# VIS Models Validation Study - 2019

**VIS Credit Rating Company Limited**

**International Affiliates**: Islamic International Rating Agency - **Bahrain**, Credit Rating Information & Services Ltd. - **Bangladesh**, Borhan Credit Rating Company Ltd. - **Iran**

# List of VIS Credit Scoring Models

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## Financial Sector Models

1. Brokerage Firms
2. Commercial Banks
3. Development Finance Institutions
4. Investment Companies
5. Leasing Companies
6. Leasing/Musharika/Morabaha
7. Manufacturing Modarbas
8. Micro Finance
9. Trading Modarabas

## Industrial Sector Models

10. Apparels
11. Auto-Batteries
12. Automotive Assemblers
13. Auto-Parts
14. Beverages
15. Building Products
16. Cables & Conductors
17. Carpets
18. Cement
19. Ceramics
20. Chemical/Resins/Alkalis
21. Confectionery Products
22. Constructions
23. Dairy Products
24. Distribution & Trading
25. Electronics & Electrical Goods
26. Engineering (Diversified)
27. Fabrics (Synthetic)
28. Fertilizers
29. FMCGs
30. Food & Allied
31. Glass
32. Hotels
33. Jute
34. Leather Products
35. Leather Tanneries
36. LPG Distribution
37. LPG Production
38. Medical Services
39. Miscellaneous - Manufacturing
40. Miscellaneous - Nonmanufacturing
41. Natural Gas Transmission
42. Oil & Gas Exploration
43. Oil Marketing Companies
44. Packaging Film
45. Paper & Board
46. Paper Products
47. Petroleum Refining
48. Petroleum Transmission
49. Pharmaceuticals
50. Plastic Products
51. Polyester Fiber/Chips/Filament
52. Polypropylene Products
53. Power Generation & Distribution
54. Recording Media
55. Rolled Products
56. Steel Pipes
57. Storage Services
58. Sugar & Allied Industries
59. Technology & Communication
60. Textile Composite
61. Textile Semi Composite
62. Textile Spinning
63. Textile Weaving
64. Tobacco
65. Toiletries
66. Transport
67. Vegetable Oil
68. Yarn & Fabric (Woolen)
69. Yarn (Synthetic)

# The Model Testing Methodology

# The Model Testing Methodology

- **Measures recommended in the 'Guidelines on the validation and review of Credit Rating Agencies' methodologies' published by European Securities & Market Authority (ESMA) on 23/03/2017 were used for validation of VIS models;**
- ESMA Guidelines are the most Detailed & Extensive Validation Requirements any where Globally for Credit Rating Agencies (CRAs);
- **Basel Committee on Banking Supervision has also published 'Studies on the Validation of Internal Rating Systems – Working Paper 14' in May 2005 outlining the validation requirements for Internal Rating Systems in Banks. Our validation exercise also covers most of the measures referred to in the working paper for extra confidence;**
- External Mapping with Internationally Recognized Models and published Data were also conducted for cross verification of VIS Models;
- Few ratings of Corporates from different jurisdictions were also conducted to test the models against their credit ratings announced by different licensed Rating Agencies;
- **Data of SMEs was not blended with Corporate Data in validation exercise considering the variability in legal and corporate structuring of the two (as per the Basel-II treatment);**
- Results of studies conducted on **SMEs** with the co-operation of the Central Bank of Pakistan as well as on **Sovereigns** are presented separately. *Validation study on Sovereign model is conducted by Islamic International Rating Agency, Bahrain (an international affiliate of VIS)*

# Details of Model Testing Exercise

- The exercise was completed in March 2020;
- As approved under Para 29 of ESMA Guidelines, VIS enhanced the dataset by including observations from its proprietary database VISTA Plus along with credit ratings announced by VIS Credit Rating Company Limited; *data pools are respectively referred to as non-contractual and contractual observations in this study*;
- **Non-contractual data is included since FY2000 whereas contractual rating data included since FY2001 pertaining to entities/issuers from a large group of industrial and financial sectors;**
- This composition of the dataset enables VIS to review and recalibrate its models on an ongoing basis as recommended by ESMA and Basel Committee;
- **As allowed under Para 30 of ESMA Guidelines, VIS used a 'relaxed definition of default' for observations in 'non-contractual' entities; Here, an observation is considered an 'observed default' in case the share capital is eroded by 40% or more in the year of scoring; *similar strategy is also practiced in various jurisdictions for negative classification or stock market delisting of companies*.**
- Where publicly reported, actual default instances are included for observations in 'contractual' as well as 'non-contractual' entities;
- Validation results of SME and Sovereign Models are presented separately.

# Summary of Dataset

# Summary of Dataset

## TOTAL OBSERVATIONS

**Number of Observations (2000-2018)**

| Type of Relationship | Type of Entity | Data Source: a. Entity / Issuer | Data Source: b. Publicly Available | Grand Total |
|---|---|---|---|---|
| 1. Contractual | Corporate | 521 | 0 | 521 |
| | Financial | 833 | 0 | 833 |
| 2. Non-contractual | Corporate | 0 | 4,849 | 4,849 |
| | Financial | 0 | 0 | 0 |
| **Grand Total** | | 1,354 | 4,849 | 6,203 |

For the purpose of validation, VIS enhances the data set by including observations from its proprietary database (VISTA) of public limited entities listed on Pakistan Stock Exchange (PSX) since FY2000. Only annual audited financial statements data is included.

Please refer to **cell # 2b** in the adjacent grid.

***ESMA Reference**: Para 29. A CRA should, as part of the process of validating its methodologies with limited quantitative evidence, consider enhancing the data sample…for example…expanding the data sample with the use of third-party data. (please refer to page # 10 of Annexure 1)*

# Summary of Dataset

## DEFAULT OBSERVATIONS

**Number of Default Observations (2000-2018)**

| Type of Relationship | Type of Entity | Data Source | | Grand Total |
|---|---|---|---|---|
| | | a. Entity / Issuer | b. Publicly Available | |
| 1. Contractual | Corporate | 3 | 0 | 3 |
| | Financial | 1 | 0 | 1 |
| 2. Non-contractual | Corporate | 0 | 86 | 86 |
| | Financial | 0 | 0 | 0 |
| **Grand Total** | | 4 | 86 | 90 |

For the purpose of validation, VIS uses a mix of default definitions; if publicly reported, actual default instances are included for observations in both datasets whereas for most observations in 'non-contractual' entities (segment 2b) a 'relaxed definition of default' is used. Here, an observation is considered an 'observed default' in case the share capital is eroded by 40% or more in the year of scoring. In both segments, an entity is not included subsequent to instance of default unless cured.

***ESMA Reference**: Para 30. A CRA should also consider techniques enabling it to perform quantitative measures for demonstrating the discriminatory power of its methodologies…for example…the use of a 'relaxed' default definition for the purposes of validation. (please refer to page # 10 of Annexure 1)*

# Summary of Dataset

## YEAR-WISE OBSERVATIONS

### Number of Year-wise Observations (2000-2018)

| Year | Corporate | | Financial | Total |
|---|---|---|---|---|
| | Contractual | Non-contractual | Contractual | |
| 2000 | 0 | 247 | 0 | 247 |
| 2001 | 2 | 254 | 35 | 291 |
| 2002 | 5 | 256 | 39 | 300 |
| 2003 | 16 | 258 | 45 | 319 |
| 2004 | 23 | 264 | 49 | 336 |
| 2005 | 26 | 277 | 50 | 353 |
| 2006 | 20 | 277 | 49 | 346 |
| 2007 | 23 | 272 | 56 | 351 |
| 2008 | 19 | 261 | 53 | 333 |
| 2009 | 21 | 256 | 50 | 327 |
| 2010 | 23 | 235 | 46 | 304 |
| 2011 | 25 | 248 | 42 | 315 |
| 2012 | 28 | 251 | 42 | 321 |
| 2013 | 29 | 245 | 39 | 313 |
| 2014 | 29 | 250 | 39 | 318 |
| 2015 | 27 | 262 | 48 | 337 |
| 2016 | 34 | 262 | 50 | 346 |
| 2017 | 54 | 259 | 51 | 364 |
| 2018 | 117 | 215 | 50 | 382 |

**In order to review and recalibrate rating models on an on-going basis, VIS uses a consistent size of enhanced dataset since FY2000**. VIS conducts annual review and, if required, recalibration exercise every year.

***ESMA Reference****: Para 4. These guidelines also clarify ESMA's expectations and ensure consistent application of Article 8(5) of the CRA Regulation which states, inter alia, that a CRA shall* 'review its credit ratings and methodologies on an ongoing basis and at least annually'. *(please refer to page # 5 of Annexure 1)*

# Summary of Dataset

## SECTORS COVERAGE

### Financial Sectors

Commercial Banking
Commodity Contracts Brokerage
Consumer Lending
Investment Banking and Securities Dealing
Leasing Companies
Lessors of Nonresidential Buildings (except Mini warehouses)
Mortgage and Nonmortgage Loan Brokers
Other Activities Related to Credit Intermediation
Other Financial Vehicles
Portfolio Management
Sales Financing
Savings Institutions
Securities and Commodity Exchanges
Securities Brokerage

### Manufacturing & Non-manufacturing Sectors

Alkalies and Chlorine Manufacturing
Amusement and Theme Parks
Animal (except Poultry) Slaughtering
Automobile Manufacturing
Basic Organic Chemical Manufacturing
Books Printing
Breweries
Broad-woven Fabric Mills
Carpet and Rug Mills
Cement Manufacturing
Ceramic Wall and Floor Tile Manufacturing
Chocolate and Confectionery Manufacturing from Cacao Beans
Cigarette Manufacturing
Civic and Social Organizations
Commercial and Institutional Building Construction
Communication and Energy Wire Manufacturing
Concrete Pipe Manufacturing
Confectionery Manufacturing from Purchased Chocolate
Converted Paper Product Manufacturing
Crude Petroleum and Natural Gas Extraction
Cutlery and Flatware (except Precious) Manufacturing
Dairy Product (except Dried or Canned) Merchant Wholesalers
Data Processing, Hosting, and Related Services
Deep Sea Freight Transportation
Dry, Condensed, and Evaporated Dairy Product Manufacturing
Electrical and Electronic Appliance, Television, and Radio Set Merchant Wholesalers
Electronic Coil, Transformer, and Other Inductor Manufacturing
Executive Search Services
Explosives Manufacturing
Fabricated Metal Product Manufacturing
Fats and Oils Refining and Blending
Fertilizer (Mixing Only) Manufacturing
Flat Glass Manufacturing
Flour Milling
Fossil Fuel Electric Power Generation
Frozen Cakes, Pies, and Other Pastries Manufacturing
Frozen Specialty Food Manufacturing
General Medical and Surgical Hospitals
General Purpose Machinery Manufacturing
General Warehousing and Storage
Glass Container Manufacturing
Glove and Mitten Manufacturing
Gum and Wood Chemical Manufacturing
Highway, Street, and Bridge Construction
Hotels (except Casino Hotels) and Motels
Industrial Gas Manufacturing
Iron and Steel Mills
Iron and Steel Pipe and Tube Manufacturing from Purchased Steel
Leather and Hide Tanning and Finishing
Leather Good Manufacturing
Light Truck and Utility Vehicle Manufacturing
Marine Cargo Handling
Mayonnaise, Dressing, and Other Prepared Sauce Manufacturing
Medicinal and Botanical Manufacturing
Miscellaneous Chemical Product and Preparation Manufacturing
Miscellaneous Electrical Equipment and Component Manufacturing
Miscellaneous Textile Product Mills
Motor and Generator Manufacturing
Motor Vehicle Parts Manufacturing
Narrow Fabric Mills
Natural Gas Distribution
Natural Gas Liquid Extraction
Nitrogenous Fertilizer Manufacturing
Non-cellulosic Organic Fiber Manufacturing
Nonwoven Fabric Mills
Other Concrete Product Manufacturing
Other Electric Power Generation
Other Hosiery and Sock Mills
Other Household Textile Product Mills
Other Knit Fabric and Lace Mills
Other Major Household Appliance Manufacturing
Other Oilseed Processing
Other Warehousing and Storage
Paint and Coating Manufacturing
Paper (except Newsprint) Mills
Paperboard Mills
Pesticide and Other Agricultural Chemical Manufacturing
Petroleum Lubricating Oil and Grease Manufacturing
Petroleum Refineries
Pharmaceutical Preparation Manufacturing
Plastics Bottle Manufacturing
Plastics Product Manufacturing
Publishers
Ready-Mix Concrete Manufacturing
Rice Milling
Rolled Steel Shape Manufacturing
Scheduled Passenger Air Transportation
Sheer Hosiery Mills
Snack Food Manufacturing
Soap and Other Detergent Manufacturing
Soft Drink Manufacturing
Software Publishers
Soybean Farming
Steel Wire Drawing
Storage Battery Manufacturing
Structural Steel and Precast Concrete Contractors
Sugarcane Mills
Synthetic Organic Dye and Pigment Manufacturing
Telecommunications Resellers
Television Broadcasting
Textile and Fabric Finishing Mills
Thread Mills
Un-laminated Plastics Film and Sheet (except Packaging) Manufacturing
Urethane and Other Foam Product (except Polystyrene) Manufacturing
Wheat Farming
Wired Telecommunications Carriers
Wireless Telecommunications Carriers (except Satellite)
Wood Product Manufacturing
Yarn Spinning Mills

As VIS's rating models are used by its affiliates in various jurisdictions, **VIS has adopted 'North American Industry Classification Standards' (NAICS) to maintain consistency.**

Adjacent table lists the NAICS sectors covered in this validation exercise.

# Validation Results: DISCRIMINATORY POWER

**Following tests, as prescribed by ESMA and BIS Committee, are conducted to assess 'Discriminatory Power' of VIS Models:**

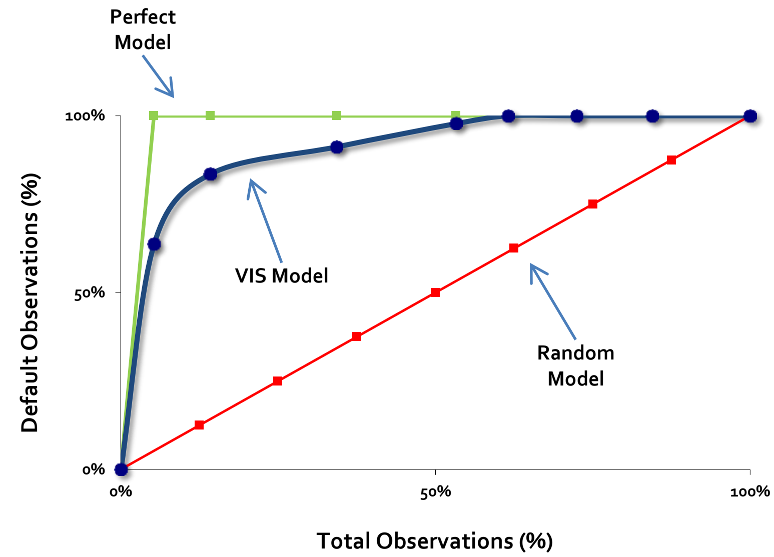
1. Cumulative Accuracy Profile (CAP)
2. Accuracy Ratio (AR)
3. Bootstrapping 95% Confidence for AR
4. Receiver Operating Characteristic (ROC)
5. Area under the Curve (AUC)
6. Kolmogorov-Smirnov (KS) Statistics
7. Distribution of Defaults

# Validation Results

# DISCRIMINATORY POWER

## Cumulative Accuracy Profile (CAP)

| a. Model Grades | b. Total Observations | c. Default Observations | d. Cumulative Observations (%) | e. Cumulative Defaults (%) |
|---|---|---|---|---|
| Worst 1 | 327 | 58 | 5.27 | 63.74 |
| 2 | 556 | 18 | 14.24 | 83.52 |
| 3 | 1,245 | 7 | 34.29 | 91.21 |
| 4 | 1,177 | 6 | 53.26 | 97.80 |
| 5 | 514 | 1 | 61.57 | 100.00 |
| 6 | 674 | 0 | 72.43 | 100.00 |
| 7 | 744 | 0 | 84.43 | 100.00 |
| Best 8 | 966 | 0 | 100.00 | 100.00 |
| Total. | **6,203** | **90** | | |




**DEFINITION:** "The cumulative accuracy profile (CAP) is used in data science to visualize the discriminative power of a model. The CAP of a model represents the cumulative number of positive outcomes along the y-axis versus the corresponding cumulative number of a classifying parameter along the x-axis." *(Wikipedia)*.

**INTERPRETATION:** "A perfect rating model will assign the lowest scores to the defaulters. In this case the CAP is increasing linearly and than staying at one. For a random model without any discriminative power, the fraction x of all debtors with the lowest rating scores will contain x percent of all defaulters. Real rating systems will be somewhere in between these two extremes." *(Page # 36, Studies on the Validation of Internal Rating Systems by BIS)*

***ESMA Reference****: Para 18. In demonstrating the discriminatory power of a methodology, ESMA typically expects a CRA to use the* ***cumulative accuracy profile (CAP)****…(please refer to page # 8 of Annexure 1)*

# Validation Results

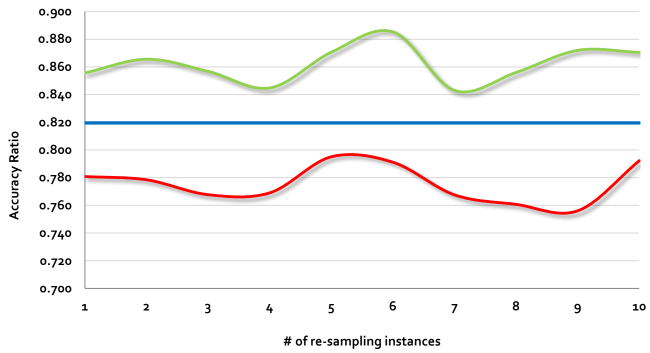
# DISCRIMINATORY POWER

## Accuracy Ratio (AR)

| a. Model Grades | b. Total Observations | c. Default Observations | d. Cumulative Observations (%) | e. Cumulative Defaults (%) | f. AR (CAP) |
|---|---|---|---|---|---|
| Worst 1 | 327 | 58 | 5.27 | 64.44 | 0.017 |
| 2 | 556 | 18 | 14.24 | 84.44 | 0.067 |
| 3 | 1,245 | 7 | 34.31 | 92.22 | 0.177 |
| 4 | 1,177 | 6 | 53.28 | 98.89 | 0.181 |
| 5 | 514 | 1 | 61.57 | 100.00 | 0.082 |
| 6 | 674 | 0 | 72.43 | 100.00 | 0.109 |
| 7 | 744 | 0 | 84.43 | 100.00 | 0.120 |
| Best 8 | 966 | 0 | 100.00 | 100.00 | 0.156 |
| Total | **6,203** | **90** | | | |

| | |
|---|---|
| A (Area below VIS Model) – sum(col.f) | **0.909** |
| B (area between VIS Model & Random Model) - A- 0.5 | 0.409 |
| Total PD – sum(col.c)/sum(col.b) | 0.015 |
| A+B = (0.5*1-Total PD) | 0.493 |
| **Accuracy Ratio or Gini Coefficient – B/(A+B)** | **0.830** |

**Bootstrapping: 95% Confidence for Accuracy Ratio**




**DEFINITION:** "The accuracy ratio (AR) is defined as the ratio of the area between the model CAP and the random CAP and the area between the perfect CAP and the random CAP." *(Wikipedia).*

*The core idea of bootstrapping (CAPs or ARs) is to re-sample from the data used for estimation and re-estimate the statistics with this new, re-sampled data. One can derive a distribution of the statistic by having done this many times..*

**INTERPRETATION:** "The most common summary index of the CAP is the Accuracy Ratio (or Gini coefficient). The rating method is the better the closer AR (Accuracy Ratio) is to one" *(Page # 37, Studies on the Validation of Internal Rating Systems by BIS).*

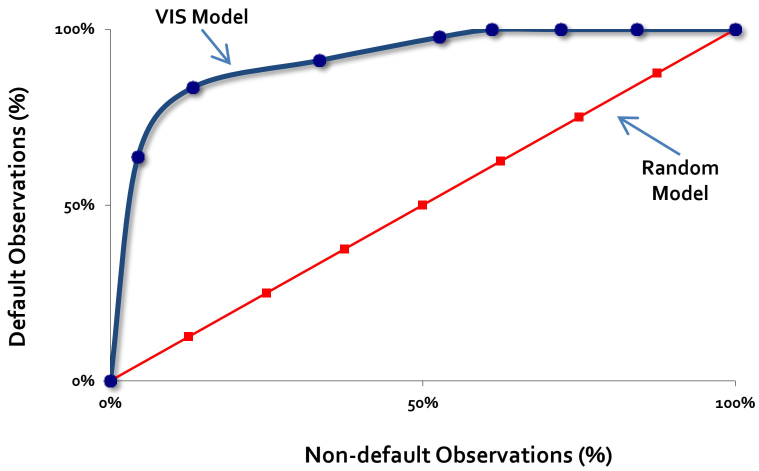
***ESMA Reference****: Para 18. In demonstrating the discriminatory power of a methodology, ESMA typically expects a CRA to use the cumulative accuracy profile (CAP)…**in conjunction with the accuracy ratio** (the term 'accuracy ratio' **also encompasses the Gini coefficient** or other similar measures)…(please refer to page # 8 of Annexure 1)*

# Validation Results

**DISCRIMINATORY POWER**

## Receiver Operating Characteristic (ROC) & Area under the Curve (AUC)

| a. Model Grades | b. Total Observations | c. Default Observations | d. Cumulative Non-defaults (%) | e. Cumulative Defaults (%) | f. AUC |
|---|---|---|---|---|---|
| Worst 1 | 327 | 58 | 4.40 | 64.44 | 0.014 |
| 2 | 556 | 18 | 13.20 | 84.44 | 0.066 |
| 3 | 1,245 | 7 | 33.45 | 92.22 | 0.179 |
| 4 | 1,177 | 6 | 52.61 | 98.89 | 0.183 |
| 5 | 514 | 1 | 61.00 | 100.00 | 0.083 |
| 6 | 674 | 0 | 72.03 | 100.00 | 0.110 |
| 7 | 744 | 0 | 84.20 | 100.00 | 0.122 |
| Best 8 | 966 | 0 | 100.00 | 100.00 | 0.158 |
| Total | **6,203** | **90** | | AUC = sum(col.f) | **0.915** |




**DEFINITION:** "A receiver operating characteristic curve, or ROC curve, is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied. A common summary statistic of a ROC analysis is the area under the ROC curve (AUC) which is equal to the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one." *(Wikipedia).*

**INTERPRETATION:** "A rating model's performance is the better the 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 the better the larger the area under the ROC curve is. The area A is 0.5 for a random model without discriminative power and it is 1.0 for a perfect model. It is between 0.5 and 1.0 for any reasonable rating model in practice. " *(Page # 38, Studies on the Validation of Internal Rating Systems by BIS).*

***ESMA Reference**: Para 18. In demonstrating the discriminatory power of a methodology, ESMA typically expects a CRA to use the cumulative accuracy profile (CAP)…**in conjunction with the accuracy ratio** (the term 'accuracy ratio' **also encompasses the Gini coefficient** or other similar measures)…(please refer to page # 8 of Annexure 1)*

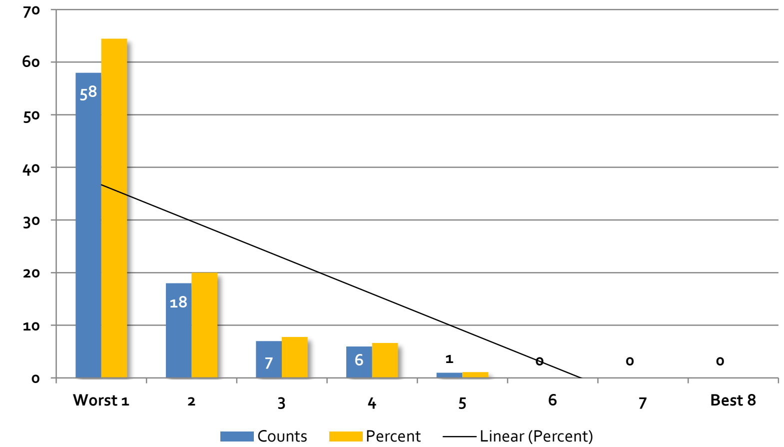
# Validation Results

## Complementing DISCRIMINATORY POWER

### Kolmogorov-Smirnov (KS) Statistics

| a. Model Grades | b. Total Observations | c. Default Observations | d. Cumulative Non-defaults (%) | e. Cumulative Defaults (%) | f. KS (e-d) |
|---|---|---|---|---|---|
| Worst 1 | 327 | 58 | 4.40 | 64.44 | 60.0% |
| 2 | 556 | 18 | 13.20 | 84.44 | 71.2% |
| 3 | 1,245 | 7 | 33.45 | 92.22 | 58.8% |
| 4 | 1,177 | 6 | 52.61 | 98.89 | 46.3% |
| 5 | 514 | 1 | 61.00 | 100.00 | 39.0% |
| 6 | 674 | 0 | 72.03 | 100.00 | 28.0% |
| 7 | 744 | 0 | 84.20 | 100.00 | 15.8% |
| Best 8 | 966 | 0 | 100.00 | 100.00 | 0.0% |
| Total | **6,203** | **90** | | | |

### Distribution of Defaults




**DEFINITION:** "Kolmogorov-Smirnov (KS) Statistics, a non-parametric test, compares two cumulative distributions and returns the maximum difference between them. " *(https://www.listendata.com/2019/07/KS-Statistics-Python.html). For further details, please also refer to Wikipedia (https://en.wikipedia.org/wiki/Kolmogorov%E2%80%93Smirnov_test)*

**INTERPRETATION:** "KS is where the difference (…between cumulative events and non-events) is maximum. If KS is in top 3 (…categories) and score above 40, it is considered a good predictive model." *(https://www.listendata.com/2019/07/KS-Statistics-Python.html). For further details, please also refer to Wikipedia (https://en.wikipedia.org/wiki/Kolmogorov%E2%80%93Smirnov_test).*

***ESMA Reference**: Para 19. A CRA should consider complementing the above measures with additional quantitative measures, for example the **Kolmogorov-Smirnov statistic**, and qualitative measures, such as the **distribution of the observed default rates**. (please refer to page # 8 of Annexure 1)*

# Validation Results: PREDICTIVE POWER

**Following tests, as prescribed by ESMA and BIS Committee, are conducted to assess 'Predictive Power' of VIS Models:**

1. Comparison of Observed vs. Expected Default Rates
2. Brier Score
3. Binomial Distribution Test
4. Normal Approximation
5. Traffic Lights Analysis
6. Hosmer and Lemeshow (Chi-square) Test

# Validation Results

## PREDICTIVE POWER

### Observed vs. Expected Default Rates

| a. Model Grades | b. Total Observations | c. Default Observations | d. Observed Defaults (%) | e. Mean Predicted Default (%) |
|---|---|---|---|---|
| Worst 1 | 327 | 58 | 17.7 | 16.3 |
| 2 | 556 | 18 | 3.2 | 4.3 |
| 3 | 1,245 | 7 | 0.6 | 0.9 |
| 4 | 1,177 | 6 | 0.5 | 0.2 |
| 5 | 514 | 1 | 0.4 | 0.1 |
| 6 | 674 | 0 | 0.0 | 0.0 |
| 7 | 744 | 0 | 0.0 | 0.0 |
| Best 8 | 966 | 0 | 0.0 | 0.0 |
| Total. | **6,203** | **90** | **1.5%** | |

Although VIS models are not *Logit Models*, Probability of Default (PD) is calculated by running Logistic Regression on Scores generated for each observation.

### Complementing Predictive Power using Brier Score

$$\text{Brier Score} = \frac{1}{N}\sum_{i=1}^{N}(d_i - PD_i)^2$$

**VIS Model Brier Score: 0.00037**

**INTERPRETATION:** "The closer the Brier score is to zero the better is the forecast of default probabilities" *(Page # 46 Studies on the Validation of Internal Rating Systems BIS).*

***ESMA Reference****: Para 20, 21, 22 & 23. The predictive power of a methodology can be demonstrated by* ***comparing the expected behavior of the credit ratings to the observed results****. For performing this comparison, ESMA typically expects a CRA to define internally its expectations (absolute numbers or ranges) per credit rating category with regards to the measure of creditworthiness its credit ratings refer to. A CRA may use different* ***approaches for defining its internal expectations*** *(e.g. …****by reference to the historical performance of its credit ratings****). A CRA should consider complementing these measures with …for example the* ***Brier Score*** *(please refer to page # 8 & 9 of Annexure 1)*

# Validation Results

# PREDICTIVE POWER

## Recalibration with Binomial Test & Normal Approximation

| a. Model Grades | b. Mean PDs (2000-2014) | c. Observed Defaults (2015-2018) | d. Binomial | e. Normal |
|---|---|---|---|---|
| Worst 1 | 16.33% | 11.76% | 86.0% | 85.8% |
| 2 | 4.30% | 6.38% | 22.5% | 23.7% |
| 3 | 0.89% | 0.83% | 63.4% | 67.1% |
| 4 | 0.19% | 0.28% | 48.6% | 58.0% |
| 5 | 0.07% | 1.89% | 7.2% | 6.0% |
| 6 | 0.03% | 0.00% | NA | 99.1% |
| 7 | 0.01% | 0.00% | NA | 100.0% |
| Best 8 | 0.00% | 0.00% | NA | 100.0% |
| Count. | 4,774 | | | |

1. In order to test that default probabilities are not underestimated; binomial tests and normal approximation are conducted separately for each Model Grade.
2. With the assumption that defaults are independent (i.e. default correlation is zero), the number of defaults in a given year and grade then follows a binomial distribution.
3. As the binomial distribution of large datasets tends to converge to the normal, a normal approximation is also conducted considering the size of VIS's testing dataset.
4. VIS uses a walk-forward out-of-sample method to conduct these tests on an annual basis where 15 years of data is used in PD calculation tested against defaults observed in the later 4 years.
5. **Traffic lights approach:**
   - Significance level **Red**: p-value ≤ 1% represents that an underestimation of the default probability is very likely.
   - Significance level Yellow: p-value ≥ 1% and ≤ 5% represents that an underestimation of the default probability is very likely a warning that the PD might be an underestimate.
   - Significance level **Green**: p-value ≥ 5% rejects the hypothesis that the default probability is underestimated.
6. Currently, none of the Grades represents that PDs are underestimated.
7. A recalibration of the Models is conducted only if 2 or more Grades fall in Red zone.

**INTERPRETATION:** *As long as validation of default probabilities per rating category is required, the traffic lights testing procedure appears to be a promising tool…Page # 34, Studies on the Validation of Internal Rating Systems BIS. (For further details on Binomial Distribution test and Normal Approximation, please refer* https://en.wikipedia.org/wiki/Binomial_distribution)

***ESMA Reference**: Para 23. ESMA typically expects a CRA to compare the expected probabilities of default to the observed default rates using the **binomial and the chi-square tests**. (please refer to page # 9 of Annexure 1)*

# Validation Results

## PREDICTIVE POWER

### Hosmer and Lemeshow (Chi-square) Test

| a. Model Grades | b. Observed Defaults | c. Observed Non-Defaults | d. Mean Predicted Default (%) | e. Expected Defaults | f. HL Statistic |
|---|---|---|---|---|---|
| Worst 1 | 58 | 269 | 16.3 | 53.0 | 0.56 |
| 2 | 18 | 538 | 4.3 | 23.9 | 1.53 |
| 3 | 7 | 1238 | 0.9 | 11.1 | 1.50 |
| 4 | 6 | 1171 | 0.2 | 2.2 | 6.51 |
| 5 | 1 | 513 | 0.1 | 0.4 | 1.11 |
| 6 | 0 | 674 | 0.0 | 0.2 | 0.20 |
| 7 | 0 | 744 | 0.0 | 0.1 | 0.06 |
| Best 8 | 0 | 966 | 0.0 | 0.0 | 0.02 |

| | |
|---|---|
| Degree of freedom | 7 |
| Chi – Square | 11.48 |
| P- value | 0.1191 |
| Significance level | 5% |
| **HL Test Result** | **Model fits data well** |

**DEFINITION:** "Hosmer and Lemeshow or Chi-square Test measures the association between actual events and predicted probability. In other words, it is a measure of how close the predicted probabilities are to the actual rate of events. In HL test, null hypothesis states that sample of observed events and non-events supports the claim about the predicted events and non-events. In other words, the model fits data well." *(https://www.listendata.com/2015/01/calculate-hosmer-lemeshow-hl-test-with.html). For further details, please also refer to Wikipedia (https://en.wikipedia.org/wiki/Hosmer%E2%80%93Lemeshow_test)*

**INTERPRETATION:** "The p-value of a chi-square test could serve as a measure of the accuracy of the estimated default probabilities: the closer the p-value is to zero, the worse the estimation is." *(Page # 52, Studies on the Validation of Internal Rating Systems by BIS)*

***ESMA Reference**: Para 23. ESMA typically expects a CRA to compare the expected probabilities of default to the observed default rates using the **binomial and the chi-square tests**. (please refer to page # 9 of Annexure 1)*

# Validation Results: HISTORICAL ROBUSTNESS

**Following tests, as prescribed by ESMA and BIS Committee, are conducted to assess 'Historical Robustness' of VIS Models:**

1. 1 & 2 Year Transition Matrices using Cohort Approach
2. 1 & 2 Year Transition Matrices using Hazard Rate Approach
3. Calculation of Diagonal, Upwards and Downwards Transition Ratios for both approaches
4. Bootstrapped 95% Confidence Bounds for the Hazard Rate Approach for 2 target rating classes
5. Rating Distribution
6. Benchmarking with External Credit Risk Measures: Comparison with Basel Default Probabilities (CDRs)
7. Benchmarking with External Credit Risk Measures: Comparison with Altman's Z-Scores
8. Benchmarking with External Credit Risk Measures: Comparison with Ratio Medians of Japan Credit Rating Agency Limited
9. Univariate Analysis of Financial Ratios
10. Population (System) Stability Index (PSI)

# EXPLAINING TRANSITION MATRICES

# Historical Robustness: TRANSITION MATRICES

In order to test historical robustness of its rating models, VIS constructs rating transition or migration matrices for various periodicities. Details pertaining to development of transition matrices for this study are as follows:

1. Being based on through-the-cycle (TTC) methodology, observations only from contractual dataset are used for analysis of rating migrations;
2. **Transition matrices are developed on 1,400 medium to long term entity/ issuer ratings announced by VIS Credit Rating Company Ltd. during January 1, 2002 to March 19, 2020;**
3. On an accumulated basis, one-year and two-year transition matrices are developed using the Cohort Approach and Hazard Rate Approach;
4. **Cohort Approach**: A cohort comprises all entities/issuers holding a given rating at the start of a given period. Ratings at the 'beginning-of-the-period' are displayed on the Y axis of the matrix and an accumulated migration percentage for each rating class at the 'end-of-the-period' is depicted on the X axis;
5. **Hazard Rate Approach**: The estimates of the cohort approach are not affected by the timing and sequencing of transitions 'within the period'. An alternative approach that captures within-period transitions is called the duration or hazard rate approach;
6. The matrices on the following pages display two empirical findings that are common to the matrices published by global rating agencies. First, on-diagonal entries are the highest; they are in the range of 87% to 100% depicting higher stability of VIS models. Second, default frequencies for the best two rating classes are zero.

*For a detailed exposition of the cohort and the hazard approach, see Lando, D. and Skodeberg, T., 2002, Analyzing ratings transitions and rating drift with continuous observations, Journal of Banking and Finance 26, 423–444 or Lando, D., 2004, Credit Risk Modeling, Princeton University Press.*

# Transition Matrices

**COHORT APPROACH**

## One-year Transition Matrix

| | AAA | AA | A | BBB | BB | B | CCC | CC-C | Default |
|---|---|---|---|---|---|---|---|---|---|
| AAA | 100.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| AA | 0.8% | 96.7% | 2.0% | 0.4% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| A | 0.0% | 1.0% | 97.1% | 1.5% | 0.1% | 0.0% | 0.0% | 0.0% | 0.4% |
| BBB | 0.0% | 0.0% | 5.0% | 93.0% | 1.4% | 0.0% | 0.2% | 0.2% | 0.2% |
| BB | 0.0% | 0.0% | 0.0% | 1.8% | 97.2% | 0.9% | 0.0% | 0.0% | 0.0% |
| B | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% | 0.0% | 0.0% | 0.0% |
| CCC | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% | 0.0% | 0.0% |
| CC-C | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% | 0.0% |

| | No Transition | Upgrade Ratio | Downgrade Ratio |
|---|---|---|---|
| AAA | 100.0% | 0.0% | 0.0% |
| AA | 96.7% | 0.8% | 2.4% |
| A | 97.1% | 1.0% | 1.9% |
| BBB | 93.0% | 5.0% | 2.0% |
| BB | 97.2% | 1.8% | 0.9% |
| B | 100.0% | 0.0% | 0.0% |
| CCC | 100.0% | 0.0% | 0.0% |
| CC-C | 100.0% | 0.0% | 0.0% |

## Two-year Transition Matrix

| | AAA | AA | A | BBB | BB | B | CCC | CC-C | Default |
|---|---|---|---|---|---|---|---|---|---|
| AAA | 100.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| AA | 1.6% | 93.6% | 4.0% | 0.8% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| A | 0.0% | 1.9% | 94.3% | 2.8% | 0.3% | 0.0% | 0.0% | 0.0% | 0.7% |
| BBB | 0.0% | 0.0% | 9.5% | 86.6% | 2.6% | 0.0% | 0.4% | 0.4% | 0.5% |
| BB | 0.0% | 0.0% | 0.1% | 3.5% | 94.6% | 1.8% | 0.0% | 0.0% | 0.0% |
| B | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% | 0.0% | 0.0% | 0.0% |
| CCC | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% | 0.0% | 0.0% |
| CC-C | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% | 0.0% |

| | No Transition | Upgrade Ratio | Downgrade Ratio |
|---|---|---|---|
| AAA | 100.0% | 0.0% | 0.0% |
| AA | 93.6% | 1.6% | 4.8% |
| A | 94.3% | 1.9% | 3.8% |
| BBB | 86.6% | 9.5% | 3.9% |
| BB | 94.6% | 3.6% | 1.8% |
| B | 100.0% | 0.0% | 0.0% |
| CCC | 100.0% | 0.0% | 0.0% |
| CC-C | 100.0% | 0.0% | 0.0% |

***ESMA Reference**: Para 26. As a quantitative measure, ESMA typically expects a CRA to **demonstrate the stability of the credit ratings assigned by its methodologies by producing transition (migration) matrices** and analyzing the movement of the credit ratings. Examples of this type of analysis include the **upgrade / downgrade / diagonal ratios**… (please refer to page # 9 of Annexure 1)*

# Transition Matrices

## HAZARD RATE APPROACH

### One-year Transition Matrix

| | AAA | AA | A | BBB | BB | B | CCC | CC-C | Default |
|---|---|---|---|---|---|---|---|---|---|
| AAA | 100.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| AA | 0.7% | 97.2% | 1.8% | 0.4% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| A | 0.0% | 0.8% | 97.5% | 1.4% | 0.0% | 0.0% | 0.0% | 0.0% | 0.2% |
| BBB | 0.0% | 0.0% | 4.4% | 93.4% | 1.7% | 0.0% | 0.2% | 0.0% | 0.2% |
| BB | 0.0% | 0.0% | 0.0% | 1.6% | 95.0% | 1.6% | 0.0% | 0.1% | 1.7% |
| B | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 94.1% | 0.0% | 5.9% | 0.0% |
| CCC | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% | 0.0% | 0.0% |
| CC-C | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% | 0.0% |

| | No Transition | Upgrade Ratio | Downgrade Ratio |
|---|---|---|---|
| AAA | 100.0% | 0.0% | 0.0% |
| AA | 97.2% | 0.7% | 2.1% |
| A | 97.5% | 0.8% | 1.6% |
| BBB | 93.4% | 4.5% | 2.1% |
| BB | 95.0% | 1.6% | 3.3% |
| B | 94.1% | 0.0% | 5.9% |
| CCC | 100.0% | 0.0% | 0.0% |
| CC-C | 100.0% | 0.0% | 0.0% |

### Two-year Transition Matrix

| | AAA | AA | A | BBB | BB | B | CCC | CC-C | Default |
|---|---|---|---|---|---|---|---|---|---|
| AAA | 100.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| AA | 1.4% | 94.4% | 3.5% | 0.7% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| A | 0.0% | 1.6% | 95.2% | 2.7% | 0.0% | 0.0% | 0.0% | 0.0% | 0.4% |
| BBB | 0.0% | 0.1% | 8.5% | 87.3% | 3.2% | 0.1% | 0.4% | 0.0% | 0.5% |
| BB | 0.0% | 0.0% | 0.1% | 3.0% | 90.3% | 3.1% | 0.0% | 0.2% | 3.3% |
| B | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 88.5% | 0.0% | 11.5% | 0.0% |
| CCC | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% | 0.0% | 0.0% |
| CC-C | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% | 0.0% |

| | No Transition | Upgrade Ratio | Downgrade Ratio |
|---|---|---|---|
| AAA | 100.0% | 0.0% | 0.0% |
| AA | 94.4% | 1.4% | 4.2% |
| A | 95.2% | 1.6% | 3.2% |
| BBB | 87.3% | 8.5% | 4.1% |
| BB | 90.3% | 3.2% | 6.5% |
| B | 88.5% | 0.0% | 11.5% |
| CCC | 100.0% | 0.0% | 0.0% |
| CC-C | 100.0% | 0.0% | 0.0% |

***ESMA Reference****: Para 26. As a quantitative measure, ESMA typically expects a CRA to* ***demonstrate the stability of the credit ratings assigned by its methodologies by producing transition (migration) matrices*** *and analyzing the movement of the credit ratings. Examples of this type of analysis include the* ***upgrade / downgrade / diagonal ratios****… (please refer to page # 9 of Annexure 1)*

# Transition Matrices

## Bootstrapping HAZARD RATE APPROACH

1. In both the cohort and the hazard approach, entries of the transition matrix are estimates of transition probabilities, which like any estimate, are affected by sampling error.
2. VIS strives to quantify sampling error by estimating bootstrapped confidence intervals for the estimates.
3. Results of bootstrapped confidence bounds for the hazard rate approach for 2 target rating classes are presented here.
4. Details of bootstrap simulations are as follows:
    - Confidence level simulated = **95%**
    - # of repetitions = **100 times**
    - Target rating classes = **BB** (first speculative class) and **D** (Default)

**Simulation Results**

| Target: BB | Lower Bound | Upper Bound |
|---|---|---|
| AAA | 0.00% | 0.00% |
| AA | 0.00% | 0.01% |
| A | 0.00% | 0.03% |
| BBB | 0.89% | 2.77% |
| BB | 88.26% | 98.77% |

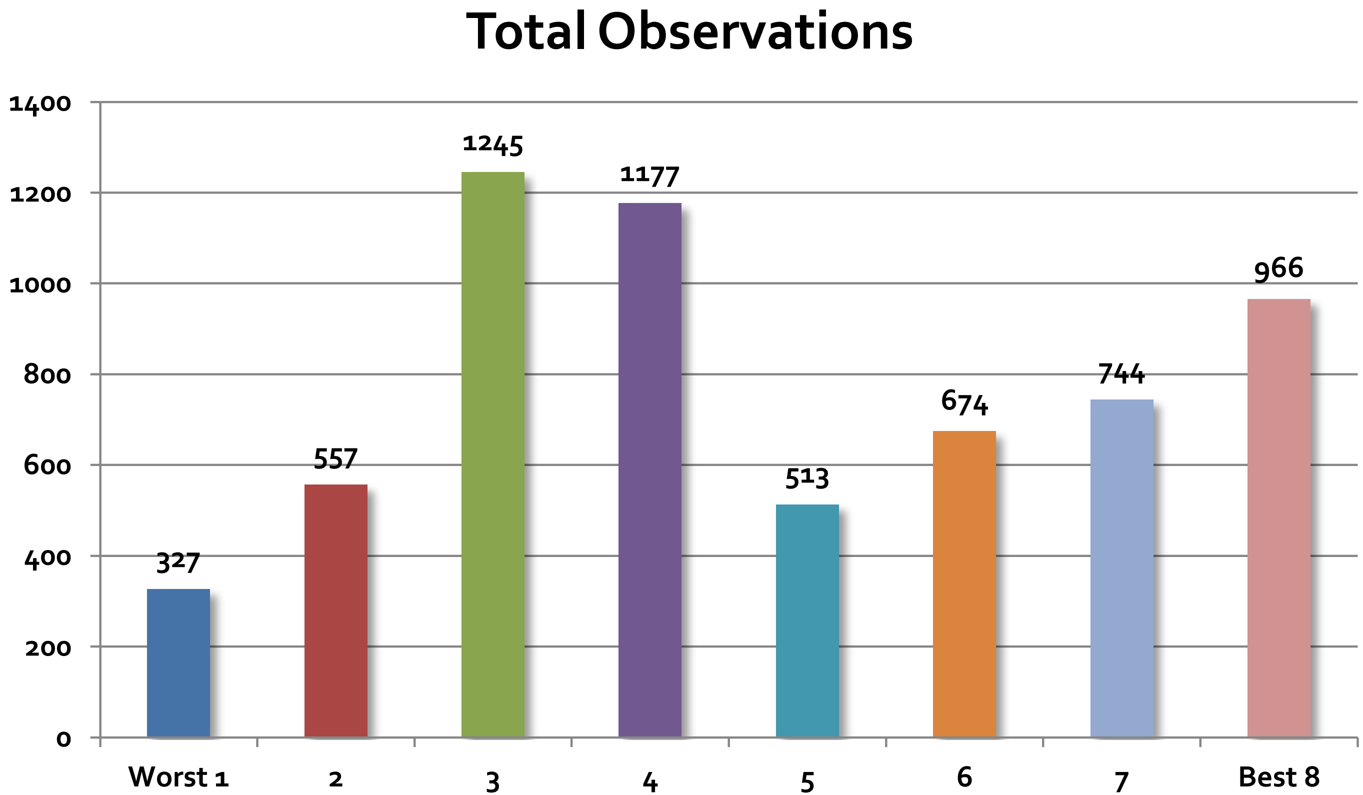
| Target: D | Lower Bound | Upper Bound |
|---|---|---|
| AAA | 0.00% | 0.00% |
| AA | 0.00% | 0.01% |
| A | 0.00% | 0.55% |
| BBB | 0.00% | 0.72% |
| BB | 0.00% | 6.31% |
| B | 0.00% | 0.00% |
| CCC | 0.00% | 0.00% |
| CC-C | 0.00% | 0.00% |
| D | 100.00% | 100.00% |

***ESMA Reference**: Para 26. As a quantitative measure, ESMA typically expects a CRA to **demonstrate the stability of the credit ratings assigned by its methodologies by producing transition (migration) matrices** and analyzing the movement of the credit ratings. Examples of this type of analysis include the **upgrade / downgrade / diagonal ratios**… (please refer to page # 9 of Annexure 1)*

# OTHER HISTORICAL ROBUSTNESS TESTS

## Complementing Historical Robustness

**RATINGS' DISTRIBUTION**




***ESMA Reference**: Para 27 A CRA should consider complementing these measures with further qualitative analysis, for example the **analysis of the ratings' distributions**… (please refer to page # 9 of Annexure 1)*

# BENCHMARKING TO EXTERNAL MEASURES

# Complementing Historical Robustness

## BENCHMARKING TO BASEL CDRs

1. For the purpose of benchmarking with external credit risk measures, Model Predicted and Observed Default Rates are compared with benchmarks issued under Basel Guidelines.

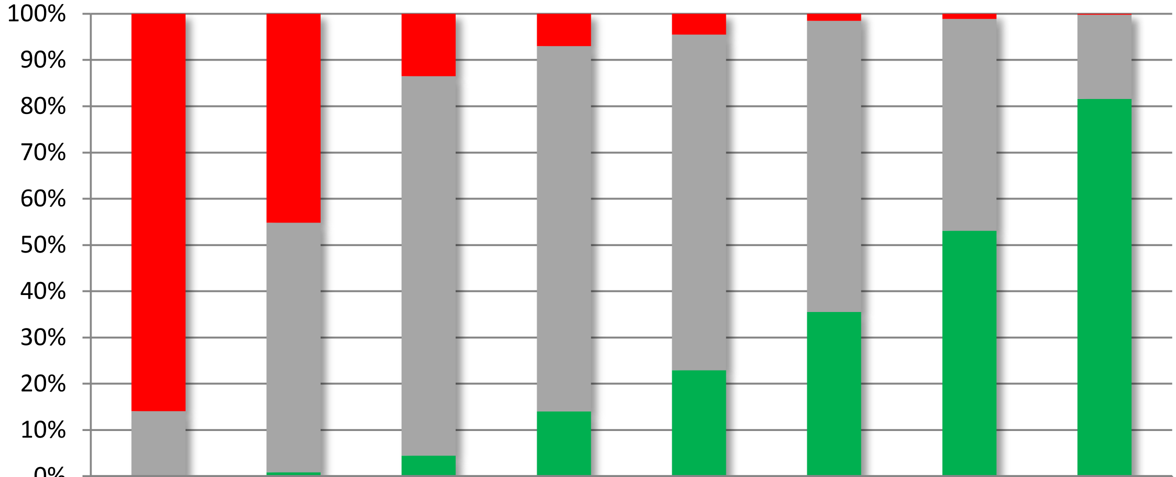
| Model Grades | Model Default Rates | | Mapping with BASEL Guidelines | | |
|---|---|---|---|---|---|
| | Predicted | Observed | CRA Rating | Recommended CDRs | Monitoring Level |
| 8 | 0.0% | 0.0% | AAA-AA | 0.1% | 0.8% |
| 7 | 0.0% | 0.0% | AAA-AA | 0.1% | 0.8% |
| 6 | 0.0% | 0.0% | AAA-AA | 0.1% | 0.8% |
| 5 | 0.1% | 0.4% | AAA-AA | 0.1% | 0.8% |
| 4 | 0.2% | 0.5% | A | 0.3% | 1.0% |
| 3 | 0.9% | 0.6% | BBB | 1.0% | 2.4% |
| 2 | 4.3% | 3.2% | BB | 7.5% | 11.0% |
| 1 | 16.3% | 17.7% | B | 20.0% | 28.6% |

***ESMA Reference****: Para 27 A CRA should consider complementing these measures with further qualitative analysis, for example… the* ***benchmarking of the ratings to external credit risk measures****… (please refer to page # 9 of Annexure 1)*

# Complementing Historical Robustness

## BENCHMARKING TO ALTMAN Z-SCORES

**Distribution of Altman's Z Scores per Model Grade 2001-2018**




| | 1 (327) | 2 (458) | 3 (917) | 4 (543) | 5 (515) | 6 (459) | 7 (744) | 8 (886) |
|---|---|---|---|---|---|---|---|---|
| BAD | 281 | 207 | 124 | 38 | 23 | 7 | 8 | 2 |
| GRAY | 46 | 247 | 752 | 429 | 374 | 289 | 341 | 161 |
| GOOD | 0 | 4 | 41 | 76 | 118 | 163 | 395 | 723 |

**Model Grades (Data Count)**

GOOD GRAY BAD

1. For the purpose of benchmarking with external credit risk measures, Model Score for each observation is compared with Altman's Z-Scores.
2. Altman's Z-Scores are calculated for all observations (a total of 4,849) obtained from non-contractual dataset.
3. **A grade-wise-accumulated distribution is presented in the adjacent graph and table which depicts a high correlation between the two models. More importantly, none of the determinant variables are common in both models.**
4. For a detail description, determinant variables and calculation methodology of Altman's Z-Scores, please refer to "Financial ratios, discriminant analysis and the prediction of corporate bankruptcy" by Altman, E., 1968 published in Journal of Finance 23, 589-609.

***ESMA Reference****: Para 27 A CRA should consider complementing these measures with further qualitative analysis, for example… the* ***benchmarking of the ratings to external credit risk measures****… (please refer to page # 9 of Annexure 1)*

# Complementing Historical Robustness

## BENCHMARKING TO JAPANESE MEDIANS

| Operating Income Margin (%) | | JCRA | VIS | JCRA | VIS | VIS |
|---|---|---|---|---|---|---|
| Ratings | Model Grades | 2014-2018 | | 2013-2017 | | 2000-2018 |
| AAA | 7 & 8 | 21.7 | 13.3 | 21.6 | 13.1 | 12.9 |
| AA | 5 & 6 | 10.8 | 8.96 | 10.3 | 8.9 | 9.2 |
| A | 4 | 7.4 | 5.9 | 7.3 | 6.2 | 7.1 |
| BBB | 3 | 5.8 | 3.9 | 5.7 | 4.0 | 6.6 |
| BB | 2 | 8.9 | 0.3 | 9.3 | 0.6 | 4.3 |
| | Total Counts | 1,784 | 1,248 | 1,788 | 1,278 | 4,849 |

| Business Income/Total Capital Employed (%)* | | JCRA | VIS | JCRA | VIS | VIS |
|---|---|---|---|---|---|---|
| Ratings | VIS Grades | 2014-2018 | | 2013-2017 | | 2000-2018 |
| AAA | 7 & 8 | 8.4 | 23.2 | 8.4 | 24.4 | 27.2 |
| AA | 5 & 6 | 8.1 | 14.01 | 7.7 | 14.7 | 15.7 |
| A | 4 | 5.9 | 9.1 | 5.8 | 9.9 | 11.4 |
| BBB | 3 | 4.9 | 6.6 | 4.8 | 6.5 | 9.0 |
| BB | 2 | 4.2 | 2.5 | 4.3 | 2.2 | 4.8 |

** VIS Ratio: EBIT/Total Capital Employed (%)*

| Net Income Margin (%) | | JCRA | VIS | JCRA | VIS | VIS |
|---|---|---|---|---|---|---|
| Ratings | VIS Grades | 2014-2018 | | 2013-2017 | | 2000-2018 |
| AAA | 7 & 8 | 13.0 | 10.0 | 12.6 | 9.7 | 8.9 |
| AA | 5 & 6 | 6.8 | 5.97 | 6.3 | 5.8 | 5.2 |
| A | 4 | 4.9 | 3.2 | 4.8 | 3.1 | 3.2 |
| BBB | 3 | 3.4 | 1.1 | 3.3 | 1.1 | 1.6 |
| BB | 2 | 4.7 | -1.7 | 4.5 | -1.8 | -0.4 |

| Interest-bearing Debt/EBITDA | | JCRA | VIS | JCRA | VIS | VIS |
|---|---|---|---|---|---|---|
| Ratings | VIS Grades | 2014-2018 | | 2013-2017 | | 2000-2018 |
| AAA | 7 & 8 | 2.7 | 0.2 | 2.7 | 0.2 | 0.3 |
| AA | 5 & 6 | 2.4 | 2.59 | 2.5 | 2.5 | 2.4 |
| A | 4 | 3.5 | 4.2 | 3.6 | 4.2 | 3.9 |
| BBB | 3 | 4.4 | 6.8 | 4.5 | 6.1 | 6.0 |
| BB | 2 | 7.3 | 9.6 | 6.9 | 8.7 | 9.4 |

1. For the purpose of benchmarking with external credit risk measures, Model Grade-wise medians of key financial ratios are also compared with rating-wise medians of the same ratios published by Japan Credit Rating Agency, Ltd. (JCRA).
2. Results, produced above and on the next slide, depict a reasonable correlation between the two datasets. VIS's cascading is better than JCRA in some cases.
3. VIS Medians are calculated for all observations (a total of 4,849) obtained from non-contractual dataset.
4. Please refer to Annexure 2 for medians and ratio formulae published by JCRA .

***ESMA Reference**: Para 27 A CRA should consider complementing these measures with further qualitative analysis, for example… the **benchmarking of the ratings to external credit risk measures**… (please refer to page # 9 of Annexure 1)*

# Complementing Historical Robustness

## BENCHMARKING TO JAPANESE MEDIANS

| Net Interest-bearing Debt/EBITDA | | JCRA | VIS | JCRA | VIS | VIS |
|---|---|---|---|---|---|---|
| Ratings | VIS Grades | 2014-2018 | | 2013-2017 | | 2000-2018 |
| AAA | 7 & 8 | 2.5 | 0.0 | 2.5 | 0.0 | 0.0 |
| AA | 5 & 6 | 1.8 | 2.35 | 1.8 | 2.3 | 2.1 |
| A | 4 | 2.6 | 4.0 | 2.6 | 3.9 | 3.6 |
| BBB | 3 | 2.9 | 6.3 | 3.0 | 5.8 | 5.7 |
| BB | 2 | 5.0 | 9.5 | 4.8 | 8.2 | 8.8 |

| Interest-bearing Debt/Operating Cash Flow Ratio | | JCRA | VIS | JCRA | VIS | VIS |
|---|---|---|---|---|---|---|
| Ratings | VIS Grades | 2014-2018 | | 2013-2017 | | 2000-2018 |
| AAA | 7 & 8 | 3.5 | 0.2 | 3.5 | 0.2 | 0.3 |
| AA | 5 & 6 | 4.2 | 2.36 | 4.3 | 2.4 | 2.4 |
| A | 4 | 5.5 | 1.2 | 5.4 | 1.5 | 2.9 |
| BBB | 3 | 6.7 | 1.4 | 6.6 | 1.5 | 3.4 |
| BB | 2 | 12.6 | -3.5 | 11.3 | -2.1 | -2.1 |

| Equity Ratio (%) | | JCRA | VIS | JCRA | VIS | VIS |
|---|---|---|---|---|---|---|
| Ratings | VIS Grades | 2014-2018 | | 2013-2017 | | 2000-2018 |
| AAA | 7 & 8 | 45.7 | 56.5 | 45.3 | 55.8 | 54.2 |
| AA | 5 & 6 | 50.1 | 42.45 | 49.9 | 41.3 | 40.0 |
| A | 4 | 44.8 | 36.8 | 44.3 | 34.5 | 33.4 |
| BBB | 3 | 41.9 | 30.0 | 41.1 | 30.1 | 27.2 |
| BB | 2 | 31.3 | 22.9 | 34.7 | 22.7 | 21.8 |

| Debt/Equity Ratio | | JCRA | VIS | JCRA | VIS | VIS |
|---|---|---|---|---|---|---|
| Ratings | VIS Grades | 2014-2018 | | 2013-2017 | | 2000-2018 |
| AAA | 7 & 8 | 0.8 | 0.1 | 0.9 | 0.1 | 0.1 |
| AA | 5 & 6 | 0.6 | 0.63 | 0.6 | 0.6 | 0.7 |
| A | 4 | 0.8 | 0.8 | 0.8 | 0.9 | 1.1 |
| BBB | 3 | 1.0 | 1.3 | 1.0 | 1.2 | 1.6 |
| BB | 2 | 1.7 | 1.5 | 1.6 | 1.5 | 2.2 |

| Net Debt/Equity Ratio | | JCRA | VIS | JCRA | VIS | VIS |
|---|---|---|---|---|---|---|
| Ratings | VIS Grades | 2014-2018 | | 2013-2017 | | 2000-2018 |
| AAA | 7 & 8 | 0.8 | 0.0 | 0.8 | 0.0 | 0.0 |
| AA | 5 & 6 | 0.4 | 0.55 | 0.4 | 0.6 | 0.6 |
| A | 4 | 0.6 | 0.8 | 0.6 | 0.8 | 1.0 |
| BBB | 3 | 0.7 | 1.2 | 0.8 | 1.2 | 1.6 |
| BB | 2 | 1.2 | 1.5 | 1.1 | 1.4 | 2.1 |

***ESMA Reference***: *Para 27 A CRA should consider complementing these measures with further qualitative analysis, for example… the* ***benchmarking of the ratings to external credit risk measures****… (please refer to page # 9 of Annexure 1)*

# Complementing Historical Robustness

## BENCHMARKING TO INTERNATIONAL RATINGS

- As discussed earlier too, VIS Models are used in various jurisdictions. VIS has calculated scores of various international entities domiciled in USA, Saudi Arabia, India, Malaysia, South Africa, Turkey etc.
- Results of 2 classic cases from the USA to depict validity of VIS Models' discriminatory and predictive powers are presented below. In case of GM Corp. VIS Model provided more realistic credit health in FY2003 which was later harmonized by substantial rating downgrade by global CRAs in FY2005.

| IBM Corporation | |
|---|---|
| Credit Rating Agency | FY2005 |
| S&P | A+ |
| Moody's | A1 |
| Fitch | AA- |
| | |
| Model generated Rating | A |

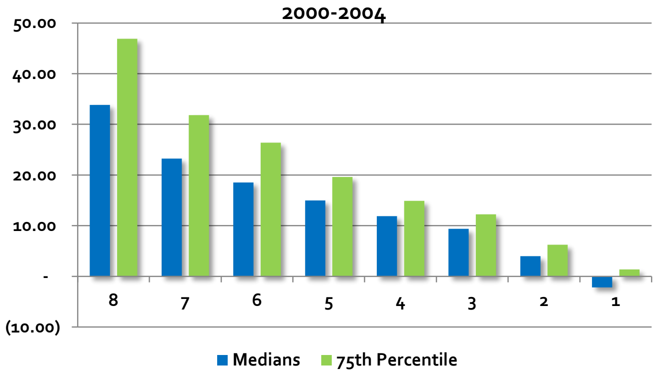
| General Motors Corporation | | |
|---|---|---|
| Credit Rating Agency | FY2003 | FY2005 |
| S&P | BBB | B |
| Moody's | Baa1 | B2 |
| Fitch | BBB+ | B |
| DBRS | A- | B+ |
| | | |
| Model generated Rating | B | C |

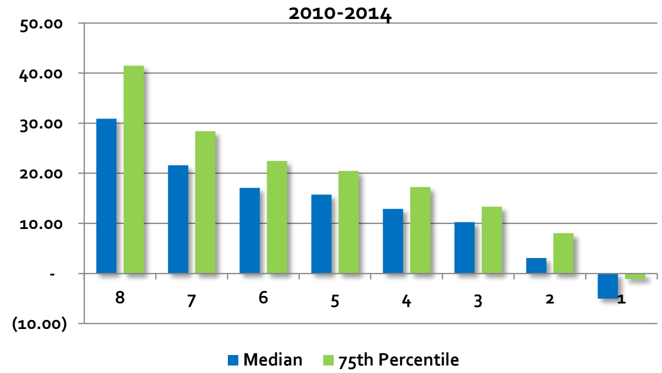
***ESMA Reference****: Para 27 A CRA should consider complementing these measures with further qualitative analysis, for example… the* ***benchmarking of the ratings to external credit risk measures****… (please refer to page # 9 of Annexure 1)*

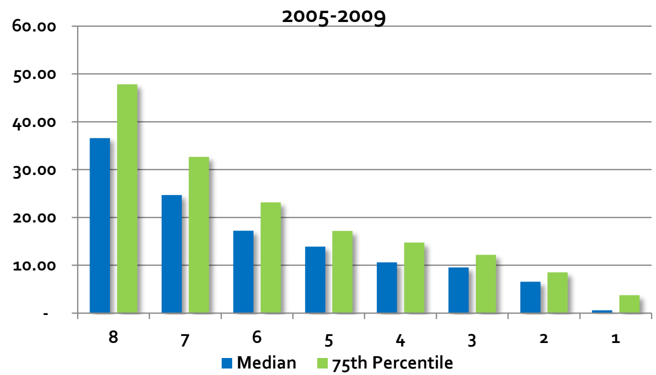
# Complementing Historical Robustness

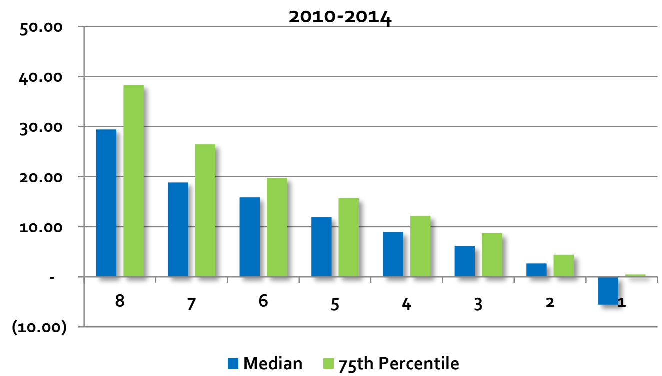
**UNIVARIATE ANALYSIS**

## EBIT/Total Capital Employed (%)



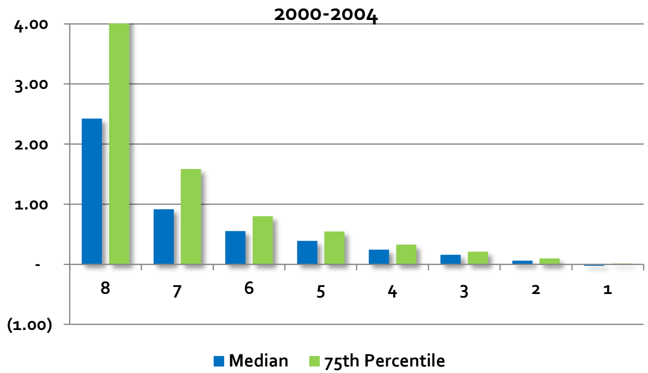

1. Although VIS Models are based on multiple variables, univariate analysis of 2 financial ratios from 'Corporate Models' are presented in the adjacent charts and on the next slide.
2. Medians and 75th Percentiles are calculated for all Model Grades in 4 economic cycles.
3. Results depict high correlation in ratio levels and probability of default.
4. VIS closely monitors direction and the quantum of the shift in Model determinants over the economic cycles for realignment purposes.

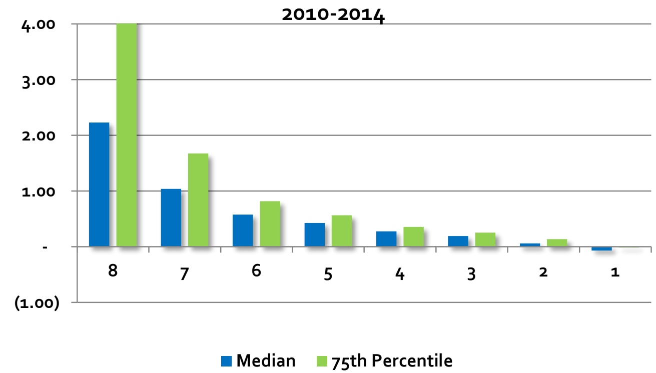
***ESMA Reference**: Para 27 A CRA should consider complementing these measures with further qualitative analysis, for example… **univariate analysis of key determinants of credit ratings**… (please refer to page # 9 of Annexure 1)*

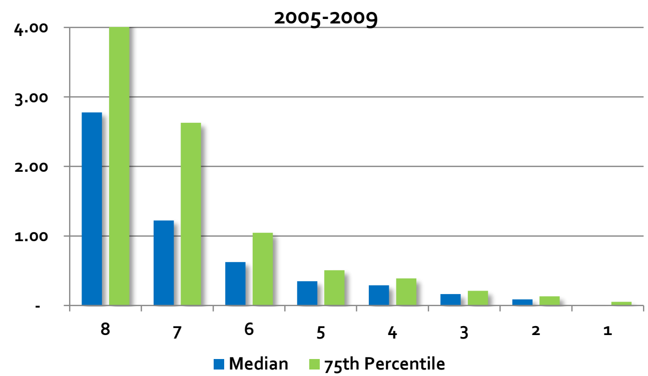
# Complementing Historical Robustness

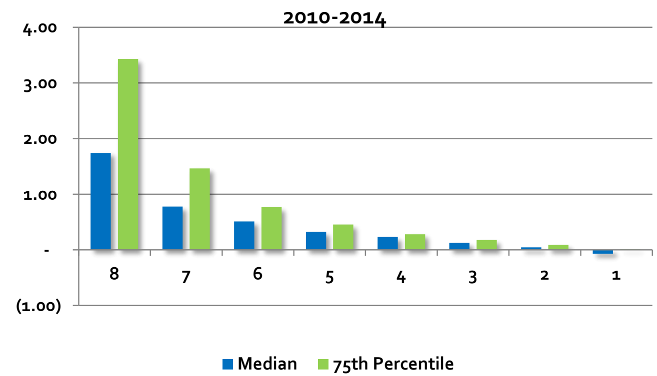
**UNIVARIATE ANALYSIS**

## EBITDA/Net Interest-bearing Debt (x)




***ESMA Reference****: Para 27 A CRA should consider complementing these measures with further qualitative analysis, for example…* ***univariate analysis of key determinants of credit ratings****… (please refer to page # 9 of Annexure 1)*

# Complementing Historical Robustness

# POPULATION STABILITY INDEX

## Population (System) Stability Index (PSI)

| a. Model Grades | b. Mean PDs (2000-2014) | c. Observed Defaults (2015-2018) | d. (c-b) | e. LN(c/b) | f. PSI = (d x e) |
|---|---|---|---|---|---|
| Worst 1 | 16.33% | 11.76% | -4.57% | -0.328 | 0.015 |
| 2 | 4.30% | 6.38% | 2.08% | 0.395 | 0.008 |
| 3 | 0.89% | 0.83% | -0.06% | -0.071 | 0.000 |
| 4 | 0.19% | 0.28% | 0.10% | 0.409 | 0.000 |
| 5 | 0.07% | 1.89% | 1.82% | 3.273 | 0.059 |
| 6 | 0.03% | 0.00% | 0.00% | NA | NA |
| 7 | 0.01% | 0.00% | 0.00% | NA | NA |
| Best 8 | 0.00% | 0.00% | 0.00% | NA | NA |
| Count. | **4,774** | | | **PSI** | **0.0830** |

**INTERPRETATION: "**...*the discriminatory power should be tested not only in the development dataset but also in an independent dataset (out-of-sample validation). Otherwise there is a danger that the discriminatory power may be overstated by over-fitting to the development dataset. In this case the rating system will frequently exhibit a relatively low discriminatory power on datasets that are independent of, but structurally similar to, the development dataset. Hence the rating system would have a low stability. A characteristic feature of a stable rating system is that it adequately models the causal relation between risk factors and creditworthiness. In contrast to stable systems, unstable systems frequently show a sharply declining level of forecasting accuracy over time." ((Page # 28, Studies on the Validation of Internal Rating Systems by BIS)*

1. In order to continuously monitor the 'information value' of Models, VIS develops Population (System) Stability Index (PSI).
2. PSI compares the distribution of PDs in an out-of-sample dataset to a training data set that was used to develop the model in order to check how the current PDs are compared to the those from training dataset.
3. Like the binomial and normal distribution tests, VIS uses a walk-forward out-of-sample method to develop PSI on an annual basis where 15 years of data is used in PD calculation tested against defaults observed in the later 4 years.
4. PSI = (PDs in Scoring Sample (col.c) – PDs in Training Sample (col.b)) * ln(col.c/col.b)
5. **RULES**:
   - PSI < 0.1 = No change required.
   - PSI >=0.1 but less than 0.2 = Slight change is required.
   - PSI >=0.2 = Significant change is required.

***ESMA Reference****: Para 27 A CRA should consider complementing these measures with further qualitative analysis, for example... the use of quantitative measures such as the* ***Population / System Stability Index****... (please refer to page # 9 of Annexure 1)*

# Validation Results: SME MODEL

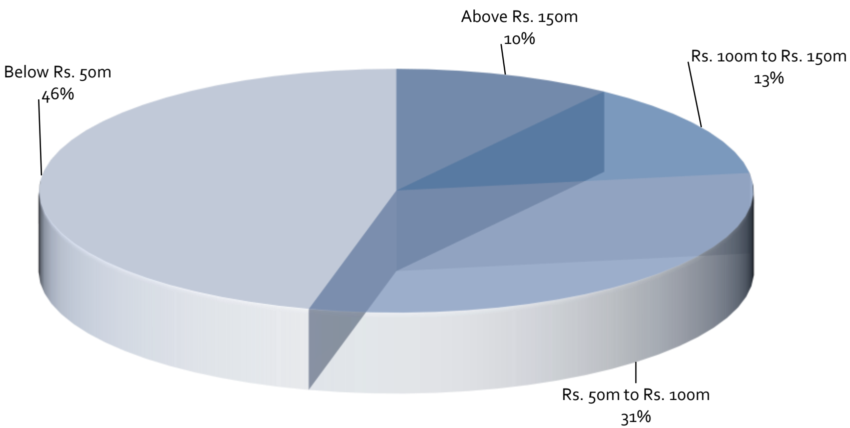
# Details of Co-operation with the State Bank of Pakistan

- **VIS Credit Rating Company Limited (VISCRC) was included in the Task Force on SME Ratings created by the State Bank of Pakistan (SBP) in June 2008;**
- VISCRC presented its SME Rating Methodology (first SME methodology developed in Pakistan);
- VISCRC proposed to conduct a study to validate its SME Rating Model based on a sample dataset provided by SBP;
- SBP provided about **600 data points** of 200 SMEs from across Pakistan in September 2008;
- VISCRC scored all data observations using its SME Model and based on final scores conducted the validation exercise
- Results were also presented to SBP and Pakistan Banks Association in October 2008.

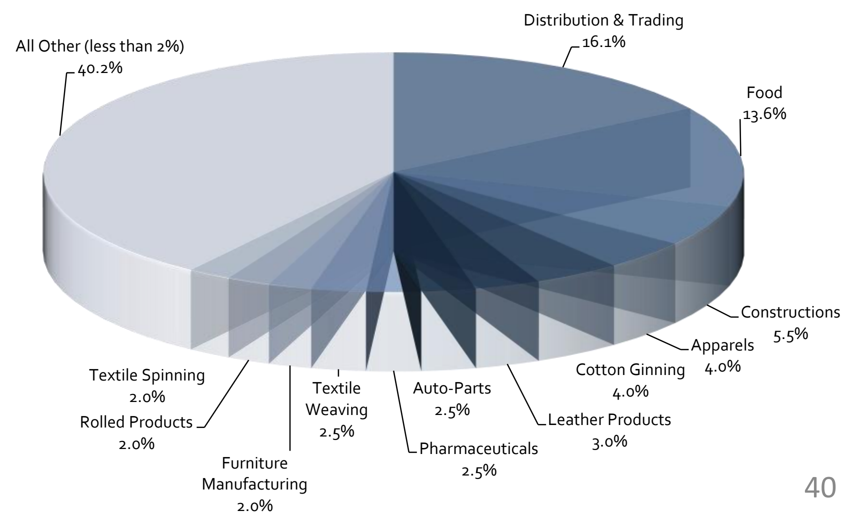
# Summary of SME Dataset

- Financial Statement and Repayment History Data collected by SBP from 10 commercial banks in Pakistan was shared with VISCRC for the purpose to conduct this study
- Details of the shared dataset is as under
  - Number of SMEs 200
  - Number of Records 568
  - Number of Workable Records 446
  - Number of Records with 'Unsatisfactory' Repayment History 27

## Asset Size Distribution of Dataset

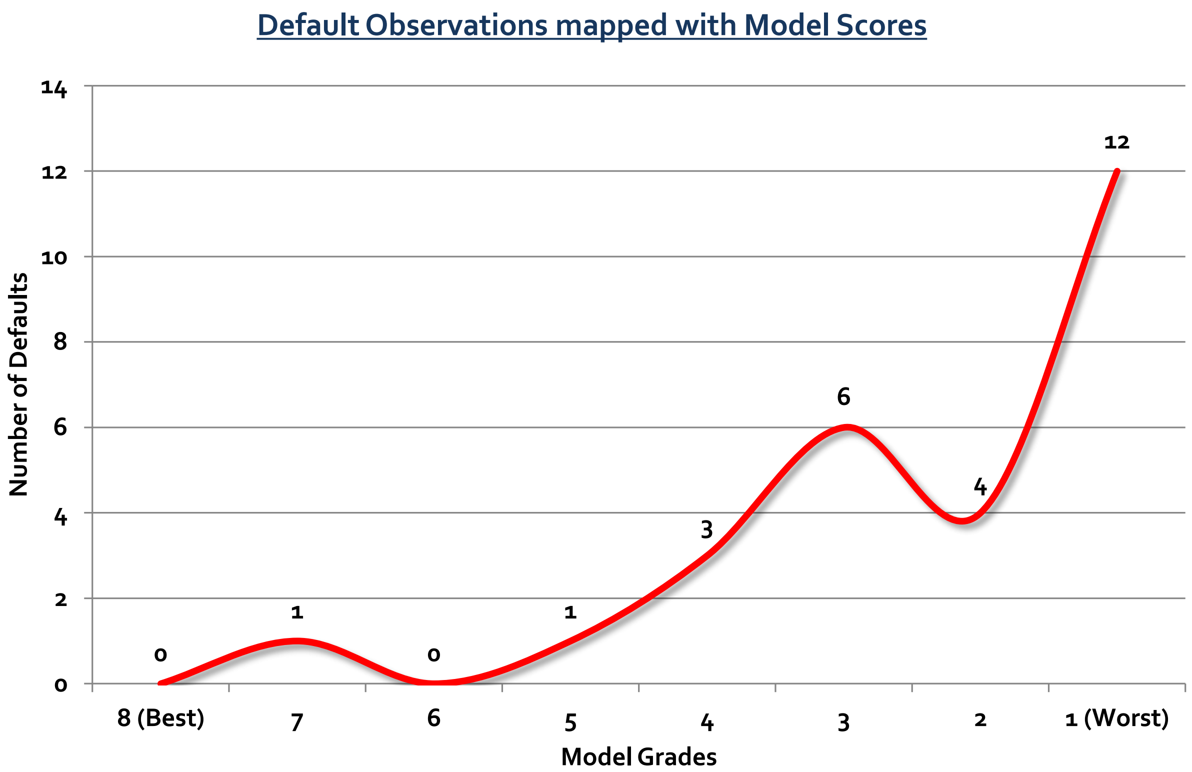



## Sector-wise Distribution of Dataset



# Exercise Results

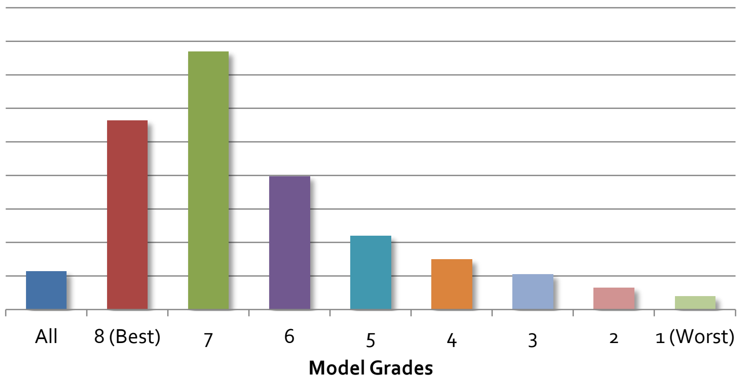
- Model Scores and Probability of Default showed high correlation



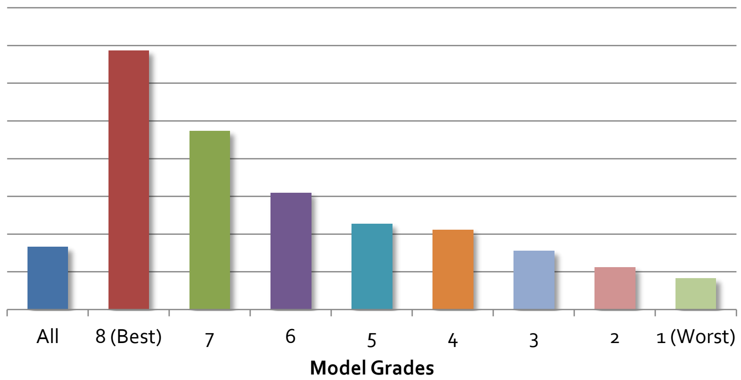
# Exercise Results

- Key financial ratios also showed deterioration going down the scoring scale

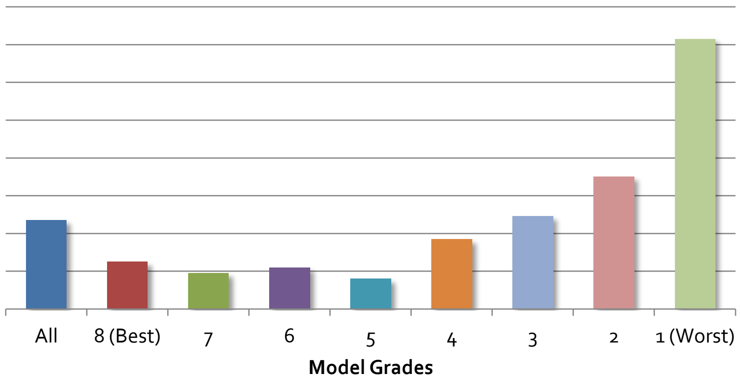
**EBIT Interest Coverage (x)**



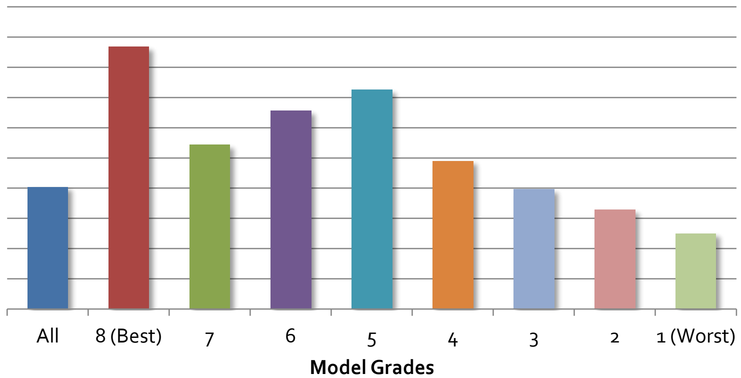

**EBIT/Total Capital Employed (%)**




**Gearing (x)**




**Current Ratio (x)**



# Validation Results: SOVEREIGN MODEL

# Sovereign Rating Model

- Sovereign Rating Scorecard (SRS) describes the factors and related correlations that forms the basis of assessing debt servicing ability and willingness of a sovereign (Sovereign or government used interchangeably). SRS tends to formulize this assessment in the form of base rating which are to be used by rating committees in order to reach final Ratings.
- SRS focuses on three main sections of an Economy.
  - Structural Parameters
  - Government Finances
  - External Position
  - Wealth Creation
- Distinguishing factors of the model include Islamic Finance penetration, status of SME financing and wealth creation related aspects including institutions, infrastructure, health and education.

# Sovereign Rating Model

**GDP per Capita**

Countries categorized on per Capita GDP. Varied scoring benchmarks for each category.

| Component Weights | Tier 1 | Tier 2 | Tier 3 | Tier 4 | Tier 5 |
|---|---|---|---|---|---|
| | **Structural Factors*** | **Structural Factors** | **Structural Factors** | **Structural Factors** | **Structural Factors** |
| 9% | Inflation 3.0% – 6.3% | Inflation 2.0% – 5.3% | Inflation 0.8% – 4.1% | Inflation 0.7% – 3.5% | Inflation 0.5% – 3.2% |
| 10.5% | GDP Growth Volatility 2.0% – 4.9% | GDP Growth Volatility 1.5% – 4.4% | GDP Growth Volatility 0.8% – 3.7% | GDP Growth Volatility 0.5% – 3.4% | GDP Growth Volatility 0.3% – 3.2% |
| | **Government Finances** | **Government Finances** | **Government Finances** | **Government Finances** | **Government Finances** |
| 10.5% | GGD % of GDP 90% – 238% | GGD % of GDP 75% – 165% | GGD % of GDP 30% – 120% | GGD % of GDP 25% – 115% | GGD % of GDP 20% – 57% |
| 16% | Fiscal Balance % of GDP -5.3% – -2.0% | Fiscal Balance % of GDP -5.6% – 1.4% | Fiscal Balance % of GDP -5.5% – 2.8% | Fiscal Balance % of GDP -6.5% – 6.3% | Fiscal Balance % of GDP -6.6% – 5.0% |
| 12% | GGIP % of Revenue 11% – 30% | GGIP % of Revenue 9% – 28% | GGIP % of Revenue 6% – 22% | GGIP % of Revenue 5% – 18% | GGIP % of Revenue 1% – 16% |
| | **External Position** | **External Position** | **External Position** | **External Position** | **External Position** |
| 12% | External Debt % of GDP 70% – 197% | External Debt % of GDP 55% – 145% | External Debt % of GDP 20% – 110% | External Debt % of GDP 18% – 108% | External Debt % of GDP 15% – 47% |
| 6% | CAB % of GDP -6.1% – -0.6% | CAB % of GDP -6.4% – 1.4% | CAB % of GDP -6.8% – 5.3% | CAB % of GDP -7.7% – 7.7% | CAB % of GDP -8.0% – 9.1% |
| 9% | FDI % of GDP -5.4% – -0.6% | FDI % of GDP -5.5% – 2.4% | FDI % of GDP -5.8% – 6.2% | FDI % of GDP -7.2% – 8.1% | FDI % of GDP -8.5% – 9.1% |
| 6% | Reserves Cover 0.5 month – 3.7 month | Reserves Cover 1.5 month – 7.2 month | Reserves Cover 3.0 month – 12.5 month | Reserves Cover 3.2 month – 14.2 month | Reserves Cover 3.4 month – 15.0 month |

**GDP Tiers for 2016 -17:**

Tier 1: >35K
Tier2: >25K & <35K
Tier3: >15K & <25K
Tier 4: >5K & <15K
Tier 5: <5k

Data for t-1 to t+2 is used where t = current fiscal year

**BASE RATING**

Wealth Creation Assessments

+/- 3 notches

INFRASTRUCTURE
HEALTH & EDUCATION
FINANCIAL MARKET DEVELOPMENT

Source: World Economic Forum

SME FINANCE

Source: Global Entrepreneurship Monitor

ECONOMIC DIVERSIFICATION

Source: World Bank

RESERVE CURRENCY
PEGGED CURRENCY
ISLAMIC FINANCIAL MARKET MATURITY

**FINAL RATING**

# Sovereign Model Results

- The model has been tested for 62 countries including both developed and developing nations for multiple years.
- The model has been instituted to bring transparency to the rating process, but assignment of the final rating is not bound by the output. We find that, 89% of our final assessments fall within 3 notches or a rating band informed by the SRS, and 11% may deviate more significantly.
- The model was back-tested on a number of defaulted countries for multiple year ranges including Russia, Belize, Pakistan and Ukraine among others and proved predictive of default in years prior to actual default.
- **Conventional validation tests could not be conducted on Sovereign Model as the exercise could present misleading results due to scarcity of default data – a situation that is also acknowledged by BIS Committee that states** *"Since TTC rating systems are based on much longer time horizons than PIT rating systems, the validation methodologies set out in this section will, in practice, be more applicable to PIT rather than to TTC rating systems. An important conclusion from the group's findings is that any application of a statistical technique has to be supplemented by qualitative checks. This finding is important when considering the following description of methodologies since uncritical use of the techniques may reach misleading results. Moreover, the choice of a specific technique to be applied for validation should depend upon the nature of the portfolio under consideration. Retail portfolios or portfolios of small- and medium-sized enterprises with large records of default data are much easier to explore with statistical methods than, for example, portfolios of sovereigns or financial institutions where default data are sparse." (Page # 29 Studies on the Validation of Internal Rating Systems BIS)*

# Sovereign Model Results – Defaulted Countries

| Year | Country | Fitch Rating | Model Score | Model Rating |
|---|---|---|---|---|
| 1997 | Pakistan | B- | 14.094 | CCC- |
| 1998 | Pakistan | CC | 13.856 | CCC- |
| 1999 | Pakistan | SD | 13.762 | CCC- |

| Year | Country | Fitch Rating | Model Score | Model Rating |
|---|---|---|---|---|
| 2013 | Ukraine | B- | 32.095 | B |
| 2014 | Ukraine | CCC | 19.999 | CCC+ |
| 2015 | Ukraine | SD | 16.666 | CCC |

| Year | Country | Fitch Rating | Model Score | Model Rating |
|---|---|---|---|---|
| 2004 | Belize | B- | 13.199 | B- |
| 2005 | Belize | CCC- | 13.402 | CCC+ |
| 2006 | Belize | SD | 14.592 | CCC+ |

# CREDENTIALS

The validation tests contained in this study are conducted and verified by the following individuals:

1. Muhammad Bilal Aftab – CEO, Vital Information Services Pvt. Ltd./ Director Compliance & Rating Analytics, VIS Credit Rating Company Limited – Team Lead – email: bilal@vis.com.pk

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Signature – Team Leader