

TFRS9 Model Validation Document   
K-Leasing

This section documented the revision history and version control of this document. It shall record every major and minor revision of the business requirement regarding the validation of Loss Given Default (LGD) models modules which are used for the purpose of calculation of ECL of the TFRS9 accounting book.

1. Revision History

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Role** | **Name** | **Title** | **Date** | **Signature** |
| Independent Validator |  |  |  |  |
| Validation Manager |  |  |  |  |
| Model Developer |  |  |  |  |
| Model Owner |  |  |  |  |
| Business Owner |  |  |  |  |
| Responsible Executive |  |  |  |  |

# 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 KLeasing. It is a loan that is secured by cars as collateral and total loan size of this portfolio is shown below.

|  |  |
| --- | --- |
| **Product** | **Outstanding** (MB) |
| New Car | 57,375 |
| Used Car | 88 |
| KCar | 11,453 |
| **Grand Total** | **68,916** |

Table

# 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

The Good/Bad definition is required to determine account performance for the scorecard validation. The Good/Bad definition is applied at the outcome point and is used to categorize the account as good, bad, or indeterminate (neither good nor bad).

The Good/Bad definition, which is used for the scorecard validation, is summarized in Table below.

|  |  |
| --- | --- |
| **Description** | **Flag** |
| BOT bucket >= 3 | Bad |
| BOT bucket = 2 | Indeterminate |
| BOT bucket = 1 | Good |
| Closed Account | Good |

Table , The good/bad definition

# 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 4: 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 4

The exemplary expected loss (EL) assessment in Table 4 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.

# 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

This probability of default model should be used to validate the PD term structure for all valid stage-1 and stage-2 K-Leasing instruments. For stage-3 instruments, they are automatically assigned to be at 100%.

## Data Management

### Overview of Input Data Set

The first step of our model development is the derivation of supermaster scale. We gathered K-Leasing portfolio data and B-score of each instrument, 2017-01 to 2017-12 for behavioral data and 2018-01 to 201812 for performance observe.

|  |  |  |  |
| --- | --- | --- | --- |
| 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 | Supermaster rating derived from 2.1 |

Table 5, Input data

From the data we observe portfolio actual default and construct a new super master rating. Subsequent to the completion of the supermaster 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 1 year from January 2018 to December 2018. The performance period for observation of actual default or rating migration is 12 month from the observation point at 201712.

### Data Cleansing and Exception Handling

|  |  |  |  |
| --- | --- | --- | --- |
| # | 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 6, Data cleansing and exception handling rules

### Final Validation Sample

Final number of observation is 164,324 customers.

## 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.

#### GINI

The Gini is a statistical measure used to gauge the separation exhibited by the model vis-à-vis a random selection. Gini coefficient represents the area covered under the Lorenz curve. Lorenz curve indicates the lift provided by the model over random selection. Higher the GINI, higher is the separation exhibited by the model.

When we plot cumulative score distribution from the goods against the cumulative score distribution from the bads, we get what is known as the Trade-off curve. For each score distribution, the plotted trade-off curve shows how many bad accounts are captured by the score at the low end of the distribution for a given number of good records.



The Gini Coefficient is defined as the ratio of area between the Trade-Off curve and the diagonal line to the area above the diagonal line.

Gini Coefficient = (Trade-Off Curve Area – 0.5)/0.5

Indicative Tolerance

* Gini >= 50% signifies strong discriminatory power of the model.
* 30% <= Gini <50% signifies moderate discriminatory power of the model
* Gini<30% signifies poor discriminatory power of the model

### PD Validation Result

For KLeasing products, binomial test is used for validating 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.

#### **TFRS9**

**By customer**



Table 7: Binomial test of KLeasing PD (by customer)

**By Outstanding**



Table 8: Binomial test of KLeasing PD (by outstanding)

#### **Propose Update PD for TFRS9**



Table 9: Binomial test of New proposed update KLeasing PD

Table 7 and Table 8 show validation results for TFRS9 PD. From the results, PD for all asset class are valid except for Restructure (TDR) so modeler propose to adjust PD for this asset class from 31.82% to 37.00%. The validation result for new proposed updated PD is shown in Table 9.

#### **Behavior Score**

Behavior Score is validated by using Gini and K-S Test and Somer’s D. Validation result is shown below. From the result, Behavior score model still performs well in this validation sample.



Table , Behavior Score validation statistics

# Exposure at Default

All K-Leasing loan products are term loan product so exposure at default (EAD) are related to term structure and prepayment rate. EAD for term loan products is express as a result of combining outstanding by term structure with prepayment rate but as nature of auto loan is charged at a fixed rate of interest which the interest will remain fixed during the tenure of the loan. Therefore, borrowers may not pay off the loan before the contractual maturity leading to no partial prepayment model (%CPR=0). Then, EAD for loan with fixed rate is equal to the contractual outstanding. As well as Consumer Loan, there is no partial prepayment model and as a result, EAD will be equal to the contractual outstanding.

Due to there is no model for KLeasing ’s EAD so model validation step is not necessary.

# Loss Given Default

Loss given default, LGD, can be defined as the share of a defaulted exposure that will never be recovered by the lenders. It is important to note that a loss arises only in the event of default and is conditional on the default event; hence it is called loss given default.

LGD is commonly expressed as a ratio and related to the outstanding amount or exposure at default (EAD). In other words, LGD is essentially a loss rate given default. The recovery rate is then 1 − LGD.

The loss given default shall be assessed in an economic sense rather than a mere accounting perspective. That said the discount effect associated with the recovery cash flow and cost associated with collecting recoveries shall be considered. LGD is an important input for the calculation of economic capital, loan loss provision, and credit risk-based pricing.

## Scope of Validation

This LGD validation is to validate LGD constant that is used for downturn, through-the-cycle and point-in-time LGD. Because there is just a single LGD constant used for all cases so the validation is done all at once.

## Data Management

### Overview of Input Data Set

Data used in model development for LGD is KLeasing customers who hold any KLeasing product including New Car, Used car and KCar. The data needed to calculate LGD includes

1. Contract Data such as reference contract number, approved date, default date, exposure at default, final flag status and final pathway.
2. Cash flow collected from customer in each period after default

### Validation Sample Design

Total number of account is 19,970 of default accounts during Jan 2009 – Dec 2017 are observed. Monthly recovery payment are observed after default to Dec 2017

## Quantitative Validation

There is no model for KLeasing downturn and through-the-cycle LGD so to validate LGD constant, the hypothesis testing is done by comparing the estimated LGD constant value of the portfolio with the realized (actual) loss from the database.

### Measurement

For the LGD back testing, key assumption for LGD model is past experience can be used to predict the future (i.e. the Bank’s loss in the future would be similar to ones of the past given customers that have similar characteristic). To validate constant LGD, hypothesis testing is done. The null hypothesis is that the estimated LGD constant value of the portfolio is less than or equal to the realized (actual) loss from the database. If null hypothesis is rejected, or actual LGD is greater than current estimated LGD, then KBank will adjust estimated LGD higher to cover actual LGD.

### Validation Result

LGD for customers ending in each pathway of KLeasing product is shown in table below. The total LGD is LGD of each path weighted averaged by exposure at default. Current LGD for KLeasing is 33.42%. Current observed LGD doesn’t deviate much from current estimated constant and still lies in range of 95% prediction interval. As a result, constant LGD at 33.42% is still valid.

|  |  |
| --- | --- |
| Path | LGD |
| Self-cure | 0% |
| Early cure | 0% |
| Auction | 44% |
| Write off | 86% |
| Total LGD | **33.90%** |

Table , Observed LGD for KLeasing portfolio by ending path

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)