f(number of months active, limit utilized, maximum delinquency in last 12 month, MOB)

This behavioral score is mapped to PD by PD calibration methodologies

- The forward looking macro-economic overlay can be included by creating Time Series / OLS regression model

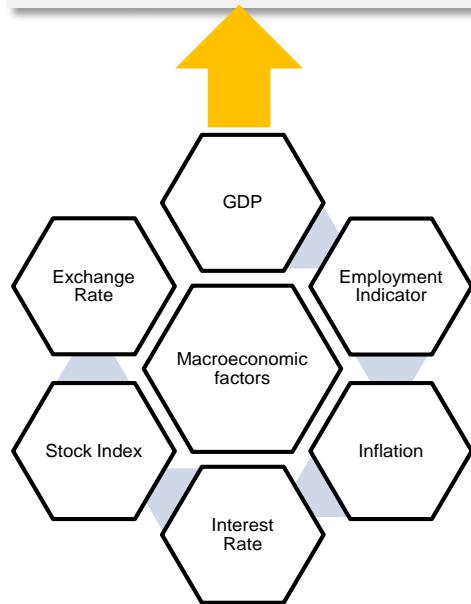
PDi = f(Maco_economic_factors) for each year or quarters

- **Pool Level PD calculations :** Once homogenous pool is created, Pool level PD is calculated which is average (weighted or normal average) PD of the borrowers present in the pool. The observed default rate is calibrated to incorporate the forward looking adjustments.

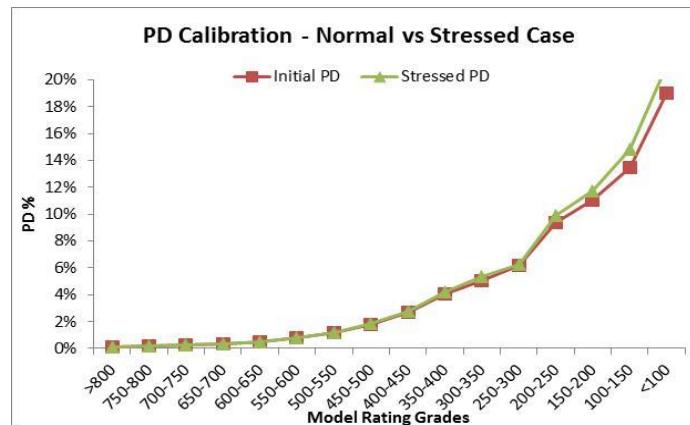
Illustration

- **Step 1** – Regression model to link Portfolio Default Rates with Macroeconomic factors

$$\begin{aligned}
 (\text{Change in Default Rates})_t = & 0.0119 - 0.00142 * (\text{Stock Index})_{t-1} - 0.00114 \\
 & *(\text{GDP})_{t-1} - 0.000211 *(\text{Employment Indicator})_{t-1} - 0.000152 *(\text{Inflation})_{t-1}
 \end{aligned}$$



- Step 2** – Change in PD Calibration as per the “**Stressed Default Rates**”

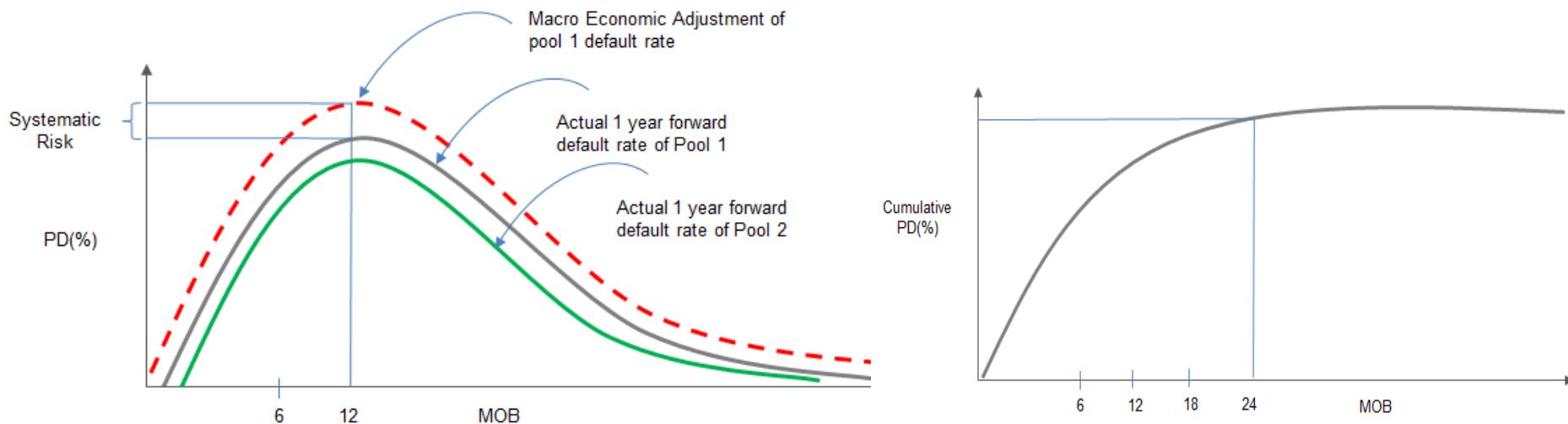


- Step 3** – PD term structure development based on the macroeconomic factors.

Collective Loss Allowance Method	Roll Rate Method	Vintage Loss Method	PD Pool Level
Macroeconomic Adjustments			
Expert Inputs could be taken for forward looking macro-economic adjustments. A scalar factor can be computed and the losses can be adjusted based on the factor. Losses can also be modeled for macroeconomic factors.	Roll rate model can be modeled for macroeconomic factors using OLS / ARIMA modeling techniques for macroeconomic adjustments.	Vintage loss model already has one of key component as macroeconomic factors. Thus macroeconomic adjustments can be done by putting forward looking macroeconomic scenarios.	PD for the pool assessment can be modeled for forward looking macroeconomic factors. Different modeling methodologies can be adopted.

Collective Loss Allowance Method

- In Retail, the first step of the collective assessment is to create homogenous pools based on origination factors like origination LTV or origination FICO etc., so that no instruments move across pools
- Any two pools are said homogeneous if the actual 1 year forward default rate of the pools don't intersect each other across the age of the loans

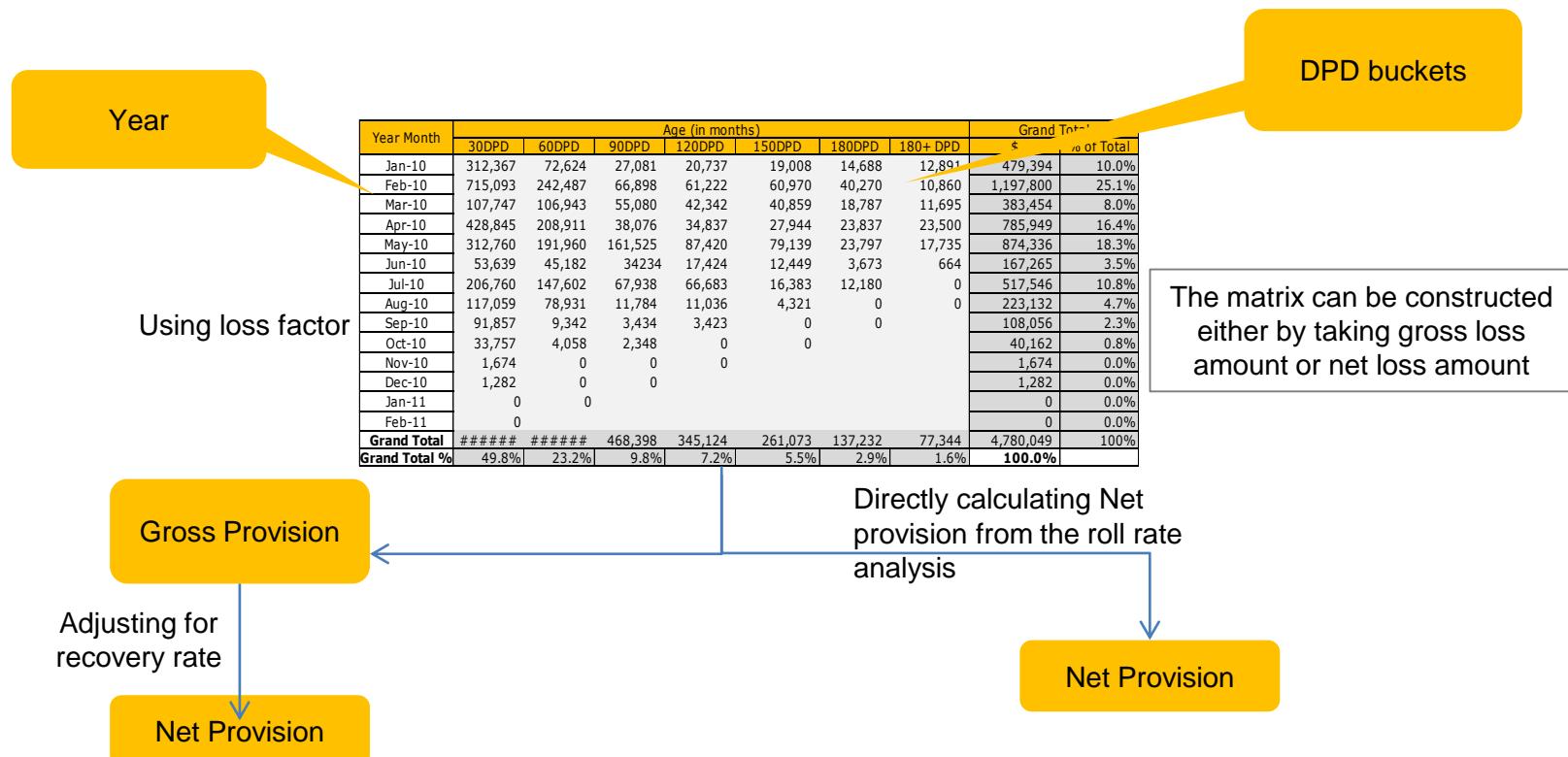


- The pool maturity can be obtained by looking at the point where the cumulative PD distribution stabilizes
- The forward looking macro-economic overlay can be included either by Judgemental overlay or by creating Time Series / OLS regression model. The observed default rate is then calibrated to for each pool to incorporate the forward looking adjustments
- Binomial approach can be used as a PD term structure for calculating lifetime PD (then for estimating the ECL LGD and EAD overlay can be applied)

PD Illustration

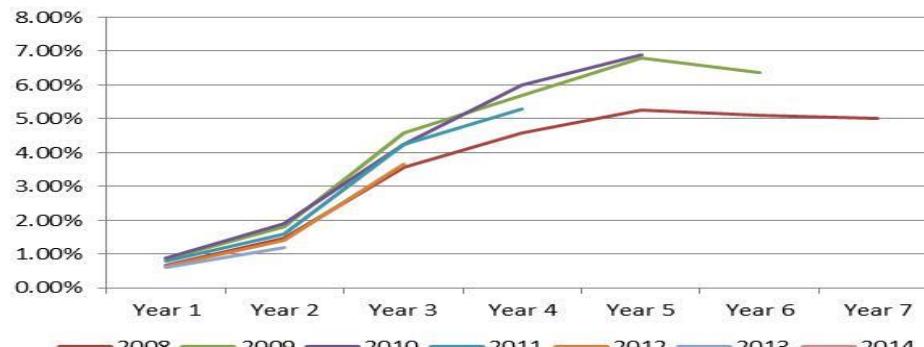
Flow Rate Method

- Roll Rate Models compute the losses based on rolling of portfolio in different DPD buckets. In this method, the entire portfolio balance is segmented by various buckets, eg. Current, 1-29 DPD, 30-59 DPD, 60-89 DPD, 90-119 DPD etc. using current balance. The model can be fit for delinquency tracking and loss forecasting.
- The process can be a one step approach where the net loss amount can directly be used or a two step approach where gross loss amount is used in the first step and then adjusted by the recovery rate.
- Loss rate can be modeled for macroeconomic factors to predict the lifetime expected losses.



Vintage Loss Method

- Under the vintage loss approach, the portfolio is segmented by various origination vintages. As a part of the modeling practice, the loss rate (for an example) can be tracked over time through full lifecycle for each of the vintages.
- The Vintage Loss model has twofold benefits. By incorporating maturation effect, the loss trend can be forecasted in a longer term. Secondly, the model takes into account the economic factors to incorporate the current and future market movements.
- Below figure explains the



$$\ln\left(\frac{\text{LossRate}}{(1 - \text{LossRate})}\right) = A * \text{Vintage_Quality} + B * \text{Economy_Driver} + S(\text{Maturation})$$

Eg. Origination_Score,
Origination_LTV

Eg. GDP, Unemployment
Rate, House Price Index

Eg. MOB Indicators, QOB
Indicators, YOB indicators

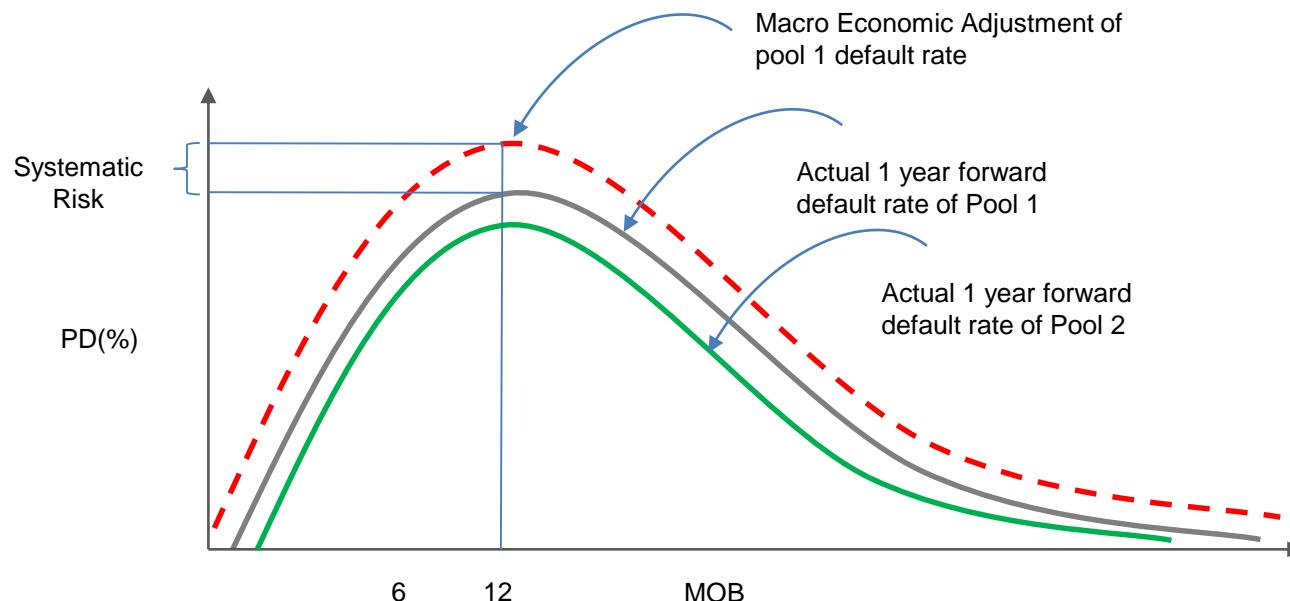
Predicting Loss rate for
a Segment for 2019 Q1

Loan origination information
will be used

2019 Q1 values of
macro economic
factors' information

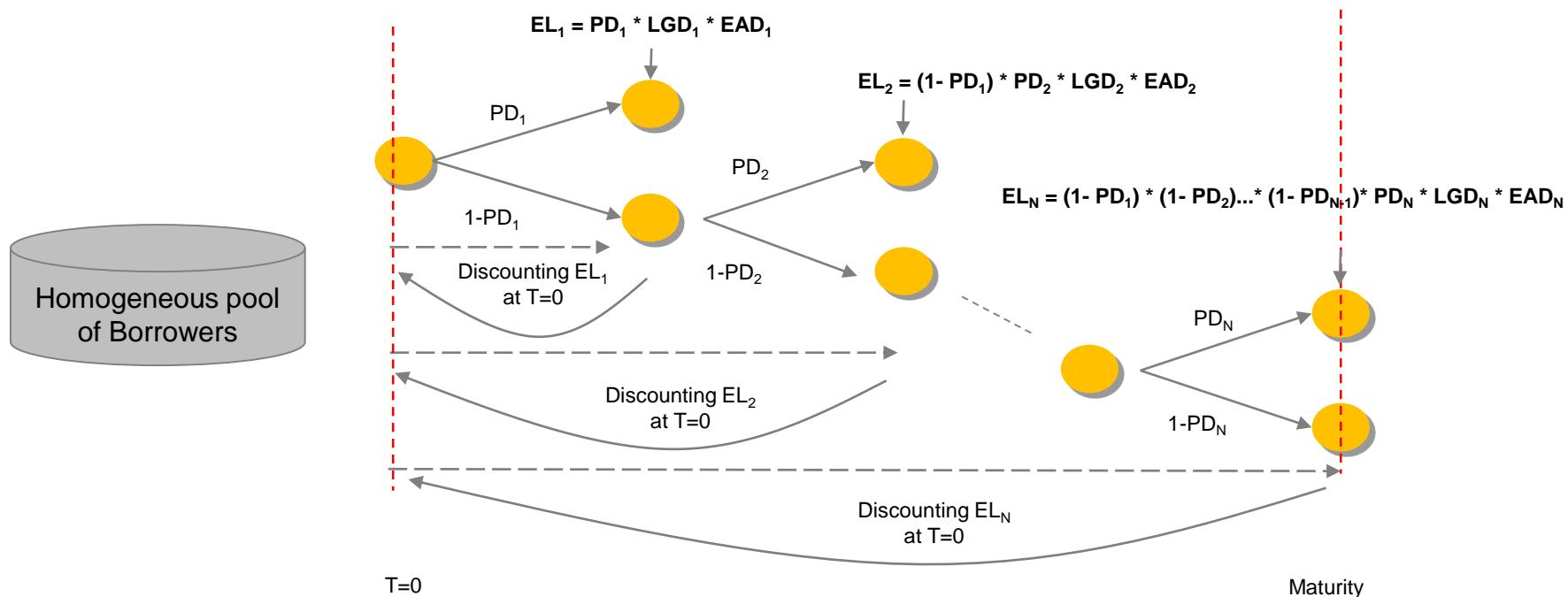
Account specific
MOB will be used

- For Pool assessment, the first step is to create homogenous pools based on origination factors like origination LTV or origination FICO etc., so that no instruments move across pools.
- Any two pools are said homogeneous if the actual 1 year forward default rate of the pools don't intersect each other across the age of the loans



- The forward looking macro-economic overlay can be included by creating Time Series / OLS regression model
- $$PDi = f(Maco_economic_factors) \text{ for each year or quarters}$$
- The observed default rate is calibrated to for each pool to incorporate the forward looking adjustments

- PD Term Structure is key to estimation of Lifetime Expected Credit Loss (LECL)
- An illustration is given below for ECL computation:

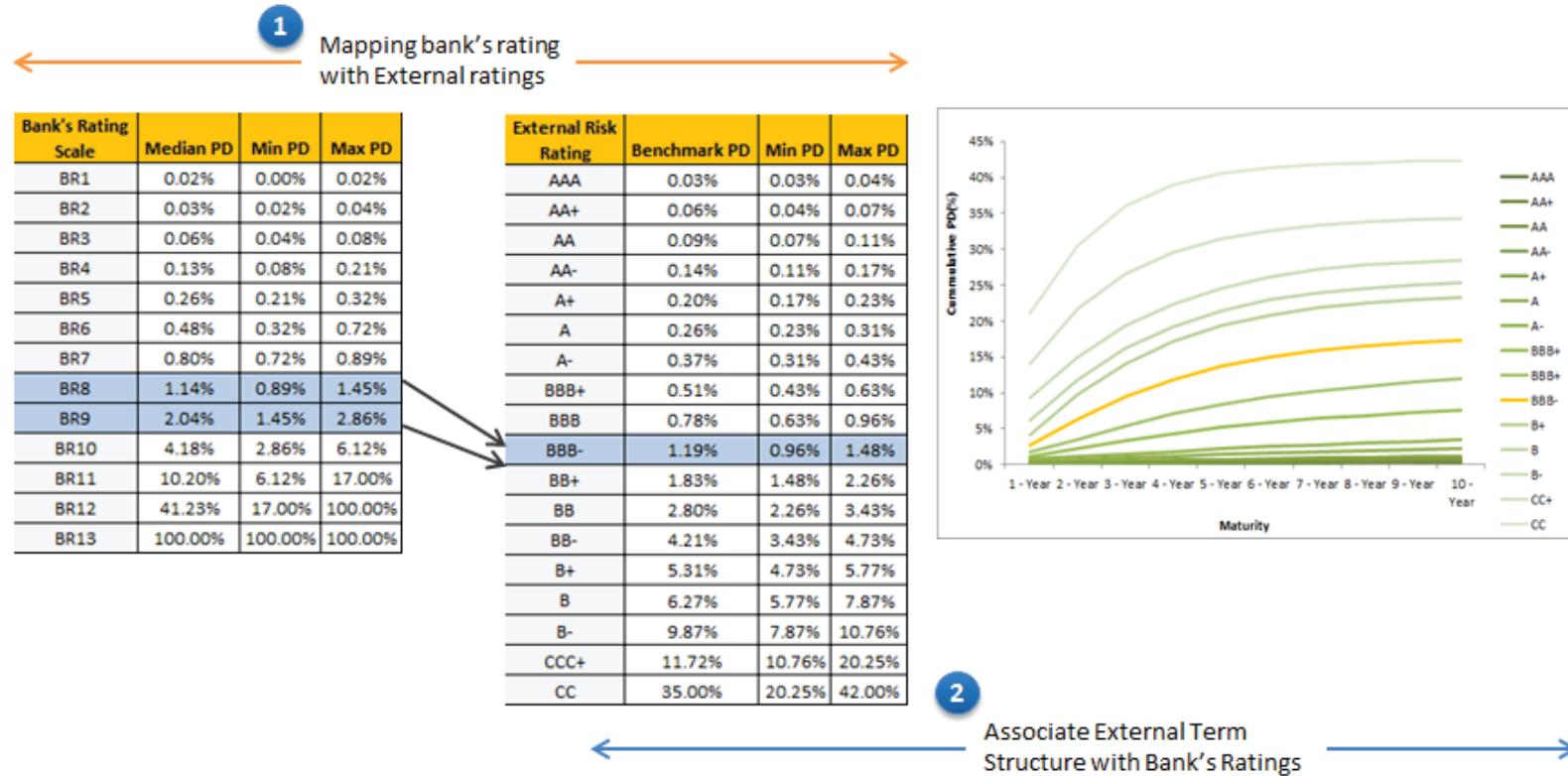


- $PD_i = f(Macroeconomic\ factors, borrower\ specific\ information)$ for each year
- EAD and LGD estimates could also vary based on different time points. For an example, an amortized loan (mortgage loan) as on 2015, will have lower LGD in 2017 compared to 2016 as the LTV will decrease (for simplicity assuming a single factor (LTV) based LGD model). EAD will also be lower in 2017 as compared to 2016.

PD modeling – LDP Portfolios

Mapping to External Rating Agency Term Structure

- Bank's can use the PD term structure provided by external global rating agencies.
- However, before using external rating agency's PD (TTC) term structure as it is for IFRS 9 purpose, banks will have to find a way to convert rating agency PD (TTC) term structure into PD (PIT) term structure and incorporate macroeconomic adjustments to it.



- 
- 1** LGD and CCF Modeling
 - 2** Staging Rules
 - 3** ECL computation – Case Study
 - 4** Advanced Topics
 - 5** Key Implementation Challenges

IFRS 9 : LGD Modeling

- LGD is calculated based on Exposure, total recovery after default and the cost associated for recovery.
Below formula typical LGD calculation:

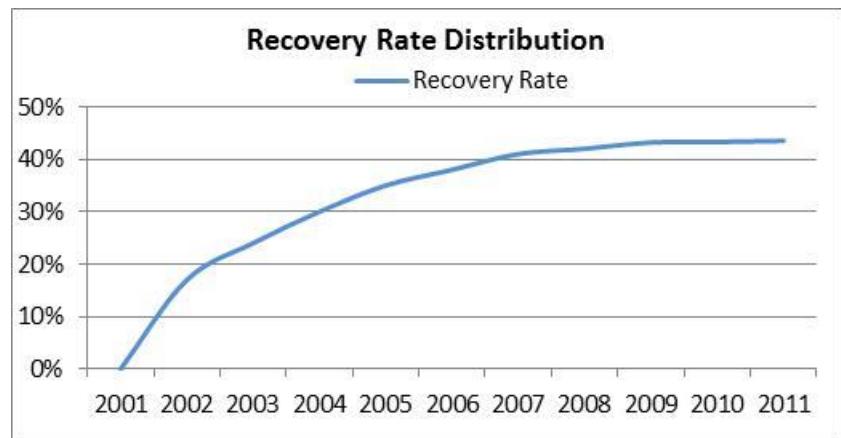
$$LGD = (EAD - PV(\text{recovery}) - PV(\text{cost})) / EAD$$

Here EAD = Exposure at default

PV (recovery) = Present value of recovery discounted till time of default

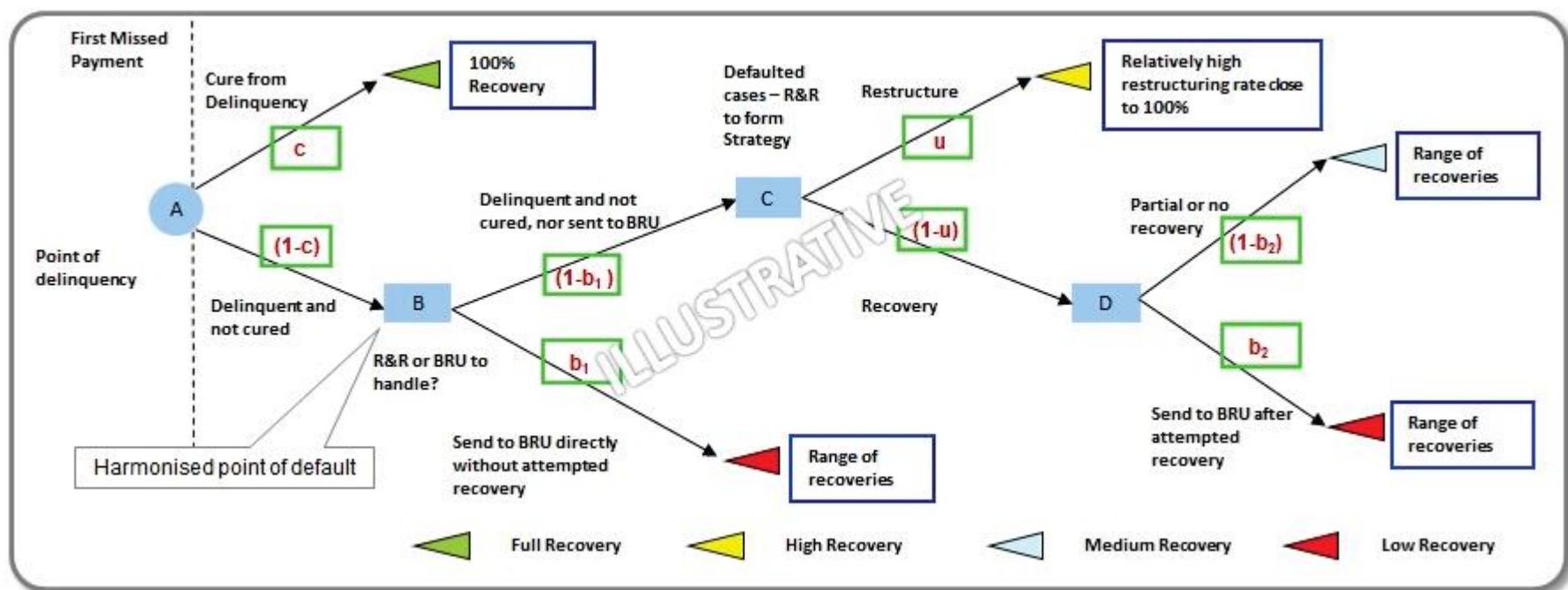
PV (cost) = Present value of cost discounted till time of default

- For computation of LGD, month on month recoveries and cost are discounted to the default month by using discount factor. Attached figure presents the recovery rate distribution.
- Industrywide, Recovery models are built to assess the full recovery for the loan. Below example typical Recovery rate function for Mortgage portfolio:
Recovery Rate = f(LTV, Property Location (region), Product Type)
- **Pool Level LGD Calculations:** Pool Level LGD is calculated as simple or weighted average of PD of the borrowers present in the pool. It is important to note here that Pools present for LGD computation can be different from the pools present for PD computation.



Decision Tree Approach

- Decision tree-based LGD models have certain advantages in environments where data is limited.
- In this approach, the recovery process is validated and all possible recovery scenarios are rendered within the model.
- 'Open' and modular structure of the Decision Tree could be used to model any of the nodes independent of the other nodes of the Tree.
- The Decision Tree based structure allows the estimation of parameters without a universal data set, i.e., separate pieces of the fragmented information & data could be used for estimating the parameters simultaneously.



Workout method

- LGD is one of the key facets of the ECL computation through PD*LGD*EAD method
- The Workout LGD method involves the cash flows that are recovered from the facility, after the facility has defaulted on its payments. It takes into account all cash flows from the distressed asset linked to the recovery
- Along with the recovery cash flows (inflow), any associated cost (outflow) is also discounted using an appropriate discount rate, for the defaulted firm.
- These discounted cash flows are added to provide the expected recovery amount. The total exposure of the firm at the time of default minus the expected recovery amount gives the loss given default in absolute terms. The ratio of loss given default in absolute value to exposure at default gives the LGD in percentage terms

$$\text{LGD}_t = \frac{\text{EAD}_t - PV \sum_{t=m}^T R(t) + PV \sum_{t=m}^T C(t)}{\text{EAD}_t}$$

- EAD is Exposure at Default
- t is the default time
- m and T are the start and finish points of the workout process respectively
- PV(R(t)) is the recoveries during the workout process
- PV(C(t)) is the costs during the workout process

FIRB LGD Computation

- Recognizable value of collateral is found by applying the judgment based haircuts to the value of the collateral
- Respective LGD % is applied to the exposure covered by the collateral value after the application of appropriate haircut for determination of LGD for individual facilities
- The collateral netting and the preference of collateral types are in line with the FIRB framework
- Applicable LGD % are depicted below:

Collateral Type	Haircut
Deposit Under Lien	0%
Equity Shares Collateral.	70%
Cash Margin	8%
CRE/RRE	50%

*Judgment based

Collateral Type	LGD
EFC	0%
Receivables	35%
CRE/RRE	35%
Others	40%
Unsecured Part	45%

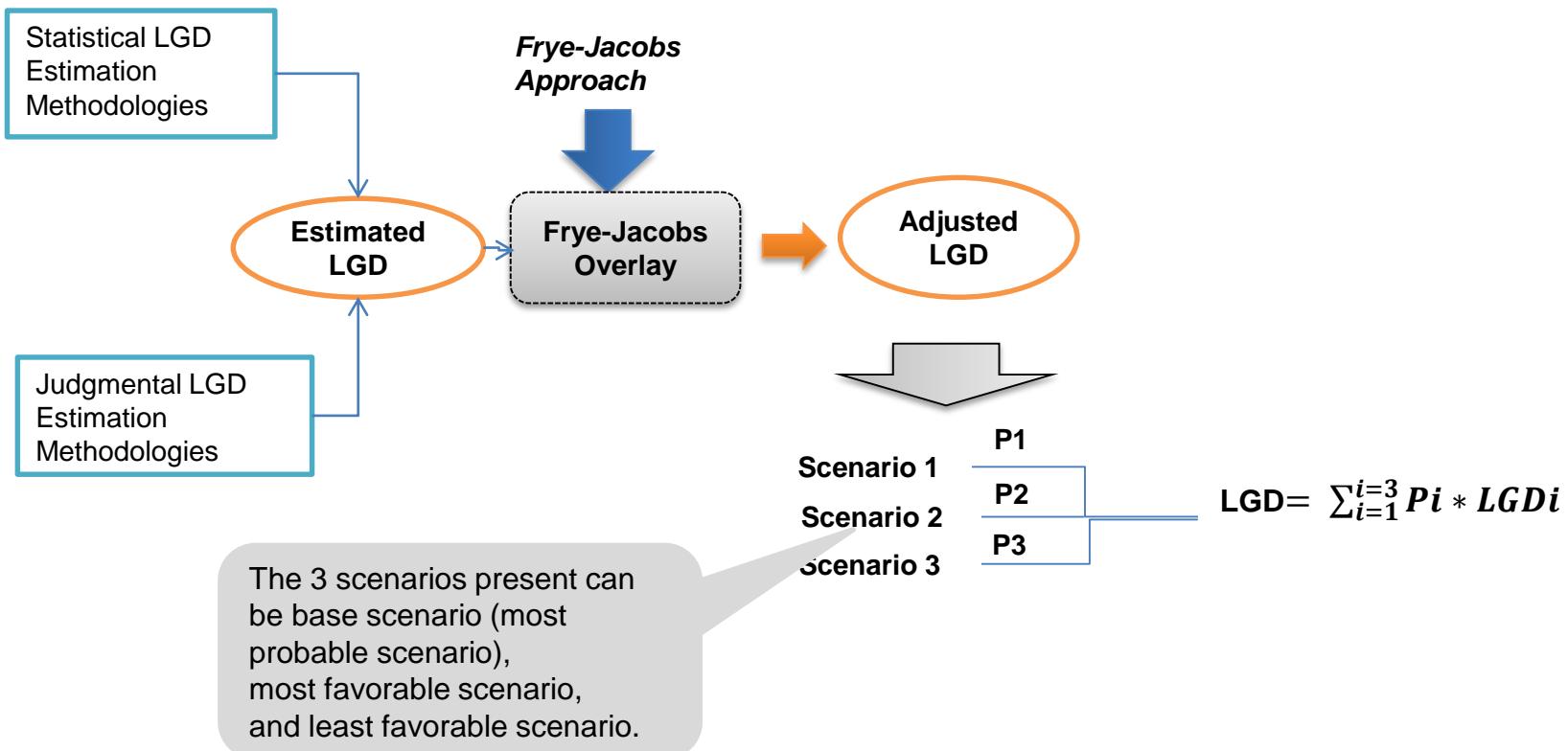
Beta Regression

- Beta regression is used to derive PIT LGD and term structure.
- The class of beta regression models is commonly used by practitioners to model variables that assume values in the standard unit interval (0, 1). It is based on the assumption that the dependent variable is beta-distributed and that its mean is related to a set of regressors through a linear predictor with unknown coefficients and a link function.
- Independent variables are selected for Beta regression by performing stepwise regression. Term structure is created based on moving average forecast for independent variables.

Sample Regression results				
formula = LGD ~ CPI.Q1 + OIL.Q1				
Standardized weighted residuals				
MIN	1Q	Median	3Q	MAX
-1.9736	-0.7801	0.1114	0.686	2.5455
Coefficients (mean model with logit link)				
X	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-0.589608	0.809415	-0.728	0.466346
CPI.Q1	59.019793	22.018195	2.681	0.007351
OIL.Q1	-0.009053	0.002577	-3.513	0.000443
Phi coefficients (precision model with identity link)				
X	Estimate	Std. Error	z value	Pr(> z)
(phi)	113.7	44.4	2.56	0.0105
Pseudo R-squared: 0.7923				

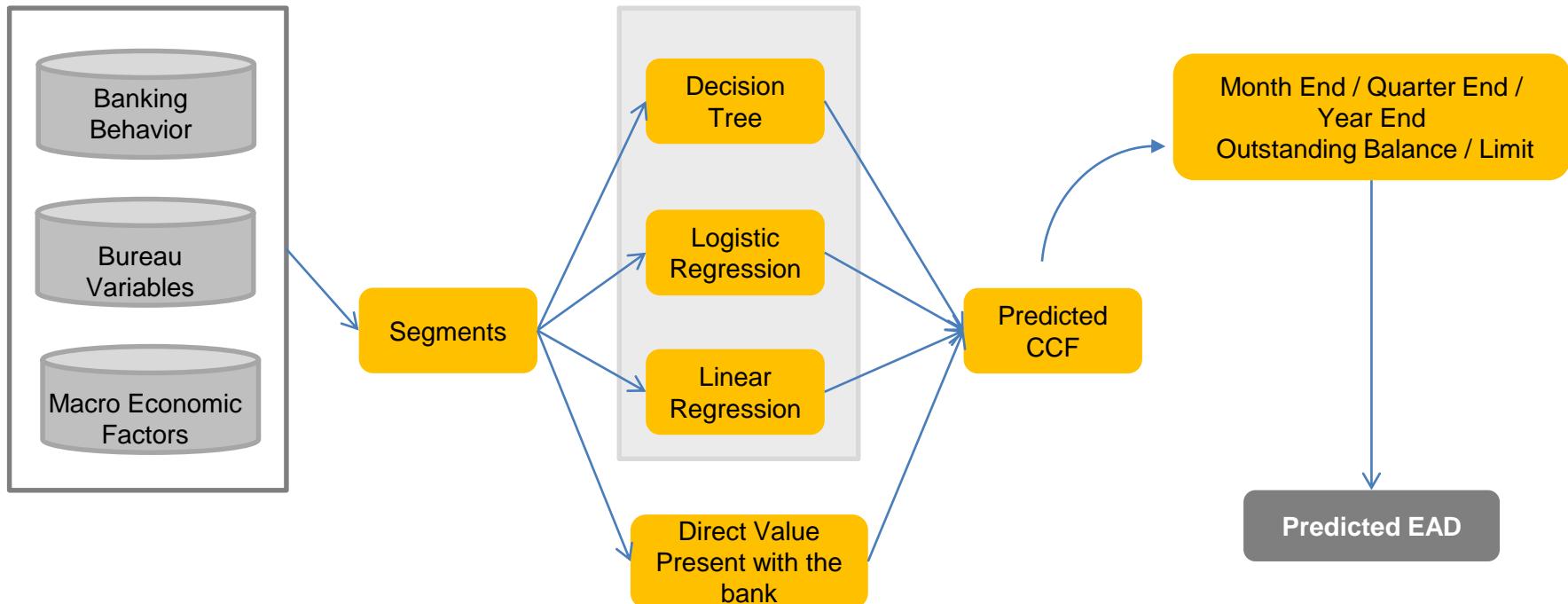
Frye Jacobs Approach

- For IFRS9, LGD should account for forward looking adjustments to best estimates of expected LGD. The estimated LGD (eLGD), as discussed in previous slide is inherently the first part of a two-step process. This estimated LGD can be adjusted over a lifetime of the facility using overlay approach given by the Frye Jacobs methodology.
- Under this approach, the impact of macroeconomic factor is linked to PD, which in turn is linked to LGD through Frye-Jacobs function.



IFRS 9 : CCF Modeling

- EAD calculation is based on type of the loan, i.e. revolving credit or term loan. For revolving credit, Credit Conversion factor (CCF) is estimated to predict the exposure at default, and for term loan Prepayment rate is calculated to predict the exposure at default.
- The CCF model is used to predict EAD where the loan is revolving in nature like credit card, Letter of credit etc.
- Predicted EAD = Net Closing Balance + predicted_CCF * (Limit – Net Closing Balance)



Credit Conversion Factor (CCF)

- Given below is the equation for estimation of CCF on the historical default cases.

$$CCF = \max\left\{0; \frac{outstanding_d - outstanding_{d-1}}{limit_{d-1} - outstanding_{d-1}}\right\}$$

Where

- Outstanding $_d$: Outstanding amount at the time of default
- Outstanding $_{d-1}$: Outstanding amount 12 months prior to default
- Limit $_{d-1}$: Limit 12 months prior to default
- Thus, this CCF shows the proportion of free limit is being utilized by the borrower a year prior to default. For each facility or rating grade, CCFs of the related transactions have to be aggregated on the basis of facility type or any other risk parameter.

Staging Rules

3 Stage expected credit loss model

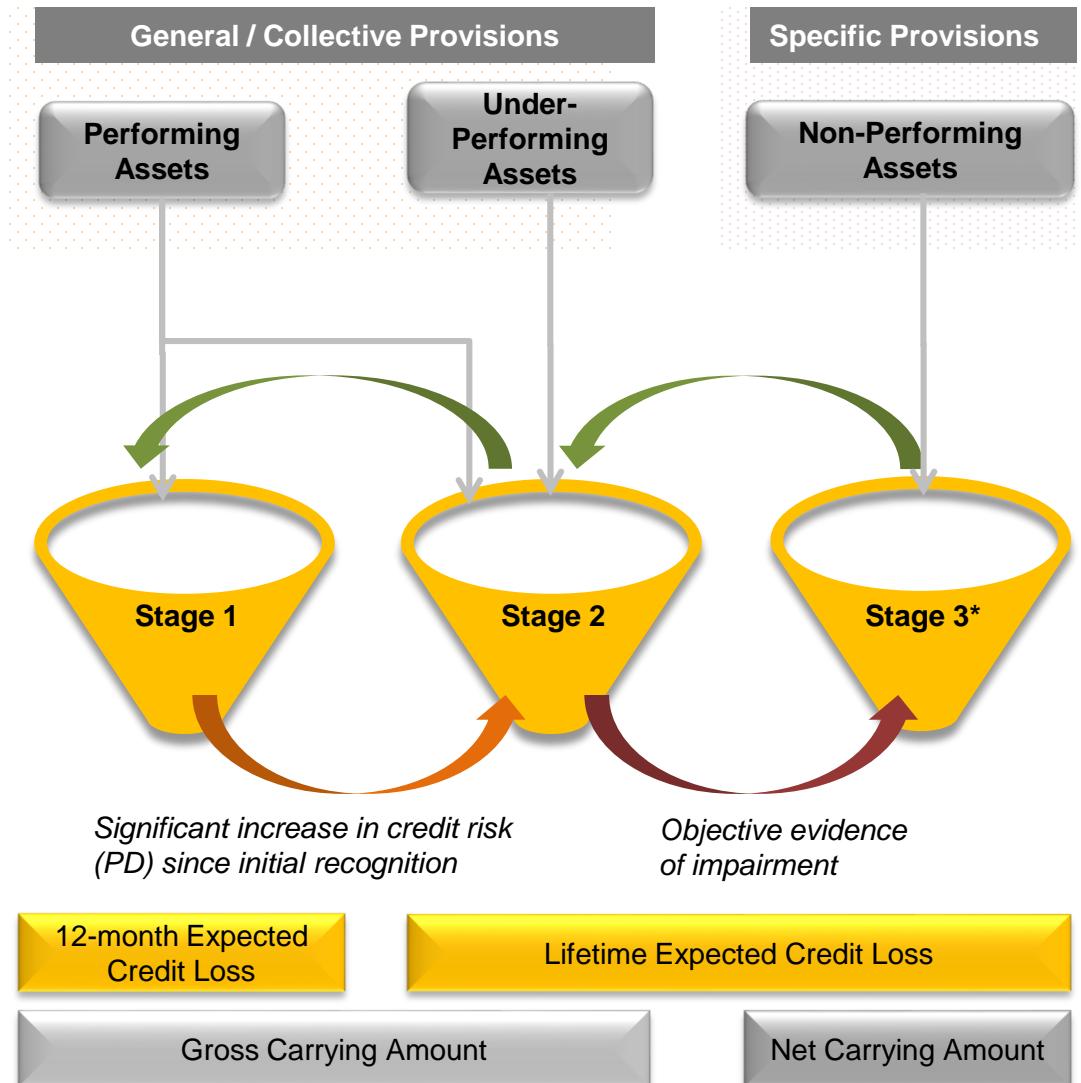
IAS 39 – Incurred Loss Model

Credit losses are recognized only on the occurrence of a loss event



IFRS 9 – forward-looking expected credit loss model

Recognizes 12-month loss allowance at initial recognition, and lifetime loss allowance on significant increase in credit risk



- ▶ IFRS 9 uses a 'three stage model' for measurement of ECL, and one of the major challenges of implementing this model was tracking and determining whether there has been a significant increase in risk of a credit exposure since origination.
 - ▶ **Stage 1** - It includes financial instruments that have not had a significant increase in credit risk since initial recognition or, indicate low credit risk at reporting date. For these assets, **12-month ECL** is recognized
 - ▶ **Stage 2** - It includes financial instruments that have significant increase in credit risk since initial recognition but do not portray any objective evidence of impairment. For these assets, **lifetime ECL** is recognized
 - ▶ **Stage 3** - It includes financial instruments that have objective evidence of impairment at the reporting date. For these assets, **lifetime ECL** is recognized
- ▶ The intention behind the stage assessment is primarily two-fold:
 - ▶ To prevent front loading of income for those accounts which have deteriorated in quality since inception, as the interest rate may no longer appropriately cover the credit risk premium
 - ▶ To recognize and provide for potential losses at an early stage, instead of waiting till the accounts become 90 days past due

Identification of indicators for increase in credit risk i.e. movement of an asset to Stage 2 from Stage 1, for calculation of lifetime expected loss

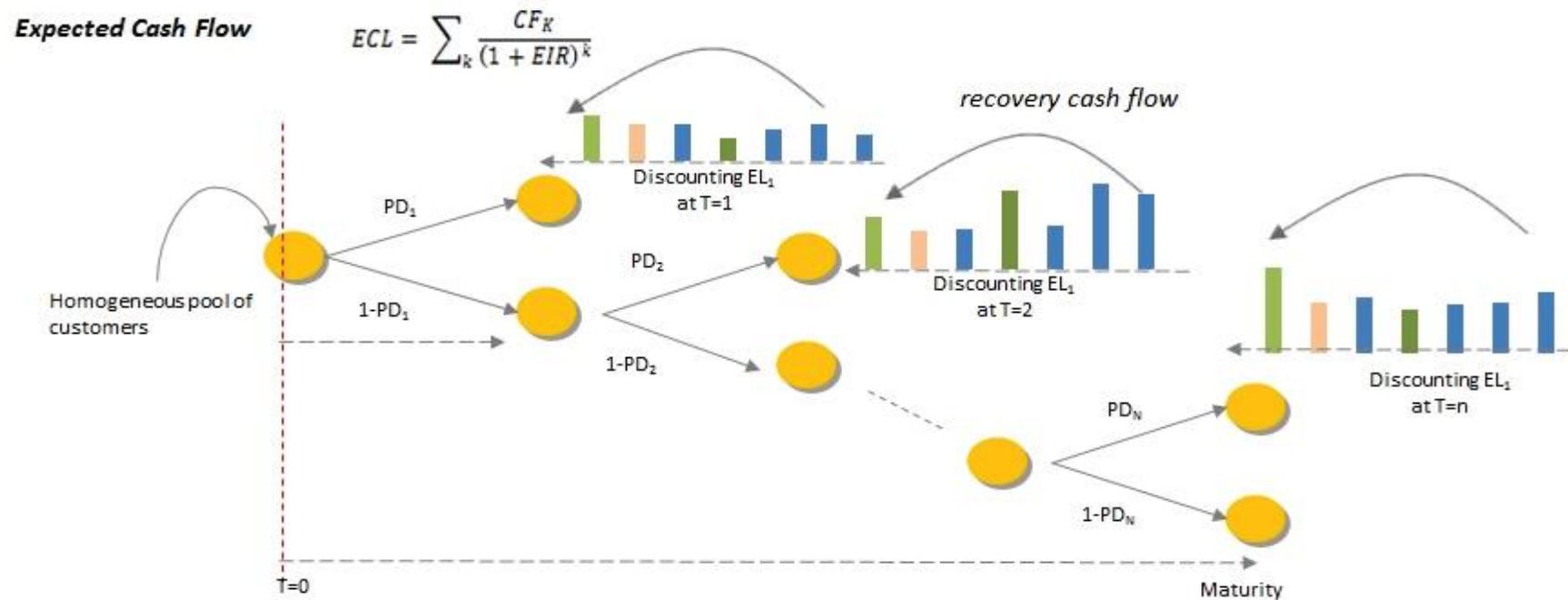
1	Change in internal credit spread (or risk premium)	2	Significant difference in rates or terms of newly issued similar contracts
3	CDS spread, equity or debt price	4	Actual or expected change in External Credit Rating
5	Actual or expected change in Internal Credit Rating or Behavioral Score	6	Existing or forecast adverse changes in business, financial or economic conditions
7	Actual or expected significant change in operating results of borrower	8	Significant increase in credit risk on other financial instruments of the same borrower
9	Regulatory, economic, or technological environment of the borrower	10	Collateral value
11	Quality of guarantee	12	Reductions in financial support from parent entity or credit enhancement quality
13	Expected change in documentation (covenant waiver, collateral top-up, payment holiday etc.)	14	Significant changes in the expected performance and behavior of borrower or group
15	Changes in bank's credit management approach (or appetite) in relation to the financial instrument	16	30-dpd rebuttable presumption

Case Study 3: ECL computation

Expected Credit Loss (ECL)

Overview

- ECL is an unbiased and probability-weighted present value of cash shortfalls determined by evaluating a range of possible default outcomes under various forward looking macro economic scenarios.
- Scenarios need to be decided by banks.
- The discount rate to be used for the measurement of expected credit losses i.e. Effective Interest Rate (EIR) should be the same as the rate used for the purpose of interest revenue recognition



Cash Shortfall = Difference between present value of Contractual Recovery Cash Flow and Expected Recovery Cash Flow

Where EIR = Effective Interest Rate

Advanced Topics

Model Capacity

Linear and Generalized Linear Models lack the capacity to identify non-linear patterns and interactions

Self-Learning

Traditional Algos are not capable of automatic feature engineering (Self-Learning), relying on the data scientist to identify patterns & interactions

Skillset

Typically there is lack of internal skillset to use and tune advanced ML and AI algorithms

Model Explanability

Lack of adoption of advanced algorithms due to failure in explaining their output (Black-box)

Under/Over fitting

Failure to adopt proper ML workflow typically leads to underfitting or overfitting on training data

Model Deployment

IT teams find it difficult to deploy advanced AI-ML models as these cannot be configured on traditional if-else rule engines

Development Time

With abundance of feature data, data science team spend too much time on feature engineering and shortlisting

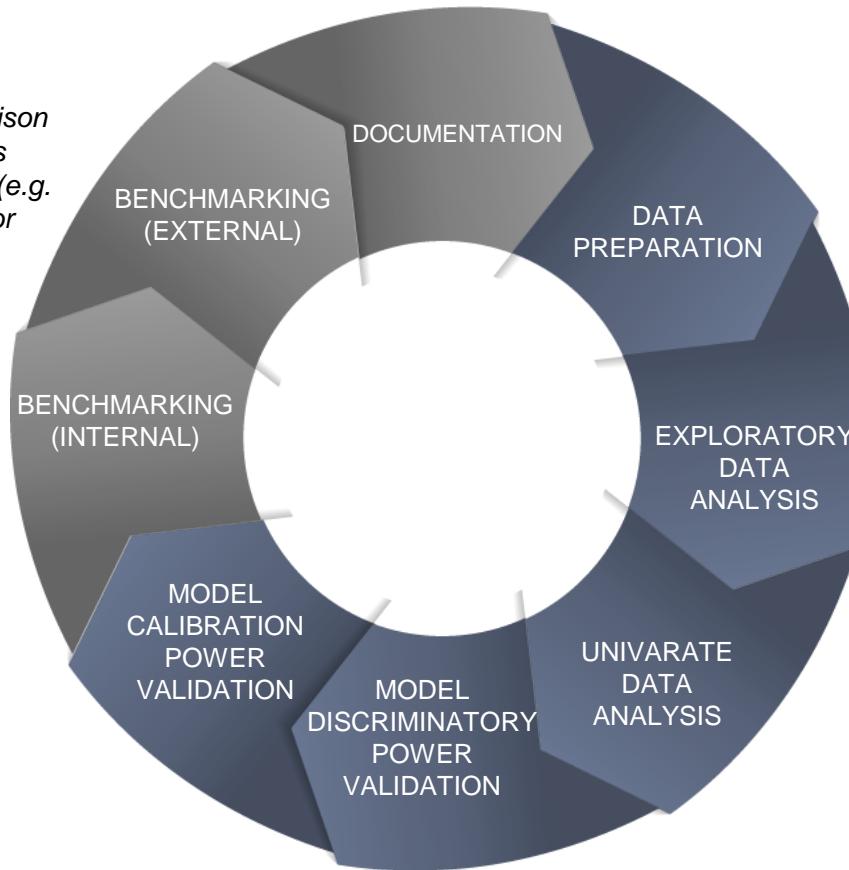
Toolset

Lack of GUI software for ease of use and tuning of advanced AI-ML algorithms

BENCHMARKING:

Benchmarking refers to a comparison of internal estimates across banks and/or with external benchmarks (e.g. external ratings, vendor models, or models developed by supervisory authorities).

Source: BIS Working Paper 14

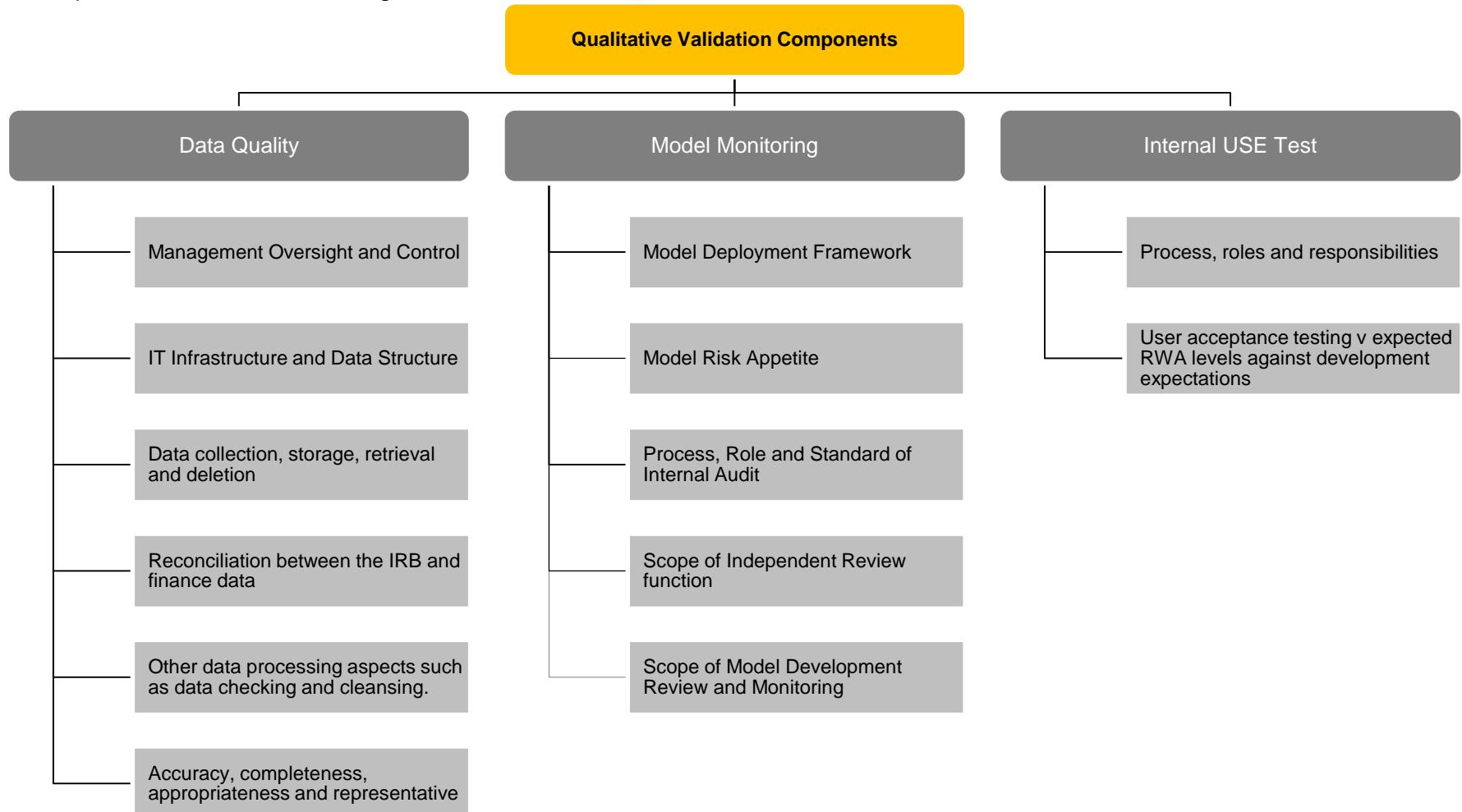


BACKTESTING:

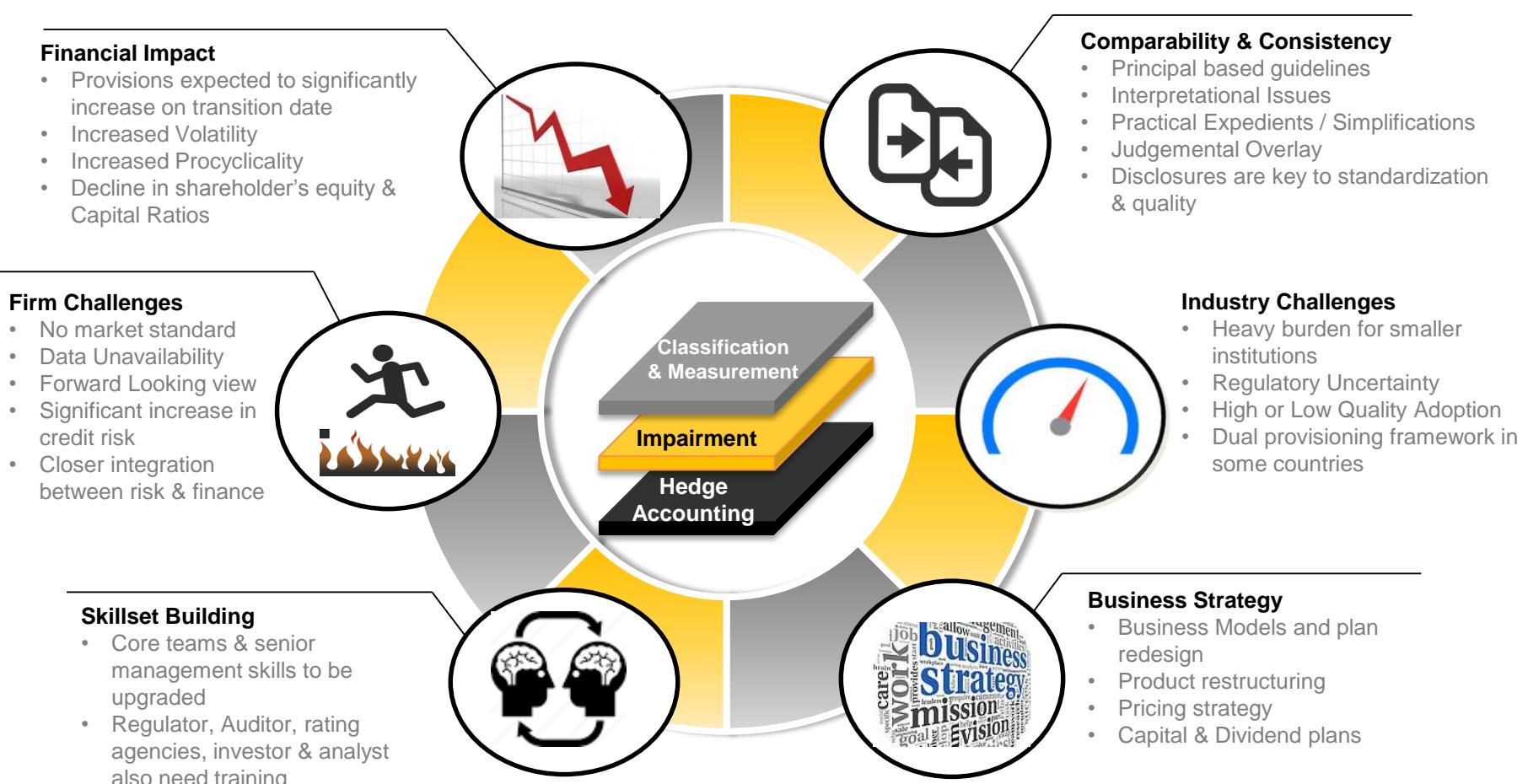
Backtesting means the use of statistical methods to compare estimates of the three risk components to realised outcomes. This differs from the traditional backtesting of market risk models in an important way. Whereas for market risk models backtesting involves the whole model, for internal rating systems only the risk components (model inputs) are tested and the “model” is provided by the supervisor in the shape of the risk-weight functions.

Source: BIS Working Paper 14

- The qualitative phase of the firm's assessment should focus on how the various parts are being used in the firms operations and are reflecting into final capital assignments.



Key Implementation Challenges



Thank You

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