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| TFRS9 Model Validation Document |
| Housing loan Portfolio |
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This section documented the revision history and version control of this document. It shall record every major and minor revision of the model validation regarding the Probability of Default (PD), Exposure at Default (EAD), and Loss Given Default (LGD) models modules which are used for the purpose of calculation of ECL of the TFRS9 accounting book.

Revision History

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| **Version** | **Phase** | **Revision Date** | **Summary of Changes** | **Page** | **File name** | **Changed by** |
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# Introduction

This model validation report describes the validation methods and results of all TFRS 9 credit risk models: Probability of Default (PD), Loss given default (LGD), and Exposure at default (EAD) for housing loan portfolio. It is a loan that is secured by the asset as collateral and total loan size of this portfolio is 287,583,879,069 Baht

In the current regulatory setting, the provisioning of expected credit loss is calculated from inherent risk parameters; the probability of default (PD), exposure at default (EAD) and loss given default (LGD). These risk parameters does not reflect future risk exposure. Hence, the TFRS9 which is a new accounting standard is introduced. The impairment under TFRS9 setting also covers forward-looking components which should help improve financial stability and improve bank credit risk.

This document outlines the validation process of all model related to the TFRS9 calculation. For each risk component, this document shall clearly state the scope of validation, measurement considered, and the validation results.

# TFRS9 Expected Credit Loss

On July 24, 2014, the International Accounting Standards Board (IASB) issued the final version of the ‘International Financial Reporting Standard (IFRS) 9 – Financial Instruments’. As a primary component of the new accounting standard, the IASB introduced a forward looking impairment model. The IASB thereby reacted to delayed recognition of credit losses identified as a weakness of existing accounting standards during the course of the global financial crisis (of 2007/08). In particular, the biggest critique of incurred loss approach under IAS 39 was the recognition of credit losses only upon evidence of a trigger event. In this regard, IASB’s approach of forward looking credit loss estimation was evident from the below extract.

*“The new standard requires an entity to recognise expected credit losses at all times and to update the amount of expected credit losses recognised at each reporting date to reflect changes in the credit risk of financial instruments. This model is forward-looking and it eliminates the threshold for the recognition of expected credit losses, so that it is no longer necessary for a trigger event to have occurred before credit losses are recognised. Consequently, more timely information is required to be provided about expected credit losses.” [“Project summary – IFRS 9 Financial Instruments”, IFRS Foundation, 07/2014, p.14][[1]](#footnote-1)*

Following the publication of IFRS 9 Financial Instruments in July 2014, the Basel Committee on Banking Supervision issued their ‘Guidance on Credit Risk and Accounting for Expected Credit Losses’ (GCRAECL) in December 2015. This covers in particular the impairment (Expected Credit Losses) element and how it should be embedded in and supported by internal processes.

Thai Accounting Standards are substantially converged with IFRS Standards, though the financial instruments Standards that are part of IFRS Standards have not yet been adopted. Thai Accounting Standards include several national financial instruments standards that differ from IFRS Standards. Henceforth TFRS9 can be considered as an adaptation from IFRS9 and replaces the existing TAS101.

***Principle 5 states****–A bank should have policies and procedures in place to appropriately validate models used to assess and measure expected credit losses. This presentation will provide an overview of the scope of work and the proposed validation approach for KBank, based on further discussions we will provide a more detailed view of the approach based on the complexity and materiality of the underlying models.*

Changes due to ‘*IFRS 9 – Financial Instruments*’ can be grouped into three categories.

* ***Classification and measurement***: Classification determines how financial assets and liabilities are accounted for in financial statements and, in particular, how they are measured on an ongoing basis:
  + Assets: one classification approach
  + Liabilities: addressing the volatility in profit or loss caused by changes in the credit risk of financial liabilities that are measured at fair value
* ***Impairments***: Forward-looking impairment model based on expected losses:
  + The new model requires entities to recognise expected credit losses at all times (12-month or lifetime expected loss) which includes measurement of changes in expected credit losses
  + It is no longer necessary for a trigger event to have occurred before credit losses are recognised
  + The new model is also accompanied by improved disclosures about expected credit losses and credit risk
* ***Hedge accounting***: Clear alignment with risk management:
  + The rules allow components of non-financial items to be hedged (previously not allowed by IAS 39)
  + IFRS 9 eliminates the distinction between financial and non-financial items and looks at whether a risk component can be identified and measured and therefore reflected in management activities

The primary change from IAS 39 to IFRS 9 is the evolution from an incurred loss view to a forward looking expected loss view which needs to be accounted for in the impairment models.

This new accounting standard will be effective from 2020. The IFRS 9 standard provides a new set of regulations that the new loss provisioning process will need to satisfy.



Figure 1, From IAS39 to IFRS 9

In particular, the new impairment rules require that the lifetime credit risk of an account be assessed at each model run to determine if there has been a significant increase in credit risk since origination. For accounts where the credit risk has significantly increased (including defaults) the lifetime expected credit losses must be used. If the credit risk has not significantly increased, then only credit losses resulting from expected defaults in the next 12 months must be used. The approach is outlined in terms of a stage classification accounting for significant increase in credit risk as a pivotal element of IFRS 9.

**Table 1: Stages under IFRS 9**

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Stage 1** | **Stage 2** | **Stage 3** |
| **Stage description** | Includes accounts for whom no significant increase in credit risk since initial recognition has been observed | Includes accounts whose credit risk has significantly increased since initial recognition but no objective evidence of impairment has been observed, with a rebuttal presumption that this occurs when the account reaches 30 days past due | Includes accounts where the objective evidence of impairment has been observed |
| 12-month expected credit losses, i.e. credit losses due to default events within subsequent 12 months, are recognised in balance sheet | Lifetime expected credit losses (LTECL) i.e. credit losses due to default events spanning the (expected) lifetime of the facility, are recognised in balance sheet | Lifetime expected credit losses (LTECL) are recognised in balance sheet |
| **Expected loss** | IFRS 9 guidelines require to assess the 1 year expected credit losses without prescribing the tangible estimation procedure    , , , represent marginal PD, EAD and LGD at time *t* | IFRS 9 guidelines require the lifetime expected credit losses without prescribing the tangible estimation procedure   Where, , , , represent marginal PD, EAD and LGD at time *t* and *T* represents the remaining lifetime of the account | Expected loss of a defaulted client given the loss rate, i.e. the shortfall in net present value of expected cash flows versus the carrying amount of the loan |

Table , Stages under IFRS 9

The exemplary expected loss (EL) assessment in **Error! Reference source not found.** listed above is based on an estimate of 1 year parameters probability of default (PD), loss given default (LGD) and exposure at default (EAD) for stage 1 and multi-year PD, LGD and EAD assessments for stage 2 including a discount factor to the reporting date.

# Definition

| **Term** | **Acronym** | **Description** |
| --- | --- | --- |
| Days Past Due | DPD | The number of days that an account is currently in arrears |
| Delinquent |  | An asset is described as delinquent if it is associated with any amount of arrears |
| Expected Loss/Expected Credit Loss | EL/ECL | Interchangeable terms. EL = PD\*EAD\*LGD |
| Exposure at Default | EAD | Exposure at Default (EAD) is defined as the expected amount drawn by borrowers at the time of default. |
| Probability of Default | PD | Probability of default (PD) is the risk that the borrower will be unable or unwilling to repay its debt in full or on time. The risk of default is derived by analyzing the obligor’s capacity to repay the debt in accordance with contractual terms. PD is generally associated with financial characteristics such as inadequate cash flow to service debt, declining revenues or operating margins, high leverage or declining liquidity |
| Default customer |  | Default customer is customer who failed to make on-time repayment (>= minimum payment rate) of their loans for more than ninety consecutive days or three months. |
| Conditional Prepayment Rate | CPR | Conditional Prepayment Rate (CPR) is the annualized percentage of the mortgage expected to prepay in each period. For example, if CPR is 5%, it means that 5% of mortgage is expected to prepay within the period. The focused population is the group of opening accounts at the end of time frame. |
| Lifetime Expected Credit Loss | LTECL / LEL | The Expected Credit Loss over the behavioural lifetime of an asset |
| Beta distribution |  | The beta distribution is a family of continuous [probability distributions](https://en.wikipedia.org/wiki/Probability_distribution) defined on the interval [0, 1] [parametrized](https://en.wikipedia.org/wiki/Statistical_parameter" \o "Statistical parameter) by two positive [shape parameters](https://en.wikipedia.org/wiki/Shape_parameter), denoted by *α* and *β*, |

Table , Term definition and description

# Probability of Default

Probability of default (PD) is the risk that the borrower will be unable or unwilling to repay its debt in full or on time. The risk of default is derived by analyzing the obligor’s capacity to repay the debt in accordance with contractual terms. PD is generally associated with financial characteristics such as inadequate cash flow to service debt, declining revenues or operating margins, high leverage or declining liquidity.

With the new IFRS9 loan loss provision, loans are classified in three stages: stage 1 – initial recognition (yet to be impaired), stage 2 – significant increase in credit risk, and stage 3 – objective indicators of impairment. For loans in stage 1, banks need to estimate 1-year expected credit losses. On the other hand for loans in stage 2 and 3, banks need to provide provision and thus estimate expected credit losses for the whole lifetime of the loans. Both the 1-year and lifetime expected credit losses estimation shall reflect the banks’ forward looking macro-economic view.

KBank’s PD estimation for IFRS9 is modeled according to the following principles: (i) the PD estimation for IFRS9 should be point-in-time (PIT) and reflect current market conditions, (ii) the PD estimates should use structural and behavior information, and (iii) estimation of PD should include the forward looking aspect of the macroeconomic outlook specific to particular sector. For loans in stage 1 and 2, the modeled probability of default will be over 12 months and lifetime respectively. For stage 3, the probability default will be at 100%.

**Validation of PD**

PD validation will be done via the validation of KBank’s constant PD model. PD in each asset class will validated by applying proper statistics to determine whether the PD values resulted from the models can represent the actual PD values from KBank’s validation sample.

## Scope of Validation

In this document, binomial test is used for validating TFRS9 probability of default of housing loan products. The tests are done based on average default rate by customer and average default rate by outstanding. After validation, PDs are adjusted to new values which are statistically tested again.

## Data Management

### Overview of Input Data Set

The first step of our model development is the derivation of super master scale. We gathered Housing loan portfolio data and B-score of each instrument from 2017-12 to 2018-12.

|  |  |  |  |
| --- | --- | --- | --- |
| No. | Field\_Name | Existing/New | Description |
| 1. | POS\_DT | Existing | Data as of observation point |
| 2. | LPM\_NO | Existing | Customer ID |
| 3. | ASSET\_CLASS | Existing | Asset class of customer is to identify Good/Bad customer. If the asset class contains “NPL” then it is defined as bad if not then it is defined as good. |
| 4. | B\_score | Existing | Customer Level B-Score (minimum from account level) |
| 5. | Supermaster\_rating | New | Super master rating derived from 2.1 |

Table 3, Input data

From the data, we observe portfolio actual default and construct a new super master rating. Subsequent to the completion of the super master rating, we observe a rating migration of the same observation and performance period. This process is outlined in the figure below.



Figure 2 Observation and outcome of default event and rating transition

We also utilize occupation data to explore the possibility of segmentation of the migration matrices.

### Validation Sample Design

The observation point is December 2017. The performance period for observation of actual default or rating migration is January 2018 to December 2018.

### Data Cleansing and Exception Handling

In the construction of our development sample, at every observation point we exclude records using the following rules

|  |  |  |  |
| --- | --- | --- | --- |
| # | Issue | Detail | Handling |
| 1 | NPL record | The record/customer is NPL at the observation | Remove from sample |
| 2 | Open less than 3 months | The record/customer is new and there is no behavioral score | Remove from sample |
| 3 | No performance | The record/customer with no performance i.e. closure, write-off etc. | Remove from sample |

Table 4, Data cleansing and exception handling rules

### Final Validation Sample

This section show step by step derivation of our final model development sample. Starting from the entire data set, working the way through record exclusion and thus the final development sample and associated bad rate.

Tables below show the number of customers in each of the observation point before and after exclusion.

|  |  |
| --- | --- |
| Asset Class | Number of customer |
| Portfolio data by asset class | |
| PL Normal | 103,043 |
| SMA/SMQ | 3,213 |
| TDR | 9,761 |
| Watch list / Reschedule | 2,264 |

Table 5, Observations and development samples

The performance of the development sample (i.e. number of bad customer within the defined performance period) is as per the table below. Please note that there are two default performance definitions for housing loan portfolio. The first definition is 90+ DPD as reflected by BOT class. The second definition is TDR loans behavioral default. For detail on the definition, please refer to the definition section of this document.

|  |  |  |  |
| --- | --- | --- | --- |
| Asset Class | Total  Customer | BAD BOT and Behave | %Bad |
| All | 118,281 | 5410 | 4.57% |
| PL Normal | 103,043 | 1558 | 1.51% |
| SMA/SMQ | 3,213 | 1461 | 45.47% |
| TDR | 9,761 | 2273 | 23.29% |
| Watch list / Reschedule | 2,264 | 118 | 5.21% |

Table 6, Default performance of the development sample

## Quantitative Validation

### Binomial Test

Binomial test is the hypothesis test whether the PD of a rating category is underestimated at a confidence level α (e.g. 95%) where null hypothesis and alternative hypothesis are stated as following

H0: The actual PD of this rating is less than or equal to the PD in model.

H1: The actual PD of this rating is more than the PD in model.

If the number of actual default event (k) exceeds a critical value (k\*), we will reject null hypothesis (H0) and conclude that the PD of a rating category is underestimated at a confidence level a.

Critical value

where denotes the inverse function of the standard normal distribution.

This test can be applied to one rating category at a time. The test statistically compares the number of actual default event to the rating’s PD. It is based on assumption that default is independent event.

### PD Validation Result

For housing loan product, binomial test is used for validating TFRS9 probability of default. The tests are done based on average default rate by customer and average default rate by outstanding. After validation, PDs are adjusted to new values which are statistically tested again. Moreover, behavior score is validated by using Gini and KS.

#### **TFRS9**

Table 7 presented the binomial test which compared the actual default rate to the assigned probability of default in each asset class. The PDs in every asset class is accepted. Therefore, we did not calibrate PDs of housing loan.

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Master  scale  Risk  grade | Asset flag | Max  Risk  grade | #Bad | #Good | Total | %Actual DR | Count all | Weight\* | PD Master Scale | Critical PD | DR | Binomial |
| 1 | PL Normal | G01 | 83 | 27795 | 27,878 | 0.30% | 27,878 | 23.57% | 0.25% | 0.31% | 0.30% | Accept |
| 2 | PL Normal | G02 | 373 | 48682 | 49,055 | 0.76% | 49,055 | 41.47% | 0.76% | 0.84% | 0.76% | Accept |
| 3 | PL Normal |  | 133 | 5639 | 5,772 | 2.30% | 5,772 | 4.88% | 1.40% | 1.63% | 3.15% | Reject |
| 3 | PL Normal | G03 | 498 | 13780 | 14,278 | 3.49% | 14,278 | 12.07% | 1.40% | 1.63% | 3.15% | Reject |
| 4 | PL Normal | G04 | 197 | 3488 | 3,685 | 5.35% | 3,685 | 3.12% | 4.00% | 4.63% | 5.35% | Reject |
| 5 | PL Normal | G05 | 153 | 1489 | 1,642 | 9.32% | 1,642 | 1.39% | 7.26% | 8.41% | 7.00% | Accept |
| 5 | Reschedule | . | 117 | 2098 | 2,215 | 5.28% | 2,215 | 1.87% | 7.26% | 8.41% | 7.00% | Accept |
| 6 | PL Normal | G06 | 91 | 475 | 566 | 16.08% | 566 | 0.48% | 11.15% | 12.78% | 9.37% | Accept |
| 6 | Watch list | . | 1 | 48 | 49 | 2.04% | 49 | 0.04% | 11.15% | 12.78% | 9.37% | Accept |
| 6 | TDR | 1 | 192 | 2224 | 2,416 | 7.95% | 2,416 | 2.04% | 11.15% | 12.78% | 9.37% | Accept |
| 7 | PL Normal | G07 | 28 | 137 | 165 | 16.97% | 165 | 0.14% | 25.89% | 27.98% | 16.95% | Accept |
| 7 | TDR | 2 | 182 | 835 | 1,017 | 17.90% | 1,017 | 0.86% | 25.89% | 27.98% | 16.95% | Accept |
| 7 | TDR | 3 | 471 | 2365 | 2,836 | 16.61% | 2,836 | 2.40% | 25.89% | 27.98% | 16.95% | Accept |
| 8 | TDR | 4 | 971 | 1731 | 2,702 | 35.94% | 2,702 | 2.28% | 49.91% | 51.84% | 35.98% | Accept |
| 8 | PL Normal | G08 | 2 | 0 | 2 | 100.00% | 2 | 0.00% | 49.91% | 51.84% | 35.98% | Accept |
| 9 | SMA | . | 1460 | 1751 | 3,211 | 45.47% | 3,211 | 2.71% | 53.04% | 55.14% | 47.91% | Accept |
| 9 | SMQ | . | 1 | 1 | 2 | 50.00% | 2 | 0.00% | 53.04% | 55.14% | 47.91% | Accept |
| 9 | TDR | 5 | 457 | 333 | 790 | 57.85% | 790 | 0.67% | 53.04% | 55.14% | 47.91% | Accept |

Table 7, Binomial test housing loan PD (by customer)

# Exposure at Default

EAD is one of the major components which are used to calculate credit risk capital and provision. Based on nature of the products, we can discriminate them into 2 product types which are Term Loan and Revolving Loan. For Retail Credit products, term loan is consisting of Housing Loan, Staff Loan, Other Secured Loan and K-Leasing. EAD-TFRS9 model will be segmented based on Term Loan and Revolving Loan as shown in Figure 3 below. The first one is model for loan products and the other one is model for revolving products.

**Retail Product**

**B. Revolving Loan**

1. **Term Loan**

**Credit Card**

**POD**

**Housing Loan**

Other Secured Loan

**Consumer Loan**

**K-Express Cash**

Other Unsecured Loan

**Staff Loan**

New Car

Used Car

K- Car

**K-Leasing**

Figure 3, Product Structure of Retail Product

This development document will solely concentrate on the model for term loan as housing loan is considered as a term loan product.

***A: Term Loan***

The mortgage industry of Thailand pays a major role in consumer lending business. The market is fiercely competitive. Both government and commercial banks attempt to attract borrowers by offering special interest rate programs. Several programs are created such as fixed 1-year rate, fixed 2-year rate, fixed 3-year rate, and etc. Borrowers can match the rate with their preference. Moreover, banks in Thailand allow borrowers to pay off the loan before the contractual maturity (pre-payment) without any penalty. So, pre-payment and pre-settlement significantly reduces Bank’s revenue. If banks can foresee which borrowers are certainly to make full prepayment or ones are to refinance, banks can prepare the rates matching borrowers’ behavior in terms of interest rate scheme and costs. Another advantage of predicting prepayment is that banks can more effectively allocate their provision matching borrowers’ behavioral life time.

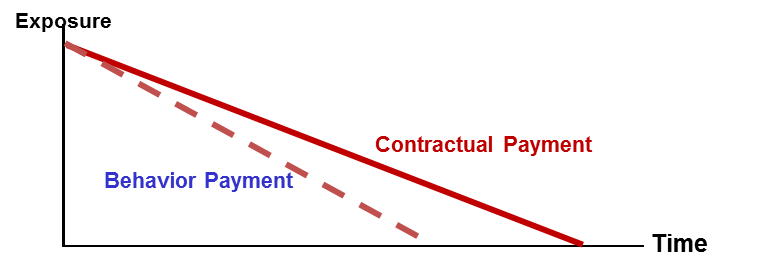
The objective of this development is to more efficiently estimate customers’ lifetime and exposure curve. In other words, banks would like to know how long the borrowers stay in the portfolio and what the exposure curve looks like.

Figure 4 Concept of Prepayment Model

As shown in Figure 4, with the effect of prepayment, the remaining of exposure would be reduced when compared to contractual exposure. The effect can be incorporated by %CPR in equation 1.

(1)

Where

= Conditional prepayment rate for month t

= The monthly contractual cash flow which generates from non-ECL part.

(2)

As described in equation 2, EL could be reduced by component. In this document, the Conditional Prepayment Rate model would be developed to assess lifetime’s expected loss.

**Conditional Prepayment Model**

Conditional Prepayment Rate (CPR) measures prepayments as a percentage of the current outstanding loan balance. It is always expressed as a compound annual rate. A 10% CPR means that 10% of the pool’s current loan balance pool is likely to prepay over the next year. The CPR is commonly used to describe the prepayment for mortgage.

**Validation of EAD**

EAD validation will be done via the validation of KBank’s CPR models. To validate CPR, the proper statistic test will be implemented to test whether the actual observe CRP is different from the developed CPR model.

## Scope of Validation

In this document, we will validate constant CPR models developed in the housing loan model development document. However, the validation of Point-in-Time CPR is not shown in this document but it will be displayed later in the next model validation document.

## Data Management

### Overview of Input Data Set

CPR model validation is performed on a portfolio level i.e. Housing loan. The input for actual CPR calculation includes schedule payment, actual payment, month-on-book, risk grade and day past due (DPD). In summary, the data requirement for the calculation of actual CPR calculation is shown as follows:

### Validation Sample Design

To validate through-the-cycle CPR, data from model development period (Jan 2010- Apr 2016) are merged with new latest sample which are active accounts at Dec 2017. For the new sample, CPR is observed monthly from Jan 2018 to Dec 2018.

### Data Cleansing and Exception Handling

Due to different period between model development and model validation, EBAN system, which is KBank’s data lake is developed before validation period. Modeler chose to use new data source from EBAN instead of old source data from legacy system. As a result, data from model development and new sample data (Dec 2017 – Dec 2018) are treated differently to properly handler issues found from different source.

Treatments for each data are described separately below. To summarize, treatments for sample from development period are same to those treatments used in model development step. For new latest sample from EBAN, less data issues are found so require less data issue handlings.

Treatment for data from model development period

All data issue has to be cleaned as table below;

|  |  |
| --- | --- |
| All Product HL Data | Exclusion Detail |
| Model scope exclusion | Account from RIW6100 (Status=NPL) |
| Data Issue/ Data missing | No contractual payment data (aging>0) |
| Unable to identify partial prepayment data for overdue customer |
| Outstanding Balance = 0 or Missing |
| Cash Flow = 0 or Missing |
| Payment Amount < 0 |
| Cash Flow month and date missing/error |
| Demographic information missing |

Table Treatment for data from model development period

Treatment for new latest sample from EBAN

|  |  |
| --- | --- |
| All Product HL Data | Exclusion Detail |
| Model scope exclusion | Account from RIW6100 (Status=NPL) |
| Data Issue/ Data missing | CPR that exceed possible range [0,1] is excluded |

Table Treatment for new latest sample from EBAN

### Final Validation Sample

The final validation sample is a result of sample from development period merged with new latest sample. Merged sample contain 58,353 accounts from development period and 148,744 accounts from validation period.

## Quantitative Validation

The final CPR model is constants for 6 segments separated by risk grade and MOB. CPR constant for each segment is weighed average CPR from the historical data of that segment. The purpose of using this model is for simplicity in strategic decision and portfolio management.

To validate through-the-cycle CPR model, modeler recalculates actual observed through-the-cycle CPR with all sample from model development period and validation period. Modeler measures error from CPR model by using mean percentage error (MAPE). Prediction Interval is created based on assumption that observed CPR is normally distributed in each segment. If observed CPR fall out of 95% prediction interval, constant of that segment will be adjust to cover actual observed through-the-cycle CPR.

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### Mean absolute percentage error (MAPE)

The model is applied on the relevant population and the resultant CPRs (Predicted CPR) are compared to the actual CPR. The idea is to check whether the Actual and the Predicted CPRs are in line with each other.Statistical measures like Mean Absolute Percentage Error (MAPE) will be calculated to assess the authenticity of the model.

Mean absolute percentage error (MAPE) is a measure of prediction accuracy in trend estimation. The difference between actual and predicted is divided by the actual. The absolute value in this calculation is summed for every forecasted point in time and divided by the number of fitted point n.

MAPE = Mean (| Actual CPR – Predicted CPR | / Actual CPR)

Indicative Tolerance

* MAPE <=10% signifies strong closeness of prediction to actual
* 10% < MAPE <= 25% signifies medium closeness of prediction to actual
* MAPE> 25% signifies poor closeness of prediction to actual

### Validation Result

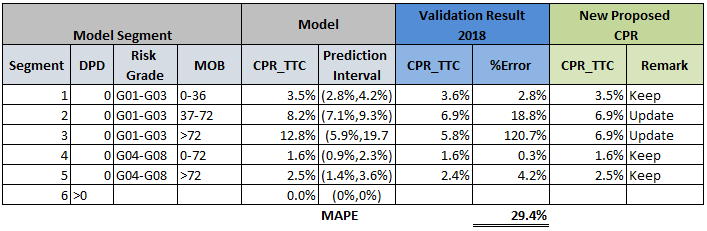


Table , validation result

From the result, CPR in segment 2 and 3 fall out of 95% prediction interval. Mean absolute percentage error (MAPE) is 29.4% which most of error is from segment 2 and 3. So modeler proposed to update CPR from 8.2 to 6.9 in segment 2 and from 12.8 to 6.9 for segment 3. The final proposed CPR model is the right most in Table 10.

# Loss Given Default

The LGD model has recently been developed in 2018, therefore, validation is not yet required at this time.

1. http://www.IFRS.org/current-projects/iasb-projects/financial-instruments-a-replacement-of-ias-39-financial-instruments-recognitio/documents/IFRS-9-project-summary-july-2014.pdf [↑](#footnote-ref-1)