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| TFRS9 Model Validation Document |
| Credit card |
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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 EL of the TFRS 9 accounting book.

Approval

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **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 Credit card portfolio. It is a revolving term loan product and the portfolio size of Credit card (CC) is about 58,339,127,785 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 1, Stages under IFRS 9

The exemplary expected loss (EL) assessment in Table 1 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. |
| Credit Conversion Factor | CCF | Credit Conversion Factor (CCF) is defined as percentage rate of current undrawn credit line that will likely be utilized by borrowers at the time of default |
| Lifetime Expected Credit Loss | LTECL / LEL | The Expected Credit Loss over the behavioral 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] [parameterized](https://en.wikipedia.org/wiki/Statistical_parameter) by two positive [shape parameters](https://en.wikipedia.org/wiki/Shape_parameter), denoted by *α* and *β*, |

Table 2, 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 Credit card 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 supermaster scale. We gathered CC 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 | Supermaster 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 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 December 2017 and the performance period for observation of actual default or rating migration is 12 month from the observation point i.e. 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 shows step by step derivation of our final model development sample.

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 | 2092995 |
| SMA/SMQ | 8126 |
| TDR | 46582 |
| Watch list / Reschedule | 742 |
| NPL |  |
| Total | 2148600 |

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 CC 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 | Total Bad | %Bad |
| All | 2119659 | 34136 | 7.12 |
| PL Normal | 439661 | 17980 | 4.09 |
| SMA/SMQ | 10507 | 6720 | 63.96 |
| TDR | 28079 | 9342 | 33.27 |
| Watch list / Reschedule | 1168 | 94 | 8.05 |

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 to the rating’s PD. It is based on assumption that default is independent event.

### PD Validation Result

#### **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 Credit card.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Masterscal Riskgrade | Asset Class | Fine Riskgrade | #Bad | #Good | Total | %Actual PD | PD Master Scale | Critical PD | DR | Binomial |
| 1 | PL Normal | 12 | 1387 | 685623 | 687,010 | 0.20% | 0.31% | 0.32% | 0.20% | Accept |
| 2 | PL Normal | 98 | 857 | 294548 | 295,405 | 0.29% | 0.51% | 0.54% | 0.29% | Accept |
| 3 | PL Normal | 11 | 848 | 160562 | 161,410 | 0.53% | 0.97% | 1.02% | 0.53% | Accept |
| 4 | PL Normal |  | 2027 | 368574 | 370,601 | 0.55% | 1.98% | 2.03% | 0.63% | Accept |
| 4 | PL Normal | 10 | 689 | 61911 | 62,600 | 1.10% | 1.98% | 2.03% | 0.63% | Accept |
| 5 | PL Normal | 9 | 7670 | 337169 | 344,839 | 2.22% | 3.94% | 4.01% | 2.22% | Accept |
| 6 | PL Normal | 8 | 3948 | 72099 | 76,047 | 5.19% | 8.70% | 8.92% | 5.15% | Accept |
| 6 | Reschedule |  | 12 | 742 | 754 | 1.59% | 8.70% | 8.92% | 5.15% | Accept |
| 7 | PL Normal | 7 | 3192 | 37138 | 40,330 | 7.91% | 14.18% | 14.61% | 8.17% | Accept |
| 7 | TDR | 2 | 302 | 1907 | 2,209 | 13.67% | 14.18% | 14.61% | 8.17% | Accept |
| 7 | Watch list |  | 1 | 155 | 156 | 0.64% | 14.18% | 14.61% | 8.17% | Accept |
| 8 | PL Normal | 5 | 4098 | 27339 | 31,437 | 13.04% | 21.05% | 21.69% | 13.03% | Accept |
| 8 | PL Normal | 6 | 964 | 7018 | 7,982 | 12.08% | 21.05% | 21.69% | 13.03% | Accept |
| 8 | TDR | 4 | 357 | 1765 | 2,122 | 16.82% | 21.05% | 21.69% | 13.03% | Accept |
| 9 | PL Normal | 3 | 1365 | 5329 | 6,694 | 20.39% | 34.67% | 35.53% | 20.39% | Accept |
| 9 | PL Normal | 4 | 1360 | 4991 | 6,351 | 21.41% | 34.67% | 35.53% | 20.39% | Accept |
| 9 | TDR | 6 | 5318 | 21072 | 26,390 | 20.15% | 34.67% | 35.53% | 20.39% | Accept |
| 10 | PL Normal | 1 | 21 | 59 | 80 | 26.25% | 50.69% | 51.51% | 27.44% | Accept |
| 10 | PL Normal | 2 | 515 | 1694 | 2,209 | 23.31% | 50.69% | 51.51% | 27.44% | Accept |
| 10 | TDR | 5 | 8391 | 21838 | 30,229 | 27.76% | 50.69% | 51.51% | 27.44% | Accept |
| 11 | SMA |  | 5742 | 8126 | 13,868 | 41.40% | 68.95% | 69.96% | 41.40% | Accept |

Table 7, Binomial test CC PD (by customer)

# Exposure at Default

Exposure at Default (EAD) is defined as expected outstanding balance at the time of default. It is one of the major components in credit risk analytics, especially expected loss (EL). Along with Probability of Default (PD) and Loss Given Default (EAD), EAD is used to calculate EL and capital of the bank expressed as PD x EAD x EAD.

### EAD of Revolving Products and CCF

In practice, the EAD of products with explicit credit line, such as credit card, tends to be the same as its balance including the potential increase in the outstanding balance from a reference date to the time of default. KBank estimates the EAD for credit card or other revolving credit products by using indirect approach focus on evaluating Credit Conversion Factor (CCF), the proportion of current undrawn amount that will be drawn down at the time of default. Exposure at Default (EAD) is defined as the expected amount drawn by borrowers at the time of default.

For an active revolving instrument (non-NPL), the EAD at reporting date is defined as

Where is current principal amount at time

is current limit amount at time

is Credit Conversion Factor (CCF)

is Effective Interest Rate (EIR)

is a variable acting as an on/off switch for interest calculation

is the number of month for accrued interest to be calculated

is realized accrued interest at time

CCF model predicts expected utilization if a customer defaults. Thus, validation is performed only on the defaulted population i.e. the NPLs. We use the following definition of actual CCF for the purpose of our model development and model validation. For an instrument , the actual Credit Conversion Factor (CCF) is defined as percentage rate of current undrawn credit line will likely be utilized by borrowers at the time of default i.e.

**Validation of EAD**

EAD validation will be done via the validation of KBank’s CCF models. Each CCF model will validated by applying proper statistics to determine whether the CCF values resulted from the models can represent the actual CCF values from KBank’s validation sample.

## Scope of Validation

In this document, Kbank will validate two CCF models that have been developed and updated in the credit card model development document namely, scorecard for the Through-the-cycle CCF and constant CCF. However, there is another model called “Point-in-Time CCF model”. The validation of this model is not carried out at this time but it will be performed later in the next validation period.

## Data Management

### Overview of Input Data Set

As mentioned previously, CCF model validation is performed based on a sample of defaulted instrument. In addition to specification of default definition and default time period, the input for actual CCF calculation includes outstanding balance at default, past outstanding balance and past limit. In summary, the data requirement for the calculation of actual CCF calculation is shown as follows:

Figure 3, Data required for actual CCF calculation

### Validation Sample Design

In model development, there are two specific time periods must be considered; observation and performance period. The observation period consists of a specific period of time prior to the point of default that used to characterize a customer’s past behavior. The performance period consists of a specific time to default. Data used to develop model is listed in Table 8.

|  |  |  |
| --- | --- | --- |
| Period | Timeframe | Data |
| Observation Period (tr) | January 2017-December 2017 | * Information of customers at 12 or 6 months prior to the time they default. |
| Performance Period (td) | December 2017-December 2018 | * Total outstanding balances of customers who default for the first time * Actual CCF calculated by using formula in TTC-EAD\_Model Development for Credit Card Document |

Table 8, Data observation and performance period

### Data Cleansing and Exception Handling

#### Exclusion Rule

Some customers may have some conditions that might not be appropriate to be used in CCF model development, such as missing credit line, months on book less than 6 months or etc. Thus, need to be excluded from the model development

The customers with all conditions listed in the table below will be excluded from the model development.

|  |  |
| --- | --- |
| No. | Exclusion Rules |
| 1 | NPL customer |
| 2 | Total outstanding balances before write-off at the time of default <= 0 THB |
| 3 | Missing credit line or credit line <= 0 at observation period(tr) |
| 4 | Missing open date |
| 5 | Months on book of customer < 6 months |
| 6 | Account is inactive |
| 7 | Cannot identify segment  HU, LU, Inactive |

Table 9, all conditions that need to be excluded.

#### Exception Handling

The purpose of this process is to reassign some variable values in the validation sample, because these values might affect the validation result.

The reassignment of these variables is shown in the table below.

|  |  |  |
| --- | --- | --- |
| No | Variables | Description |
| 1 | Actual\_CCF | If Actual\_CCF <0 then 0  If Actual\_CCF >1 then 1 |

Table 10, reassignment of variables

### Final Validation Sample

The final customers of 20,187 will be used as a validation sample

## Quantitative Validation

**Scorecard for Through-The-cycle CCF**

We begin with the CCF scorecard validation, the final customers of 20,187 will be assigned CCF rating based on their CCF scores calculated using CCF scorecard table from the model development document(This table is also known as a Masterscale table). Then, the average of actual CCF for all customers in each rating will be computed.

The result is shown in the table below,

|  |  |  |  |
| --- | --- | --- | --- |
| Segment | Rating |  | Average Actual CCF 2018 |
| HU | 1 |  | 0.283952986 |
| HU | 2 |  | 0.359524903 |
| HU | 3 |  | 0.227240514 |
| HU | 4 |  | - |
| HU | 5 |  |  |
| LU | 1 |  | 0.083789543 |
| LU | 2 |  | 0.199522487 |
| LU | 3 |  | 0.414920952 |
| LU | 4 |  | - |
| LU | 5 |  |  |

Table 11, CCF rating and actual CCF.

From

Table 11, it is evident that the average actual CCF is not ranked with the CCF rating; therefore, the scorecard for through-the-cycle CCF is not valid and need to be recalibrated. Also, there’s no defaulted records with CCF rating of 4 and 5.

Due to the fact that it takes time to redevelop the Scorecard CCF model, KBank decides to use a constant Through-The-cycle CCF model as a temporary champion model.

**Constant Through-The-cycle CCF**

After KBank decided to use constant CCF model as a temporary model, the different constant CCF values estimated from this model will be assigned to the customer based on different segments.

|  |  |
| --- | --- |
| Segment | Value |
| HU | 0.35 |
| LU | 0.55 |

Table 12, a constant CCF value for each segment

To ensure that our constant CCF model is applicable to all KBank’s credit card customer, KBank will validate this model using a statistical method called t-test.

**One-tailed t test for CCF validation**

The purpose of this test is to check whether CCF constant resultedfrom constant through-the-cycle CCF model is greater than or equal to averaged actual CCF values from our validation samples for all monthly performance period from December 2017-December 2018.

The averaged actual CCF used in this test represents the average actual CCF for all customers in each specific month and each segment from December 2017-December 2018.

The hypotheses used in this test are as follows:

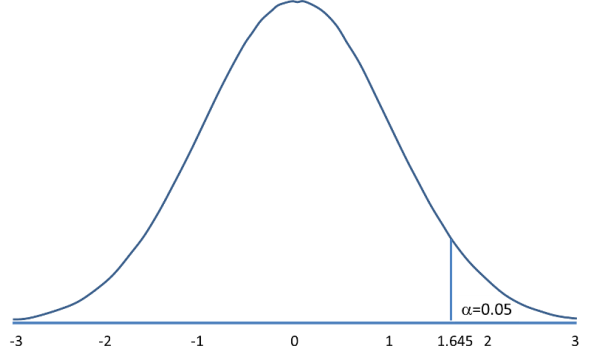
H0: Model’s constant CCF >= Averaged actual CCF

H1: Model’s constant CCF < Averaged actual CCF

The t-test equation along with the variance of validation samples are shown below,

Where is mean of averaged actual CCF

n is the number of observations sample.



To test with 95% or 99% confidence level, reject null hypothesis (H0) if t-statistic ≥ critical value.

Indicative Tolerance

* t-statistic ≥ critical value accept null hypothesis, implies actual CCF is close to predicted CCF.
* t-statistic < critical value reject null hypothesis, implies there is a high under-fitting of CCF.

The critical value for t-test can be looked up from the student t-distribution table using degree of freedom and significant level.

### Validation Result

The t-test statistics yield the following results based upon the customer segment.

#### For, high utilization customer (HU)

|  |  |  |
| --- | --- | --- |
| **One-tailed test** |  |  |
|  |  |  |
|  | 95% | 99% |
| Number of sample | 12 | 12 |
| Degree of freedom | 11 | 11 |
| p-value | 0.05 | 0.01 |
| Critical value | 1.796 | 2.718 |
| Calculated t-value | 5.984 | 5.984 |
| Result | Accept | Accept |

Table 13, CCF Validation result for HU customers

From

Table 13, it is concluded that the t-test accept the null hypothesis at 95% and 99% significant level, which means our HU CCF is greater than or equal to actual CCF value.

The plot of averaged actual CCF and KBank constant CCF over time is shown in the figure below

Figure 4, the plot of averaged actual CCF and KBank constant CCF over time for HU

Table 13, illustrates that KBank has a conservative view on High utilization CCF because the Model’s constant CCF is greater than actual CCF with amount of value.

#### For, Low utilization & Inactive customer (LU & Inactive)

|  |  |  |
| --- | --- | --- |
| **One-tailed test** |  |  |
|  |  |  |
|  | 95% | 99% |
| Number of sample | 12 | 12 |
| Degree of freedom | 11 | 11 |
| p-value | 0.05 | 0.01 |
| Critical value | 1.796 | 2.718 |
| Calculated t-value | 37.361 | 37.361 |
| Result | Accept | Accept |

Table 14, CCF Validation result for LU& Inactive customers

From Table 14, it is concluded that the t-test accept the null hypothesis at 95% and 99% significant level, which means our LU& Inactive CCF is greater than or equal to actual value.

The plot of averaged actual CCF and KBank constant CCF over time is shown in the figure below

Figure 5, the plot of averaged actual CCF and KBank constant CCF over time

Figure 5, illustrates that KBank has a conservative view on High utilization CCF because the Model’s constant CCF is greater than actual CCF with amount of value.

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# 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. 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.

## Scope of Validation

In this document, KBank will validate two LGD models that have been developed and updated in the credit card model development document namely, scorecard for the Through-the-cycle LGD and constant LGD. However, there is another model called “Point-in-Time LGD model”. The validation of this model is not carried out at this time but it will be performed later in the next validation period.

## Data Management

### Overview of Input Data Set

The input for actual LGD calculation includes outstanding balance at default, state of default, final flag and actual cumulative recovery amount. The sum of the present value (PV) of these cash flows amounted to the accumulated recovery amount which is then used to calculate the value of LGD. The states of default indicate a posterior state of action after the customer has defaulted. The final flag indicates whether there is an on-going collection attempt and thus whether the state indicated are final. In summary, the data requirement for the calculation of actual LGD is shown as follows:

### Validation Sample Design

To calculate the LGD value of each customer, the recovery cash flow is collected from the first day that the customer becomes default until the most recent data (Dec 2016). In addition, to estimate robust models, the observation period should cover the whole business cycle which is usually considered between 3 to 5 years.

|  |  |  |
| --- | --- | --- |
| Period | Timeframe | Data |
| Observation Period | Jan 2016 –  Dec 2016 | Default customers information |
| Recovery Period | Jan 2016 –  May 2019 | Recovery cash flow of default customers |

Table 15, Observation and recovery period for recovery curve

### Data Cleansing and Exception Handling

### Exclusion Rules

The accounts that meet the exclusion rules will not be included in the data sample for the scorecard development. The exclusion status is based on the customer status at the observation point

|  |  |  |
| --- | --- | --- |
| No | Variables | Description |
| 1 | Final\_flag=0 | The customers whose recovery process has not been completed. |
| 2 | Default outstanding  <= 2,000 B | The customers who have outstanding <=2000 B when they default. |

Table 16, Exclusion rules for validation sample

### Final Validation Sample

The final validation sample of 5,450 will be used to validate our model.

## Quantitative Validation

### Scorecard for Through-The-cycle LGD

We begin with the LGD scorecard validation, the final customers of 5,450 will be assigned LGD rating based on their LGD scores calculated using LGD scorecard table from the model development document(This table is also known as a Masterscale table). Then, the average of actual LGD for all customers by outstanding in each rating will be computed.

The result is shown in the table below,

|  |  |
| --- | --- |
| Rating | Average Actual LGD |
| 1 | 0.5613905102 |
| 2 | 0.6044976366 |
| 3 | 0.6117489261 |
| 4 | 0.5480874285 |
| 5 | 0.3971114454 |

Table 17, CCF rating and actual CCF

From Table 17, it is evident that the average actual LGD is not ranked with the LGD rating. Therefore, the scorecard for through-the-cycle LGD is not valid and need to be recalibrated.

Due to the fact that it takes time to redevelop the Scorecard LGD model, KBank decides to use a constant Through-The-cycle LGD model as a temporary champion model.

### Constant Through-The-cycle LGD

After KBank decided to use constant LGD model as a temporary champion model, the average KBank portfolio’s historical actual LGD of 0.6813 will be applied to all credit card customers.

### Validation Result

The average actual LGD of the validation sample by outstanding is 0.483 which is less than 0.6813 so we can conclude that our constant LGD can cover the average actual LGD for credit card portfolio.

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)