# Review of Methodologies and Rating Models Report – 2021

**Preamble**

VIS uses rating methodologies that are rigorous and systematically backed by models/criteria that are subject to validation based on historical experience, including back testing conducted at least once annually.

With an aim to comply with Regulations 11.C.b, 11.C.c and 11.C.s of CRC Regulations 2016, these activities are conducted and documented by 'Methodology, Criteria & Quality Review Group (MCQG)' of VIS which is headed by the CEO. The back testing/validation exercise (the exercise) is conducted periodically under the guidelines provided by 'VIS's Policy on Review of Methodologies and Rating Models' (the Policy) which is duly approved by the Board of Directors.

The latest exercise was conducted in the first fortnight of October 2021 and the results are documented in this report. In the remainder of this document both the words 'back testing', 'validation' and 'review' are used interchangeably.

**Exercise Functions**

1. **PERIODIC REVIEW OF METHODOLOGIES**: VIS reviewed and, where required, updated its methodologies to take into account changes in the business environment. Details of methodologies which were updated during the last 12 months are provided in the Table 1 below:

| **Table 1** | | | |
|---|---|---|---|
| **S. No.** | **Methodology** | **Updated in** | **Major Changes in Methodology** |
| 1. | Corporates | August, 2021 | The fundamental criteria as outlined in 'Rating Methodology - Industrial Corporates' dated April 2019 remains the same with no changes to the ratings framework itself. This document aims to lay out in more detail the key areas of assessment when reviewing corporate credit ratings and provides additional guidance on the relevant factors within the existing framework.<br>As the rating universe within the VIS portfolio continues to expand, it also allows us to deepen our sector specific knowledge, outside of the listed companies' universe, for which VIS already maintains a robust database. Sectoral Research are regularly disseminated in the Sector Updates posted in the Knowledge Center on the VIS website. |
| 2. | Structured Covered Bonds/Sukuk | June, 2021 | New Methodology |

| | | | |
|---|---|---|---|
| 3. | Socio-Economic Performance Grading of MFBIs | May, 2021 | New Methodology |
| 4. | Securities Broker Fiduciary | January, 2021 | New Methodology |
| 5. | Fund Stability | December, 2020 | The change in the VIS methodology for Fund Stability Rating (FSR) incorporates updated credit risk criteria whereby the fund rating shall be determined through a weighted average score (taken from the current and previous rating of the fund). |
| 6. | Toll Roads | August, 2020 | **Replaced** (The project company may sensitize volume assumptions for the initial years of commercial activity and establish the financial model on the same.) **in place of** (It will be a positive element for the project company to sensitize volume assumptions for the initial years of commercial activity and establish the financial model on the same. Early periods of commercial activity may result in resistance from daily road travelers who are hesitant at paying the toll with a portion insisting on finding alternative routes. It is only after a certain period when travelers realize the benefits of the toll road do volume numbers rise to assumed figures, if not higher.) |
| 7. | Telecommunications | July, 2020 | The distinct segments in which the role of Telecommunications is embedded are three, which were added in the methodology namely, the data generators, the data processors, the Highway providers. |
| 8. | Broker Management Ratings | July, 2020 | Recently, SECP has approved few amendments to broker regulations. Amended regulations categorize securities brokers with enhanced measures for investor protection through safe custody of their assets, improved governance standards, transparency and risk management. Impact of these developments in regulations and the impact of the same on brokerage industry will be an important part of the rating evaluation. |
| 9. | Lodging Industry | July, 2020 | Evaluation of the methodology in respect to its applicability in line with the regulations, industry standards and norms. The methodology's readability aspect was also improved. |
| 10. | Linkages Between Parent And Subsidiary Companies | July, 2020 | Major changes include addition of areas covering cross defaults and rating of instruments with underlying guarantees by the parent entity. |

| | | | |
|---|---|---|---|
| 11. | Government Support Entities | July, 2020 | Evaluation of the methodology in respect to its applicability in line with the regulations. The methodology's readability aspect was also improved. |
| 12. | Securities Firms | July, 2020 | In April 2020, SECP imposed an upward revision in the minimum capital requirements for brokerage firms. This increase in minimum capital requirements, will impact the structure of the brokerage industry, and in turn, impact the standalone performance of brokerage companies. VIS will accordingly assess the impact of such regulatory changes on the financial and business risk profile of rated entities. |
| 13. | Rating The Issue | July, 2020 | Incorporated details of instruments issued by microfinance banks and their notching criteria. |
| 14. | Commercial Banks | June, 2020 | Methodology changes cover areas including sponsor support, treatment of Liquidity Coverage Ratio and D-SIB buffer introduced by SBP as part of the methodology. restructured exposures, incorporating of Basel 3 |

2. **PERIODIC VALIDATION OF RATING MODELS:** VIS reviews and validates all its rating models at least once in a year and, if required, updates them accordingly.

   As per the Policy, VIS adopts two different approaches for validation of models with and without availability of meaningful data. Following **r**ating models along with their sub-models were back-tested in this exercise:

**Table 2**

| **Models with availability of meaningful data** | **Models without availability of meaningful data** |
|---|---|
| • Industrial Corporates (69 sub models) | • Commercial Banks<br>• General Insurer Companies (sub-model: General Takaful)<br>• Life insurance Companies (sub-model: Life Takaful)<br>• Microfinance Banks<br>• Asset Management Companies<br>• Brokerage & Securities Firms<br>• Non-banking Financial Institutions (sub-models: Investment Banks, Leasing Companies, Modarabas) |

Approach-wise results of the exercise are as under:

i. **Approach 1: For models with availability of meaningful data size**: For models where a meaningful quantum of observed and default data is available, following measures were used for the purpose of validation:

**a. An overview of the dataset**

Total Observations: The dataset used in the exercise includes indicative ratings based on financial results from year 2000 to 2020. Two types of observations were used that included financial data from VIS's contracted clients and, for enhancement of the dataset, from VIS's proprietary database of public listed companies in Pakistan. None of the data from the contracted clients has been reported here in absolute terms in order to maintain confidentiality.

Default Observations: Instances of reported defaults experienced in both types of datasets were included. However due to lack of default reporting and to enhance the meaningfulness of the dataset, capital erosion of 40% or more has also been considered as a default in both datasets.

Details of total observations and default observations are presented in Table 3 below:

| **Table 3** | | | |
|---|---|---|---|
| **Data Source** | **Total Observations** | **Default Observations** | **Default Percentage** |
| Contracted Clients | 6,042 | 1,770 | 29.3% |
| Public Companies | 2,790 | 10 | 0.4% |
| **Total** | **8,832** | **1,780** | **20.2%** |

***Important!*** *Techniques used for enhancement of the size of total data and default observations are in line with the prescriptions made by international regulatory bodies. Readers may refer to measures recommended by European Securities & Market Authority (ESMA) in their publication "Guidelines on the validation and review of Credit Rating Agencies' methodologies" issued on 23/03/2017 and recommendations of the Basel Committee on Banking Supervision published in 'Studies on the Validation of Internal Rating Systems – Working Paper 14' in May 2005.*

Probability of Default: Although the models under assessment are not Logit Models, a probability of default (PD) is calculated by running logistic regression on scores generated by respective models for each observation.

**b. Discriminatory Power**

Following tests were conducted to assess 'Discriminatory Power' of rating models:

- Cumulative Accuracy Profile (CAP)
- Accuracy Ratio (AR)/ Gini Coefficient
- Bootstrapping 95% Confidence for AR
- Receiver Operating Characteristic (ROC)
- Area under the Curve (AUC)
- Kolmogorov-Smirnov (KS) Statistics

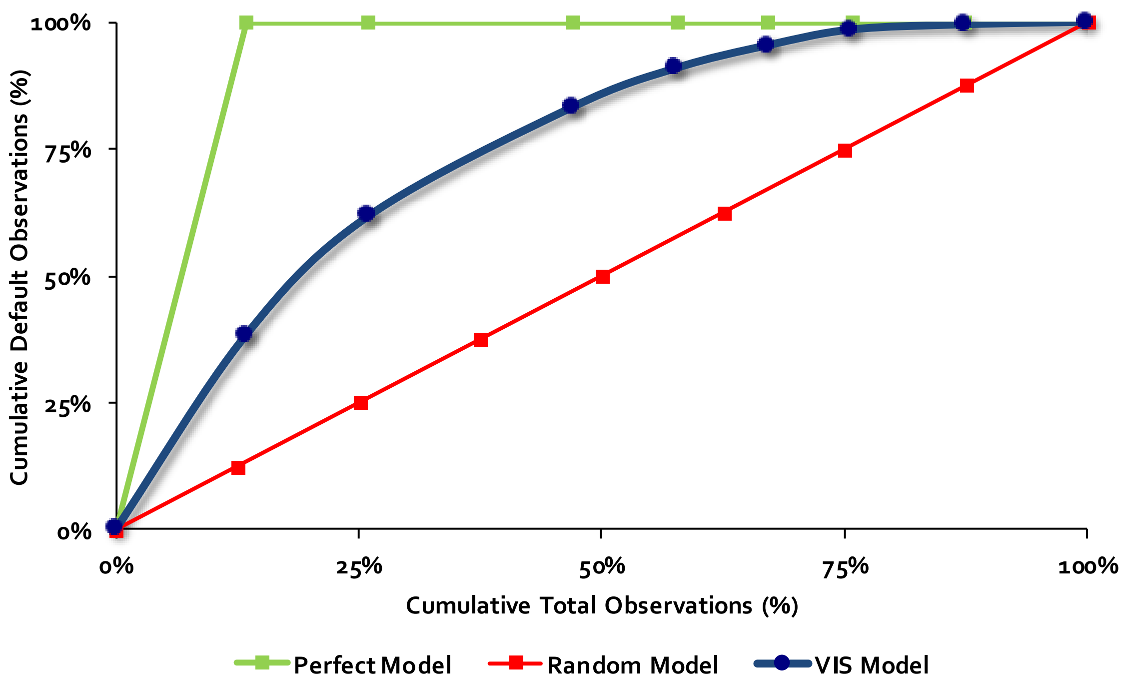
**b1. Cumulative Accuracy Profile (CAP)**

The CAP provides a way of visualizing discriminatory power. The key idea is that if a rating system discriminates well, defaults should occur mainly among borrowers with a poor rating. A perfect rating model will assign the lowest scores to the defaulters. In this case the CAP is increasing linearly and then staying at one. For a random model without any discriminative power, the fraction X of all debtors with the lowest rating scores will contain an X percent of all defaulters. Real rating systems will be somewhere in between these two extremes. Results of CAP test conducted on our models are presented in the table and the chart below:

**Table 4: CAP**

| a. Model Grades | b. Total Observations | c. Default Observations | d. Cumulative Observations (%) | e. Cumulative Defaults (%) |
|---|---|---|---|---|
| 1. (worst) | 1,182 | 681 | 13.38 | 38.26 |
| 2. | 1,110 | 417 | 25.95 | 61.69 |
| 3. | 1,858 | 383 | 46.99 | 83.20 |
| 4. | 943 | 137 | 57.67 | 90.90 |
| 5. | 835 | 80 | 67.12 | 95.39 |
| 6. | 759 | 55 | 75.71 | 98.48 |
| 7. | 1,026 | 18 | 87.33 | 99.49 |
| 8. (best) | 1,119 | 9 | 100.00 | 100.00 |
| **Total** | **8,832** | **1,780** | | |

**Chart 1: CAP**




**Conclusion**: On a cumulative basis, results of CAP on our models, presented above in Table 4 and Chart 1, depict that a high percentage of defaults (83%) have occurred in entities that were assigned lower grades (in worst 3 grades) thus plotting a fitting curve, as desired. The CAP test of discriminatory power is considered **PASSED**.

**b2. Accuracy Ratio (AR)/ Gini Coefficient**

The most common summary index of the CAP is the Accuracy Ratio (or Gini coefficient). Accuracy ratio condenses the information contained in CAP curves into a single number. It can be obtained by relating the area under the CAP but above the diagonal (random model) to the maximum area the CAP can enclose above the diagonal. The rating model is considered the better the closer accuracy ratio is to one. Gini Coefficient (or AR) of VIS models is calculated as **61.7%**.

VIS also conducted bootstrapping 95% confidence for the results of AR with multiple iterations. The core idea of bootstrapping is to re-sample from the data used for estimation and re-estimate the statistics with this new, re-sampled data and derive a distribution of the statistic by having done this many times.

**Conclusion**: Gini Coefficient result for VIS models depict a number (61.7%) better than a random model. Bootstrapping results were also encouraging showing that AR ranged within 64% to 60% when iterated multiple times. Based on these results, this test of discriminatory power is considered **PASSED**.

**b3. Receiver Operating Characteristic (ROC) & Area under the Curve (AUC)**

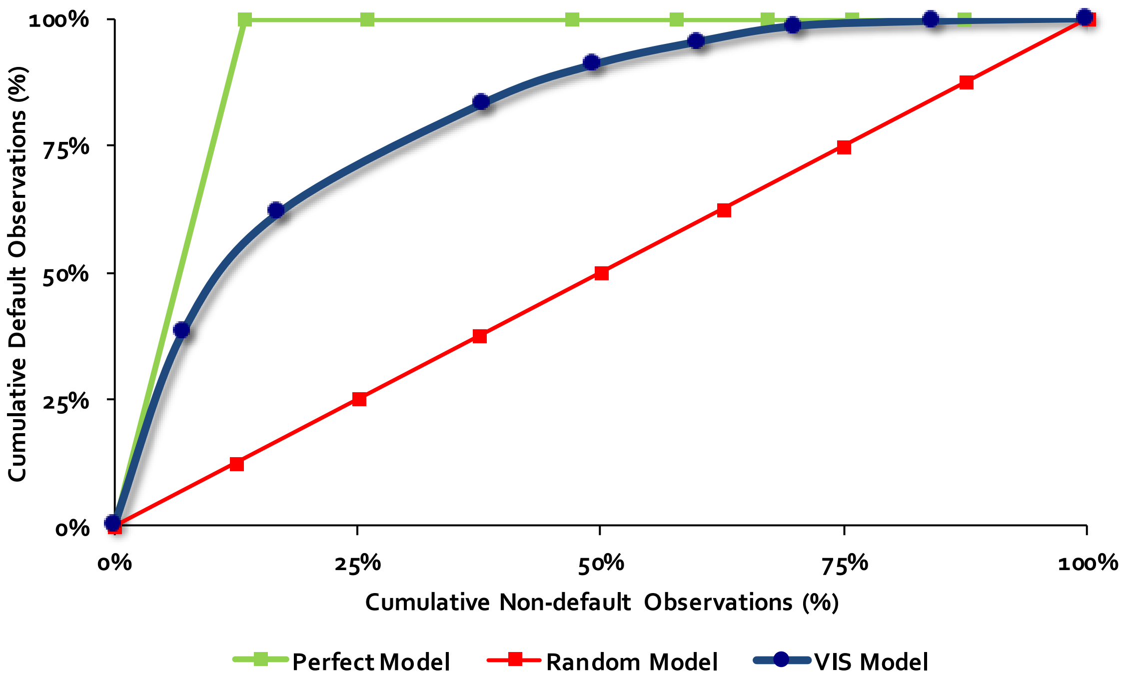
An analytic tool that is closely related to the CAP is the Receiver Operating Characteristic (ROC). The ROC can be obtained by plotting the fraction of defaulters ranked X or worse against the fraction of non-defaulters ranked X or worse. The two graphs (CAP and ROC) thus differ in the definition of the x-axis. A common summary statistic of a ROC analysis is the area under the ROC curve (AUC).

A rating model's performance is better steeper the ROC curve is at the left end and the closer the ROC curve's position is to the point (0,1). Similarly, the model is better larger the area under the ROC curve is. The AUC is 0.5 for a random model without discriminatory power and it is 1.0 for a perfect model. Any reasonable rating model in practice is recommended to have AUC between 0.5 and 1.0. Results of CAP test conducted on our models are presented in the table and the chart below:

**Table 5: ROC & AUC**

| a. Model Grades | b. Total Observations | c. Default Observations | d. Cumulative Non-defaults (%) | e. Cumulative Defaults (%) | f. AUC |
|---|---|---|---|---|---|
| 1. (worst) | 1,182 | 681 | 7.10 | 38.26 | 1.36 |
| 2. | 1,110 | 417 | 16.93 | 61.69 | 4.91 |
| 3. | 1,858 | 383 | 37.85 | 83.20 | 15.15 |
| 4. | 943 | 137 | 49.28 | 90.90 | 9.95 |
| 5. | 835 | 80 | 59.98 | 95.39 | 9.97 |
| 6. | 759 | 55 | 69.97 | 98.48 | 9.68 |
| 7. | 1,026 | 18 | 84.26 | 99.49 | 14.15 |
| 8. (best) | 1,119 | 9 | 100.00 | 100.00 | 15.70 |
| **Total** | **8,832** | **1,780** | | **AUC = sum(col.f)** | **80.90** |

**Chart 2: ROC**




**Conclusion**: Results of ROC and AUC, presented above, are well within the desired range of 0.5 to 1.0. A higher fraction of defaulted entities in comparison to total entities that defaulted were rated in the lower grades by the model which resulted in a steep ROC curve and an AUC of 80.9%. Thus for VIS models, ROC and AUC tests of discriminatory power are considered **PASSED**.

### b4. 4. Kolmogorov-Smirnov (KS) Statistics Test

Kolmogorov-Smirnov (KS) Statistics test is a non-parametric test that compares two cumulative distributions and returns the maximum difference between them and KS Statistic is where there is a maximum difference between the two distributions. In credit modeling, the test helps to understand how well a model is able to differentiate defaults and non-defaults. For any model with good discriminatory power, KS Statistics is recommended to be in the worst 3 rating categories. Results of KS test conducted on our models are presented in the table and the chart below:

**Table 6: KS Test**

| a. Model Grades | b. Total Observations | c. Default Observations | d. Cumulative Non-defaults (%) | e. Cumulative Defaults (%) | f. KS Stat (%) (e-d) |
|---|---|---|---|---|---|
| 1. (worst) | 1,182 | 681 | 7.10 | 38.26 | 31.2 |
| 2. | 1,110 | 417 | 16.93 | 61.69 | 44.8 |
| 3. | 1,858 | 383 | 37.85 | 83.20 | 45.4 |
| 4. | 943 | 137 | 49.28 | 90.90 | 41.6 |
| 5. | 835 | 80 | 59.98 | 95.39 | 35.4 |
| 6. | 759 | 55 | 69.97 | 98.48 | 28.5 |
| 7. | 1,026 | 18 | 84.26 | 99.49 | 15.2 |
| 8. (best) | 1,119 | 9 | 100.00 | 100.00 | 0.0 |
| **Total** | **8,832** | **1,780** | | | |

**Conclusion**: As presented above in Tables 6, highest KS statistics (i.e. 45.4%) for VIS models lie in the 3rd worst rating grade (yellow highlighted in above tables). The results are well within the desirable range of worst 3 rating grades portraying a high discriminatory power of the models and thus the KS Statistic test of discriminatory power is considered **PASSED**.

### c. Predictive Power

Following tests were conducted to assess 'Predictive Power' of rating models:

- Comparison of Observed vs. Expected Default Rates
- Brier Score
- Binomial Distribution Test
- Normal Approximation
- Traffic Lights Analysis

### c1. Comparison of Observed vs. Expected Default Rates

An intelligent model must have the capability to predict a high default probability for observations that actually defaulted and a low default probability for those that did not. In order to yield a default probability for each possible score generated by the model, logistic regression was applied on cumulative distribution of generated scores and an average PD was calculated for each rating grade.

In the table below, average observed/actual defaults in each rating grade are compared with the expected default rates estimated.

**Table 7: Observed vs. Expected Default Rates**

| a. Model Grades | b. Total Observations | c. Default Observations | d. Observed Defaults (%) | e. Estimated PD (%) |
|---|---|---|---|---|
| 1. (worst) | 1,182 | 681 | 57.6 | 57.0 |
| 2. | 1,110 | 417 | 37.6 | 39.0 |
| 3. | 1,858 | 383 | 20.6 | 22.3 |
| 4. | 943 | 137 | 14.5 | 12.1 |
| 5. | 835 | 80 | 9.6 | 7.8 |
| 6. | 759 | 55 | 7.2 | 5.0 |
| 7. | 1,026 | 18 | 1.8 | 2.7 |
| 8. (best) | 1,119 | 9 | 0.8 | 1.4 |
| **Total** | **8,832** | **1,780** | | |

**Conclusion**: As evident from the table above, predicted as well as observed default rates are very well stacked i.e. default values depicting a declining trend as we move towards the higher rating grades. Moreover, default rates observed in each rating grade are in close harmony with the predicted rates. The level of dispersion estimated in the predicted and observed distributions in all segments depicts that PDs for all grades are well calibrated and this test of predictive power of the models is considered **PASSED**.

**c2. Brier Score**

The Brier score is an important test of calibration and measures the accuracy of probabilistic predictions by calculating the mean squared difference between the predicted probability assigned to the possible outcomes and the actual outcome. Therefore in case of rating models, the lower the Brier score is, the better is the forecast of default probabilities or better the PDs are calibrated; for a hypothetical perfect model the Brier score will be zero. Using the grade-wise averages of the actual and predicted default observations, a cumulative Brier score of the models was estimated as **0.0003** (0.03%).

**Conclusion**: The Brier score standing almost at zero depict a high predictive power of models and good calibration of PDs. On the basis of the above, the Brier score test is considered **PASSED**.

**c3. Binomial Distribution Test & Normal Approximation**

In order to test that default probabilities are not underestimated; binomial tests and normal approximation are conducted separately for each rating grade. With the assumption that defaults are independent (i.e. default correlation is zero), the number of defaults in a given year and the grades then follows a binomial distribution. As the binomial distribution of large datasets tends to converge to the normal, hence considering the size of the testing dataset a normal approximation was also conducted. A walk-forward, out-of-sample method was adopted to conduct these tests where 18 years of past data was used in PD calculation (training data) which was then tested against defaults observed in the later 3 years. The details of grade-wise binomial and normal distributions are presented below:

**Table 8: Binomial Distribution and Normal Approximation**

| a. Model Grades | b. Mean PDs of Training Dataset (2000-17) | c. Observed Default Rates of Testing Dataset (2018-20) | d. Binomial Distribution | e. Normal Distribution |
|---|---|---|---|---|
| 1. (worst) | 56.91% | 44.12% | 99.9% | 99.9% |
| 2. | 38.94% | 18.88% | 100.0% | 100.0% |
| 3. | 22.30% | 7.59% | 100.0% | 100.0% |
| 4. | 12.07% | 8.75% | 92.6% | 92.1% |
| 5. | 7.76% | 1.47% | 100.0% | 99.8% |
| 6. | 4.98% | 4.69% | 61.8% | 63.9% |
| 7. | 2.75% | 0.72% | 97.9% | 95.7% |
| 8. (best) | 1.39% | 0.00% | - | 95.1% |
| **Total Observations** | **7,565** | **1,267** | | |

**c4. Traffic Light Analysis**

For the purpose to test calibration of PDs, a Traffic Light analysis was also conducted on the results of binomial distribution and normal approximation tests based on the following assumptions:

- If the result value for any rating grade is 1.0% or less, then an underestimation of the PDs is very likely and recalibration is required for the grade;
- If the result value for any rating grade is between 1.0% and 5.0%, it generates a warning that the PD might be an underestimate and requires strict monitoring for recalibration; and
- If the result value for any rating grade is 5.0% or above, it rejects the hypothesis that the PDs are underestimated and no recalibration is required.

**Conclusion (c3)**: Considering the results in sections c3 and assumptions outlined in section c4, results for all rating grades were over the desirable benchmark of 5.0% and thus none of the grades represented underestimation of PDs. On the basis of the above, traffic light tests of the binomial and normal distributions are considered **PASSED with no requirement of recalibration**.

## d. Historical Robustness

Following assessments were conducted to gauge the historical robustness of the rating models:

- Cumulative Default Rates
- Comparison with external benchmarks (Mapping)
- 1 & 2 Year Transition Matrices using Cohort Approach with Stability ratios

### d1. Cumulative Default Rates (CDRs)

It is important to note that for the purpose of calculating CDRs, an entity is not included subsequent to instance of default unless it is cured. With a large history of data available to VIS for this study, 5-years, 10-years and 15-years averages of 3-yearly cumulative default rates were calculated for each rating grade. Tables below show the calculation of average CDRs for different periods.

**Table 9: No. of Total Observations**

| Grades | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 22 | 26 | 20 | 30 | 48 | 42 | 28 | 20 | 24 | 16 | 25 | 25 | 29 | 27 | 21 | 30 | 23 | **456** |
| 2 | 31 | 43 | 49 | 52 | 63 | 57 | 20 | 22 | 30 | 18 | 27 | 29 | 22 | 27 | 25 | 42 | 45 | **602** |
| 3 | 56 | 61 | 78 | 71 | 77 | 80 | 50 | 62 | 52 | 42 | 51 | 58 | 55 | 74 | 81 | 100 | 92 | **1,140** |
| 4 | 38 | 30 | 28 | 37 | 34 | 47 | 25 | 27 | 28 | 34 | 32 | 28 | 33 | 35 | 56 | 48 | 32 | **592** |
| 5 | 31 | 31 | 27 | 27 | 31 | 35 | 27 | 35 | 27 | 27 | 31 | 28 | 33 | 44 | 49 | 41 | 32 | **556** |
| 6 | 20 | 29 | 26 | 22 | 28 | 39 | 35 | 20 | 35 | 28 | 28 | 29 | 31 | 44 | 42 | 33 | 40 | **529** |
| 7 | 45 | 38 | 33 | 36 | 44 | 47 | 51 | 36 | 36 | 38 | 30 | 51 | 61 | 63 | 49 | 48 | 35 | **741** |
| 8 | 59 | 53 | 50 | 43 | 46 | 58 | 50 | 41 | 44 | 64 | 49 | 53 | 65 | 48 | 53 | 32 | 21 | **829** |
| **Total** | **302** | **311** | **311** | **318** | **371** | **405** | **286** | **263** | **276** | **267** | **273** | **301** | **329** | **362** | **376** | **374** | **320** | **5,445** |

**Table 10: No. of Defaults**

| Grades | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 3 | 1 | 2 | 6 | 6 | 10 | 1 | 3 | 5 | 4 | 2 | 1 | 8 | 3 | 1 | 5 | 3 | **64** |
| 2 | 2 | 2 | 3 | - | 3 | 8 | 1 | 1 | 7 | 2 | - | 1 | 2 | 1 | - | 1 | 3 | **37** |
| 3 | - | - | - | - | - | 1 | - | 3 | 1 | - | - | 2 | - | - | - | 2 | 1 | **10** |
| 4 | 1 | - | - | - | 1 | - | - | - | - | - | - | - | 1 | - | - | 1 | - | **4** |
| 5 | - | - | - | - | - | - | - | - | - | - | - | - | 1 | - | - | - | - | **1** |
| 6 | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | **-** |
| 7 | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | **-** |
| 8 | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | **-** |
| **Total** | **6** | **3** | **5** | **6** | **10** | **19** | **2** | **7** | **13** | **6** | **2** | **4** | **12** | **4** | **1** | **9** | **7** | **116** |

**Table 11: 3-yearly Cumulative Default Rates**

| Grades | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 8.8% | 11.8% | 14.3% | 18.3% | 14.4% | 15.6% | 12.5% | 20.0% | 16.9% | 10.6% | 13.9% | 14.8% | 15.6% | 11.5% | 12.2% |
| 2 | 5.7% | 3.5% | 3.7% | 6.4% | 8.6% | 10.1% | 12.5% | 14.3% | 12.0% | 4.1% | 3.8% | 5.1% | 4.1% | 2.1% | 3.6% |
| 3 | 0.0% | 0.0% | 0.0% | 0.4% | 0.5% | 2.1% | 2.4% | 2.6% | 0.7% | 1.3% | 1.2% | 1.1% | 0.0% | 0.8% | 1.1% |
| 4 | 1.0% | 0.0% | 1.0% | 0.8% | 0.9% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 1.1% | 1.0% | 0.8% | 0.7% | 0.7% |
| 5 | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 1.1% | 1.0% | 0.8% | 0.0% | 0.0% |
| 6 | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| 7 | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| 8 | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| **Total** | **1.5%** | **1.5%** | **2.1%** | **3.2%** | **2.9%** | **2.9%** | **2.7%** | **3.2%** | **2.6%** | **1.4%** | **2.0%** | **2.0%** | **1.6%** | **1.3%** | **1.6%** |

| Table 12: Average 3-yearly CDRs | | | |
|---|---|---|---|
| **Grades** | **5 Years Avg.** | **10 Years Avg.** | **15 Years Avg.** |
| 1 | 13.6% | 14.4% | 14.1% |
| 2 | 3.7% | 7.2% | 6.6% |
| 3 | 0.8% | 1.3% | 0.9% |
| 4 | 0.9% | 0.4% | 0.5% |
| 5 | 0.6% | 0.3% | 0.2% |
| 6 | 0.0% | 0.0% | 0.0% |
| 7 | 0.0% | 0.0% | 0.0% |
| 8 | 0.0% | 0.0% | 0.0% |
| **Total** | **1.7%** | **2.1%** | **2.2%** |

**Conclusion**: The results of cumulative default rates are very promising in terms of two aspects a) the cumulative default rates in each year are well-stacked showing a declining trend as we move upwards on the rating ladder; and b) in the best 3 grades, no defaults were witnessed in any of the last 15 years.

### d2. Comparison with external benchmarks (Mapping)

On the basis of calculated long term CDRs (15 years average of 3-yearly CDRs), the model grades from 1 (worst) to 8 (best) were objectively mapped with credit rating scale at modifier-level from AAA to B- to maintain the probability of default consistent going forward. The eventual mapping of model grades is presented in the tables below.

| Average 3-yearly CDRs | |
|---|---|
| Grades | 15 Years Avg. |
| 8 | 0.0% |
| 7 | 0.0% |
| 6 | 0.0% |
| 5 | 0.2% |
| 4 | 0.5% |
| 3 | 0.9% |
| 2 | 6.6% |
| 1 | 14.1% |

| BASEL | Recommended CDRs | Monitoring Level | Trigger Level |
|---|---|---|---|
| AAA | 0.1% | 0.8% | 1.2% |
| AA | 0.1% | 0.8% | 1.2% |
| A | 0.3% | 1.0% | 1.3% |
| BBB | 1.0% | 2.4% | 3.0% |
| BB | 7.5% | 11.0% | 12.4% |
| B | 20.0% | 28.6% | 35.0% |

| Grades | Indicative Rating |
|---|---|
| 8 | AA+, AA, AA- |
| 7 | AA-, A+ |
| 6 | A+, A |
| 5 | A, A-, BBB+ |
| 4 | A-, BBB+, BBB |
| 3 | BBB+, BBB, BBB- |
| 2 | BB+, BB, BB- |
| 1 | B+, B, B- |

### d3. 1 & 2 Year Transition Matrices using Cohort Approach with Stability ratios

In order to test historical robustness of the rating models, rating transition or migration matrices for various periodicities are calculated. On an accumulated basis, one-year and two-year transition matrices and stability ratios for each rating grade were calculated using universally accepted Cohort Approach.

A cohort comprises all entities holding a given grade at the start of a given period. Grades at the 'beginning-of-the-period' are displayed on the Y axis of the matrix and an accumulated migration percentage for each grade at the 'end-of-the-period' is depicted on the X axis. Matrices of 1 year and 2 years transitions are presented in tables below.

| Table 13 | | Grade 1 year subsequent to X | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 8 | 7 | 6 | 5 | 4 | 3 | 2 | 1 | Stability* |
| X = Grade at the beginning of each cohort | 8 | 65% | 18% | 7% | 4% | 2% | 2% | 1% | 0% | 83% |
| | 7 | 22% | 37% | 16% | 10% | 7% | 5% | 2% | 1% | 75% |
| | 6 | 11% | 22% | 21% | 18% | 12% | 11% | 4% | 1% | 60% |
| | 5 | 4% | 14% | 13% | 22% | 19% | 20% | 5% | 2% | 54% |
| | 4 | 3% | 9% | 12% | 14% | 22% | 27% | 10% | 3% | 64% |
| | 3 | 1% | 4% | 5% | 10% | 13% | 44% | 17% | 8% | 74% |
| | 2 | 1% | 1% | 2% | 4% | 7% | 29% | 35% | 19% | 84% |
| | 1 | 0% | 2% | 3% | 2% | 3% | 19% | 17% | 54% | 71% |

** Stability Ratio is derived by adding up percentages of movement within 1 grade*

| Table 14 | | Grade 2 years subsequent to X | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 8 | 7 | 6 | 5 | 4 | 3 | 2 | 1 | Stability* |
| X = Grade at the beginning of each cohort | 8 | 55% | 19% | 9% | 5% | 4% | 5% | 2% | 1% | 74% |
| | 7 | 25% | 29% | 13% | 9% | 8% | 10% | 3% | 2% | 67% |
| | 6 | 12% | 18% | 15% | 17% | 13% | 15% | 8% | 2% | 50% |
| | 5 | 6% | 14% | 11% | 15% | 16% | 24% | 8% | 5% | 42% |
| | 4 | 4% | 10% | 11% | 15% | 17% | 29% | 9% | 5% | 61% |
| | 3 | 3% | 6% | 5% | 9% | 11% | 38% | 18% | 10% | 66% |
| | 2 | 2% | 4% | 3% | 7% | 7% | 28% | 27% | 22% | 77% |
| | 1 | 1% | 4% | 5% | 5% | 7% | 21% | 17% | 40% | 57% |

** Stability Ratio is derived by adding up percentages of movement within 1 grade*

**Conclusion**: Matrices of both periods depicted a very high stability in rating methodologies as on average 71% and 62% remained within one notch from the base rating in 1-year and 2-years migrations respectively. The diagonal ratio (i.e. grades remain unchanged during the transition period) were also in the desirable ranges with lowest stability witnessed in the mid-grade 5.

ii. **Approach 2: For models without availability of meaningful data size**: For models where a meaningful quantum of observed and default data is NOT available and tests described in approach 1 are not possible to be conducted, THE Policy prescribes that:

a. If more than 5% but less than 10% of all the ratings announced using a particular rating model moved upwards or downwards by two notches within a year, a limited review of the model to be conducted with assessment that whether the rating movements are due to changes in sector dynamics, in which case a caution alert to be recorded for future assessments.

**RESULT: NO SUCH INSTANCES WERE NOTED DURING THE EXERCISE**

b. If 10% or more of all the ratings announced using a particular rating model move upwards or downwards by two notches within a year, a full review of the model to be conducted. The review to include (1) assessment of validity of quantitative and qualitative parameters for inclusion or deletion, (2) weights assigned to each parameter and (3) matrix of benchmarks set for various grades of each parameter.

**RESULT: DURING THE EXERCISE ONE SUCH INSTANCE WAS NOTED IN THE MODEL OF 'FUND STABILITY RATINGS (FSR)'. THE MATTER WAS REPORTED TO THE MCQ GROUP WHICH PROVIDED THE FOLLOWING RATIONALE:**

*"The FSR methodology was reviewed and revised last year (2020) and accordingly after internal reviews and compliances was posted on the website in December 2020. The reviewed methodology provides the assessment of the fund stability by capturing the risk profile on a more broader/wider scale (than previously) in credit risk, market risk and liquidity risk. This provides a more objective assessment of fund stability in terms of principal protection, return stability and redemption risk.*

*It may be mentioned here that FSR primarily depends on the investment prospective of the issuer to provide higher returns or provide stable returns with lower risks. Accordingly, the Asset Allocation of the fund is determined by the issuer in line with the market demand. The FSR ratings thus move up as Asset Allocation becomes less risky (higher rated instruments/assets). Or down when market risk appetite increases. In the last few years, the concentration of funds is towards those having low risk (having higher rated instruments/assets). Thus a general upward movement in rating of funds may be observed over timeline. Also if the strength of the asset quality in the fund has moved up the ratings can go up by more than 2 notches.*

*The model is essentially based on capturing the level of risk present in asset quality and its market risk. Thus if from year to year the issuer changes its Operational Investment policy limits upwards/downwards within the approved range which changes the funds credit,* *market and liquidity profile and consequentially its rating would change. Given this peculiarity the FSR ratings would follow the cyclicality of the market perception of the risk hence the duration of assessment of stability of the methodology/model should be at a longer period to take account of the cyclicality.*

*On the premise of the above, MCQ Group believes that the FSR model is aptly robust and no major amendments are required."*