Vietnam Join Stock Commercial Bank for Industry and Trade (**VietinBank**)

Corporate Credit Portfolio Probability of Default (PD) Estimation

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Quality In Everything We Do

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1. Introduction

1.1 Background

VietinBank has currently implemented expert judgment scoring models to provide rating for its customers. Current scorecards cover majority clients in the bank, which are generally segmented in three major segments, namely:

- Corporate
- Financial Institution
- Individuals and household business

Although bank has implemented scorecards to measure the risk of clients, they still exhibit following limitations, which are common for traditional expert judgment models:

- The same underlying variable of scorecard is assigned different weight for various industries in order to capture industry characteristics. However, score obtained from scorecard is a relative measure of risk within each scorecard. In other words, customer with higher score is less risky than customer with lower score. This relative comparison is only valid when we compare customers within the same scorecard. The validity of the comparison cannot be guaranteed across scores from different scorecards. Customer with score 100 from scorecard A may not have the same risk level comparing to a customer with the same score from Scorecard B. In order to obtain comparable measure, we need to establish absolute measure of risk, which is Probability of Default (PD). By having PD as the basis of comparison, we can be sure that customer with PD=1% is of lower risk comparing to customer with PD=2% irrespective of the scorecard used.
- Without PD, VietinBank is not able to use output of current scorecard as one of the important inputs for risk based pricing.

It is just a small step ahead to obtain PD from scorecard's score. Therefore, it is beneficial to perform PD estimation after having the scorecards implemented. By doing PD calibration, VietinBank will not only obtain remedies for two limitations above, but it also can provide following three more advantages:

- When doing PD estimation, the first step is to calculate the Accuracy Ratio (AR) of current scorecards by using available historical data. VietinBank can know how accurate the current scorecards are.
- We need to estimate long run default rate of bank's portfolio during PD estimation. Bank can well understand the risk level of its portfolio, which is also needed when VietinBank goes for statistical modeling at later stage.
- A rating master scale can be established during PD estimation. The master scale can provide consistent rating definition across various scorecards and it is also a mapping to external rating agencies' rating.

1.2 PD Estimation Coverage

This PD estimation project will mainly focus on the corporate segment. This segment has covered approximately 75% of the bank's credit exposure as of yearend 2009.

Financial and individual clients are not included in the scope of this project. The former is excluded due to small exposure covered thus it is not a significant portfolio at this stage. While the later is excluded because the scorecards implemented for this segment are only Application scorecards. Going forward, it is recommended to perform PD estimation when Application and Behavioral scorecards have been built for this segment.

In addition, there are some obligors having unclear/missing industry classification or belonging to non-profit organization. The corresponding scorecards for this group of customers are ambiguous, and therefore need to be excluded from the scope. Table 1 below shows the coverage of this project:

Table 1. Coverage of PD estimation

Type of Clients	Percentage of Balance (Year end of 2009)
Individual clients	21.14%
Non-profit organization	0.40%
Finance services	0.39%
Clients with unknown industry	3.50%
Corporate Clients for PD estimation	**74.58%**
Total	**100.00%**

1.3 Current Scorecards Results

As shown in Table 2 below, current scorecard design has 2 major components: Financial and Non-financial. For Non-financial criteria, score up to 65 is achievable. While for financial criteria, maximum score of 35 and 30 are achievable for audited and non-audited financial statement respectively. This difference is made in order to capture difference in the reliability of financial information between audited and non-audited financial statement.

Table 2. Weight of scorecard

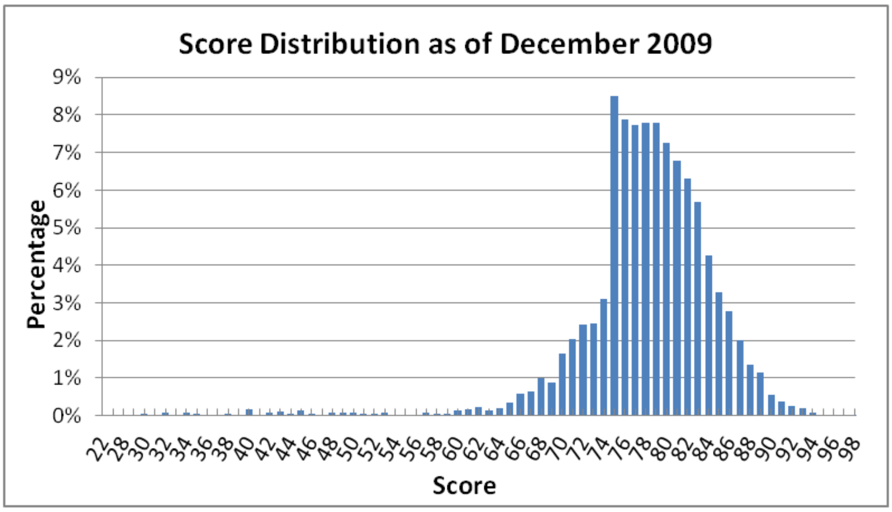
Weight	Audited Financial Reports	Non-audited Financial Reports
Set of financial criteria	35%	30%
Set of non-financial criteria	65%	65%

From current weight allocated to Financial and Non-financial components, we need to note that current scorecards performance is heavily relying on Non-financial component, rather than financial one. We need to bear this in mind since this will affect our analysis regarding Accuracy Ratio of the models in the section 4.1 below.

As of November 2010, VietinBank has obtained scores for customers using data as of December 2009 and October 2010. The scores obtained using data as of Dec 2009 are used as primary sample for PD estimation. The scores using data as of Oct 2010 are not used because performance window[1] is not available by the time of this project.

Using data as of December 2009, there are around 9,500 corporate clients have been assigned score. The following chart shows the score distribution.

Figure 1. Score distribution as of December 2009



We can observe that the scores are ranging from 20 to 98 in that date point. The percentage of score below 65 is less than 3%. It means less than 3% of clients are in the "high risk" category.

We should also note that current scorecard design is to align more to State Bank of Vietnam (SBV) and they are likely to be used for loan loss provisioning purpose rather than for risk management. Therefore, we will not go into the detailed

[1] Performance window is the period where we observe the performance of the customer, whether it becomes default customer or not. This is normally 12 months ahead from the scoring date. Scores using data as of October 2010 implies that the performance window span from November 2010 to October 2011.

discussion regarding the design of current scorecards, since they are by definition for compliance purpose.

Having say that, we nevertheless need to mention an important point that relates to PD estimation exercise. The "high risk" category by SBV definition is those which will be mapped to Non-performing loans in 5 loan categories, i.e. Sub-standard, Doubtful and Loss. This is not a common practice in the PD models for risk management purpose where default/non-default are the status of customer determined by default definition. This status is not something that is determined by score obtained from scorecards.

To align to leading practice, for PD estimation customers with score below 65 should have no PD estimates, but the PD should be equals to 100% since they are non-performing already.

Beside the "high risk category", we also observe that there is a "sudden" increase by 6% when the score moves from 74 to 75. This is untypical observation, where a common score distribution should have smoother continuous trend without any "sudden" jump in frequency for a certain score range.

Further investigation, we found that score 75 is the starting point of the "low risk" category. "Low risk" category by SBV definition is those which will be mapped to Current loans in 5 loan categories. In other words, score 74 and 75 is the threshold between Current and Special Mentioned in 5 loan categories. From the score distribution, we suspect that there is a tendency to push customers to Current rather than letting them fall under Special Mentioned whenever possible. The possibility of doing this is high for customers which have scores nearby the threshold. And this is even more "doable" since qualitative component accounts for 65% weight in the scorecard.

We should stress here that this potential tendency[2] is more a practical implementation issue rather than the scorecard issue. We suggest that special attention is needed when VietinBank will implement more advanced credit risk management tools in the future.

[2] of not being objective in assessment but result oriented qualitative assessment

2. Data and Segmentation

2.1 Data

Data used in this project is extracted from three various sources: internal data, expert judgment ranking and external data. Each of which will be elaborated in more details in subsections below. These data will be used for estimating Accuracy Ratio (AR) of current scorecards and long run average default rate (Central Tendency or CT) of the corporate credit portfolio.

2.1.1 Internal Data

VietinBank provided four data sets to perform the PD estimation:

- **Scoring data:** Scorecards were implemented in the second half of year 2010, and the scorecards were used to obtain scores of customer as of Dec 2009 and Oct 2010. Score of sample customers using data as of Dec 2009 will be used to calculate the accuracy ratio of the scoring models.
- **Provision data:** There are 2 sets of provision data used in the calculation: as of November and December of last 5 consecutive years. We understand from the bank that the provision reporting date per SBV requirement is as of end of November every year and the bank usually writes off bad debts in December. Therefore, provision data as of end of November may provide more conservative estimation. In this exercise, provision rate of the year is estimated from both November and December. The data period covers nearly five years from 2006 to Oct 2010. The provision rates will be used to derive the approximate long run default rate. For the detail calculation logic, please refer to section 3.2.4.
- **Write off data**: There are all five years data, from 2006 to Oct 2010, extracted from the system . The write off rate will be used to derive the

approximate long run default rate as well. For the detail calculation logic, please refer to section 3.2.4.

- **Loan classification information of customers:** This data contains historical loan category information from 2006 to Oct 2010. The loan category information in the provision data will be used to calculate count based default rate and Accuracy Ratio.

2.1.2 Expert Judgment Ranking

VietinBank's corporate scorecard was implemented in the second half of 2010. Although it also used the scorecard to assign score to customers as of Dec 2009, the scoring results for customers are not fully reliable. This is a common issue when we are doing "back scoring[3]".

The time when we were assigning score to customers as of a past date, we have already known the good/bad credit status of the customers. For objective part such as financial ratios, it is not an issue. However for the subjective part (Non-financial), it may lead to a extremely high accuracy. The reason for this excessively accurate assessment is that the subjective judgment for the non-financial part of the scorecard is inevitably impacted by revealed credit records when tracing back to assign the score to the clients as of yearend 2009. Customers who are known (at the time of scoring) have been defaulted, would be assigned to very low non-financial score subjectively.

This extremely high accuracy is only possible when the status is already known. In reality, during scorecard implementation, the status is unknown and we are trying to predict the future. Therefore, the accuracy of subjective assessment will not be as accurate as those shown in the "back scoring" sample.

[3] "Back Scoring" is assigning score to the customer as of a date in the past.

Using the objective part, i.e. the financial score, only to perform assessment of the accuracy of the scorecard is not an ideal solution either. The financial components just account for 30-35% weight of the total score. Therefore, using financial ratios alone are not able to provide a complete picture of how accurate the current scorecard is.

In addition, in the performance window 2010 (up to October only), the number of default customer is quite low. Therefore, the reliability of AR estimate is quite low. In order to assess the predictive power of current scorecard, we need credit officers to give rankings for the non-default accounts. This will provide another basis for assessing the accuracy of current scorecards. The technical details will be further elaborated in the following section.

In order to obtain expert judgment ranking to a sample customers, we firstly need to perform sampling. Due to time limitation, all selected branches are from Hanoi and Ho Chi Minh City, where it is more efficient to bring credit officers together to give the ranking in short time. A total of fifteen branches were selected, nine branches in Hanoi and 6 branches in Ho Chi Minh city. In each branch, maximum of ten companies of each segment are selected. The general selection principles are:

- If total number of companies in that segment is less than or equal to 10, all companies will be selected for ranking.
- If total number of companies in that segment is greater than 10, we will select companies as below table showed. If companies are concentrated in several ratings, we will select the companies with different customer types.

Table 3. Company selection method of expert ranking

Rating	No. of Companies
AAA	1
AA	1
A	2
BBB	2
BB	2
B	1
Below B	1

2.1.3 External Data

Central Tendency (CT) which refers to the average default rate of the credit portfolio across a complete economic cycle. Due to short period of historical data in VietinBank, we can only obtain average default rate for the last four years. The default rates in the last 4 years, although it includes 2008/2009 financial tsunami period, we are of opinion that it does not consist a downturn of the default rate cycle. Financial tsunami was accompanied by massive government stimulus program which in turn provided huge amount of liquidity which prevented companies to go into default. Therefore, in order to obtain a more reasonable estimate of long run average default rate, external data is needed as comparison benchmark or reference.

Based on EY's past projects[4], however, there's no reference default information specifically for Vietnam. Therefore, we need to find proxy countries to obtain external benchmark. We chose to use reference default rates of listed companies of Philippine and Indonesia. Both countries have the same sovereign and are in the same region (South East Asia) as Vietnam. The time period of this data is long enough: from 1997 to current, therefore it is long enough to cover at least one complete economic cycle.

[4] This should also be the case for other consulting firms since no PD modeling project (as far as our knowledge) has been executed for Vietnamese banks.

2.2 Segmentation

There are thirty-four industry segments defined in the current scorecards, and there are twenty industry segments in other historical data (provision and write-off data). For each of these sub-industries, we may not obtain enough number of default cases to calculate long run default rate and AR. For PD calibration, we need to merge some industries which have similar characteristics into the same segment. The segmentation is done judgmentally based on our past experiences. We proposed to group those 34 sub-industries into 7 large segments.

Prior to scorecards implementation, VietinBank has its own industry classification (20 industries). In this industry classification, there is no separation between real estate and construction. Therefore, long run average default rate for real estate and construction segment cannot be estimated separately by using internal data. The detail of industry mappings are shown below:

Table 4. Seven segmentations of PD estimation

Segment	Segment Name
1	Capital intensive manufacturing
2	Light manufacturing
3	Retail/Wholesale
4	Transportation and communications (infrastructure)
5	Services
6	Real estate
7	Construction

Table 5. 34 Industries mapping

Industry Code	Industry Name	Segment	Industry Code	Industry Name	Segment
N001	Coal mine exploration	1	N018	Retail	3
N002	Crude oil, natural gas exploration	1	N019	Retail/Wholesale	3
N003	Forestry	2	N020	Hotel, Restaurant and entertainment services	5

Industry Code	Industry Name	Segment	Industry Code	Industry Name	Segment
N004	Maritime transportation	4	N021	Shipbuilding	1
N005	Aviation transportation	4	N022	Electricity and other power manufacturing	1
N006	Road and waterway transportation	4	N023	Fishing	2
N007	Steel manufacturing	1	N024	Consultancy services	5
N008	Cement manufacturing	1	N025	Wooden processing and other wood-originated products manufacturing	2
N009	Industrial materials manufacturing	1	N026	Medical services; educational training services and other social assistance services	5
N010	Construction	7	N027	Communication and telecommunication	4
N011	Mineral exploitive (excluding coal)	1	N028	Infrastructure	4
N012	Real estate	6	N029	Food and beverage manufacturing	2
N013	Agriculture	2	N030	Garment, leather and shoe manufacturing	2
N014	Pharmacy manufacturing	2	N031	Cattle-feed manufacturing	2
N015	Paper and other paper originated products manufacturing	2	N032	Fertilizer, plastic, synthetic rubber and other chemical synthesis manufacturing	2
N016	Electronic devices, electric devices, optical devices and medical machine manufacturing	2	N033	Household commodities, office equipment manufacturing	2
N017	Automobile assembling and manufacturing	1	N034	Transportation assistance services	4

As mentioned in section 1, financial institution, non-profit origination and unknown industry are excluded from analysis. Therefore, there are four industries in table below which are not merged into any segments.

Table 6. 20 Industries mapping

Industry Name	Segment	Industry Name	Segment
Agricultural and Forestry	2	Transport, warehouse and communications	4
Aquaculture	2	Science and technology	1
Mining and quarrying	1	Business and advisory services	5
Manufacturing and processing	2	Education and training	5
Electricity, Petroleum & Water	1	Science and technology	5
Construction	7	Recreational, culture, sporting activities	5
Wholesale and retail trade; repair of motor vehicles, motor cycles and personal goods	3	Community, social and personal service activities	5
Hospitality services	5	Households	5
Financial intermediation		International organizations and bodies	
State management, security and national defense: Party, union, social guarantee		Others	

3. Methodology

In this project, we utilize Power Curve calibration method to estimate PD. Using this approach, there are 5 steps involved:

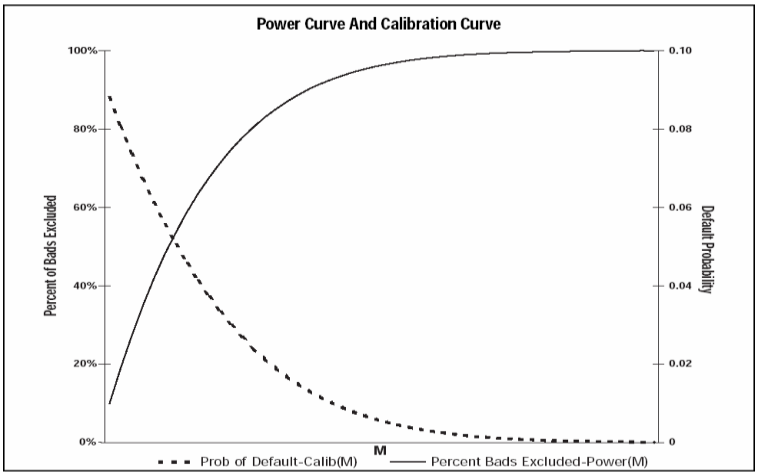
- Step1: Calculate the discriminatory power of scorecard
- Step2: Determine the shape of the power curve using reference
- Step3: Determine the central tendency (CT) or Long Run Average PD
- Step4: Determine the shape of the PD Curve
- Step5: Obtaining the PD estimate

Each step will be elaborated in more details in sub-sections below after having an overview of Power Curve calibration methodology.

3.1 Overview of Power Curve Calibration Methodology

The power curve calibration approach utilizes the slope of power curve to derive the PD curve. Figure 2 below illustrates the relationship between the power curve and the PD curve. The PD curve (dotted line) seems to be the mirror image of the Power curve. In plain words, the PD curve represent the slope or the tangent of the power curve in a small range of M. The more accurate the rating model, the steeper the Power curve, and it implies a steeper PD curve.

Figure 2. Sample: Power curve and calibration curve



Mathematically, the calibrated PD curve can be obtained using the following formula:

$$p(m) = \bar{p} \cdot \left[\frac{\partial power(m)}{\partial m} \right] \text{......(1)} \ ,$$

where: $\bar{P}$ is the long run default rate of the portfolio

The following are the steps in performing Power Curve Calibration:

1. Group the sample into bins based on the risk grading of external rating agency
2. Calculate the total number of obligors in each bin (N) as well as the number of default (D)
3. Calculate the cumulative total obligor (M) and also the cumulative default (power(M)):

$$M(b) = \frac{\sum_{i=1}^{b} M(i)}{\sum_{i=1}^{B} M(i)} \quad \textbf{and} \quad power(b) = \frac{\sum_{i=1}^{b} D(i)}{\sum_{i=1}^{B} D(i)} \text{......(2)}$$

4. The first derivative of the power curve with respect to M is calculated using the following formula:

$$\frac{\partial power(m,i)}{\partial m} = \begin{cases} \dfrac{power(1)}{M(1)}, & for\ i = 1 \\ \dfrac{power(i) - power(i-1)}{M(i) - M(i-1)}, & for\ i = 2,\ldots n, \end{cases} \quad \textbf{......(3)}$$

5. The calibration is performed by utilizing the estimated CT and the slope of the power curve derived in (4):

$$p(m) = \bar{p} \cdot \left[\frac{\partial power(m)}{\partial m} \right] \textbf{......(4)}$$

6. The resulted $p(m)$ is not a smooth curve. Exponential fitting is conducted in order to derive a smooth PD curve. The exponential fitting utilizes 2 different types of estimation:

   The assumption that we need to make is that PD curve follows an exponential shape:

$$PD = \exp(\alpha + \beta X) \textbf{......(5)}$$

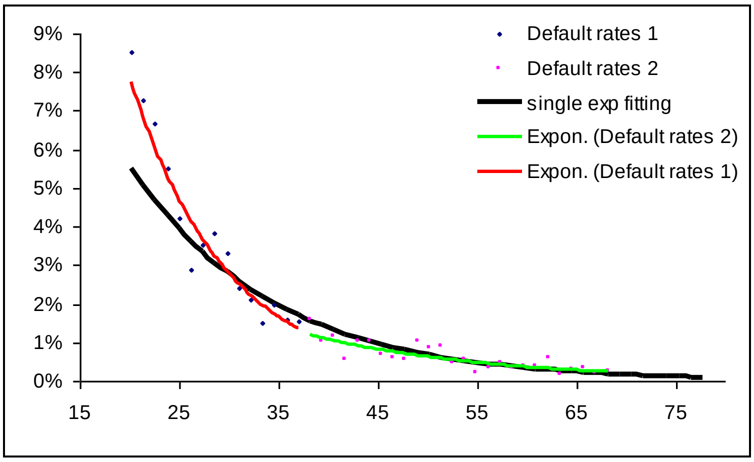
   There are 2 parameters: α and β that need to be estimated. There are 2 different approaches that can be used to estimate α and β. One is using transformation and another one is without transformation.

The first estimation we use log transformation to the left and right of the equation, and the PD function specification becomes:

$$\ln(PD) = \alpha + \beta X \textbf{ ......(6)}$$

In this case α and β can be estimated using Ordinary Least Square (OLS) method. Theoretically, this estimation method is more robust since the transformation may well handle the heteroscedasticity issue of the error term. Under this estimation method, one exponential curve typically cannot gives the best fit to the PD given that the lower end (similar to speculative grades) typically have steeper PD curve and hence having different exponential curve parameters. The following figure illustrates the differences between one exponential fitting and two exponential fittings:

Figure 3. Sample: Exponential fitting



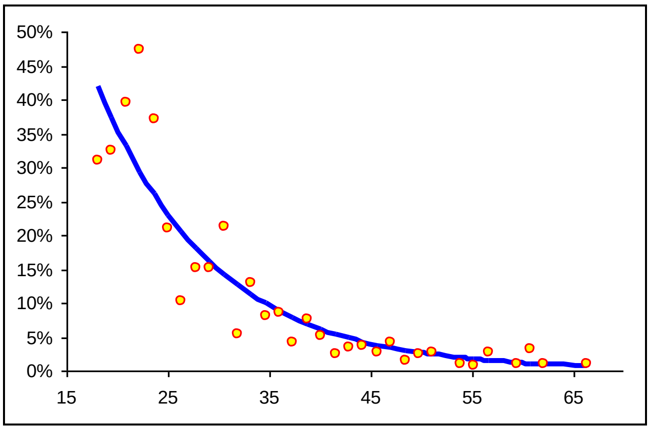
The limitation with this estimation approach is that it tends to overestimate PD on the right end of the score distribution. The second curve in green color may give too conservative estimate for PD. The empirical figures that are used to estimate the second exponential curve are those which are non-zero only. The bins which have zero defaults need to be deleted in the estimation (since Logarithmic of zero may not give a result). Therefore, by construction, the sample is upward biased. As a result, the line seems to be best fit to the empirical PD but in reality the best fit means overestimate PD since the zeros have been eliminated.

The second estimation approach may solve the issues encountered in previous estimation method, where we may estimate α and β numerically via error minimizing formula below without performing transformation to the PD.

$$\min_{\alpha,\beta} \sum (Exp(\alpha + \beta.Sc_i) - PD_i)^2 \text{ ......(7)}$$

The limitation about this is that the statistical inference about α and β may not valid due to heteroscedaticity issue. Nevertheless, this is still acceptable since we are more interested in the fitting rather than making statistical inference about α and β. This approach is adopted in the project. The following curve illustrates the estimation result using this method.

Figure 4. Sample: Minimize error fitting



3.2 Steps of PD Estimation

3.2.1 Step 0: Default Definition

Prior to the PD estimation, we need firstly to define what is called "default". This is required for estimating the AR and long run average default rate.

In VietinBank, as it is the case in many banks, loans are classified into five categories (1-Current, 2-Special mentioned, 3-Substandard, 4-Doubtful and 5-Loss). If a loan is classification as Substandard, Doubtful and Loss, among other criteria, they all share one common characteristic, i.e. principal and/or interest has been past due for at least 90 days. This is also one of the most important default definition in Basel II. Therefore, loan category above 2 is regarded as the default trigger in this project.

Table 7. Default definition

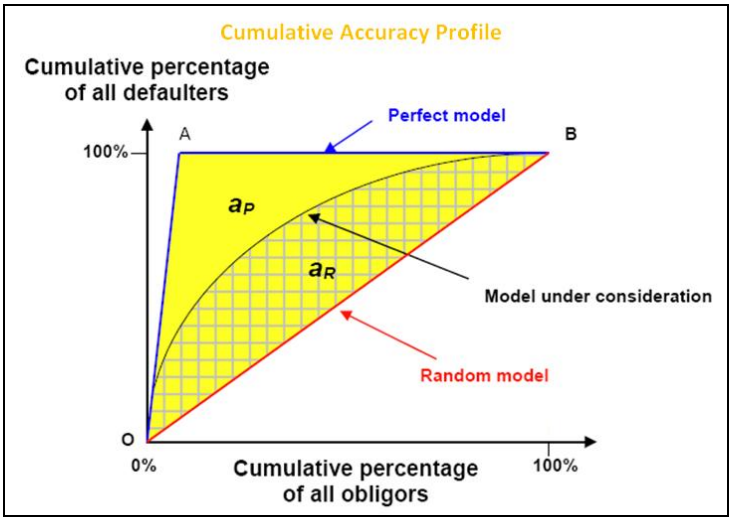
	Non-Default	Default
Loan Category	1-Current 2-Special mentioned	3-Substandard 4-Doubtful 5-Loss

3.2.2 Step 1: Determine the Discriminatory Power of the Scorecard

3.2.2.1 CAP and AR

CAP (Cumulative Accuracy Profile) is also known as the Gini curve, Power curve or Lorenz curve. It is a visual tool whose graph can be drawn if two samples of obligor grades (or scores) for defaulters and non-defaulters are available. Consider a rating model that is intended to produce higher rating scores for obligors of lower default probability. To obtain a CAP curve, all obligors are first rank-ordered by their respective scores, from the riskiest to the safest, i.e. from the obligor with the lowest score to the obligor with the highest score. The CAP curve is then constructed by plotting the cumulative percentage of all obligors on the horizontal axis and the cumulative percentage of all defaulters on the vertical axis, as illustrated in below figure.

Figure 5. Sample: Cumulative Accuracy Profile (CAP)



AR (Accuracy Ratio) is the most commonly used statistics for discriminatory power of a scorecard, and it is a summary index of a CAP. It is also known as the Gini coefficient and Power Stat. It is defined as the ratio of the area $\propto_R$ between the CAP of the rating system being validated and the CAP of the random model, and the area $\propto_P$ (area of triangle AOB) between the CAP of the perfect rating model and the CAP of the random model, i.e

$$\mathbf{AR} = \frac{\propto_R}{\propto_P} \text{......}(8)$$

AR is always between 0% and 100% for any rating system better than random assignment of ratings. The better the rating system, the closer is AR to 100%.

3.2.2.2 Somer's D

Somers' D is so-called rank order statistics, and as such measure the degree of comonotonic dependence of two random variables. The notion of comonotonic dependence generalizes linear dependence that is expressed via (linear) correlation. In particular, any pair of random variables with correlation 1 (i.e. any linearly dependent pair of random variables) is comonotonically dependent. But in addition, as soon as one of the variables can be expressed as any kind of increasing transformation of the other, the two variables are comonotonic. In the actuarial literature, comonotonic dependence is considered the strongest form of dependence of random variables.

If (X,Y) is a pair of random variables, Kendall's τ is defined by

$$\tau_{XY} = P(X_1 < X_2, Y_1 < Y_2) + P(X_1 > X_2, Y_1 > Y_2) - P(X_1 < X_2, Y_1 > Y_2) - P(X_1 > X_2, Y_1 < Y_2) \text{ ......(9)}$$

where (X_1, Y_1) $\mathrm{AR} = \frac{\propto_R}{\propto_P}$ and (X_2, Y_2) are independent copies of (X, Y). Hence $\tau_{X,Y}$ can be seen as the difference between two probabilities, namely the probability that the larger of the two *X*-values is associated with the larger of the two *Y*-values and the probability that the larger *X*-value is associated with the smaller *Y*-value. In case of continuous random variables, Kendall's τ takes on the value 1 if the variables are comonotonic.

Somers' D is defined as the difference of the conditional probabilities that correspond to the probabilities in the definition of Kendall's τ, given that the two *Y*-values are not equal. Formally, the definition of Somers' D can be expressed as

$$D_{XY} = \frac{\tau_{XY}}{\tau_{YY}} \quad \text{......(10)}$$

Note that $\tau_{XY} = \tau_{YX}$, but in general $D_{XY} \neq D_{YX}$. Denote, similarly to the section on the connection of ROC and CAP curves, by S the random variable that describes the score of an obligor that is chosen at random from the whole portfolio. Let *J* denote the (complementary) default indicator with value 0 if the obligor under consideration defaults and 1 otherwise. By a short calculation one then obtains that

$$D_{SJ} = P(S_D < S_{ND}) - P(S_D > S_{ND}) = AR \quad \text{......(11)}$$

whereas above S_D and S_{ND} denote scores of defaulters and non-defaulters respectively and AR stands for Accuracy Ratio as it was defined in the context of CAP curves. Thus, Somers' D may be interpreted as a generalization of the Accuracy Ratio. Since *J* in a certain sense is nothing but a perfect rating – which is unfortunately known only at a time when it is not of interest any longer – this observation on the connection between Somers' D and the Accuracy Ratio suggests to choose Somers' D as a criterion for the concordance of the scores *S* and any other rating *R*.

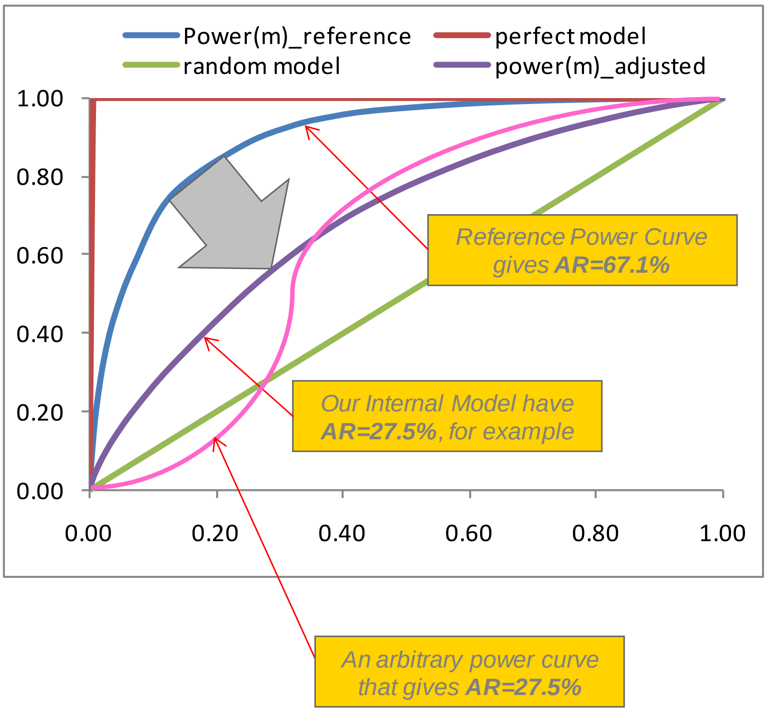
For this project, scores *S* is scores of corporate clients and other rating *R* is the expert ranking. By calculating the Somers' D between score and expert ranking, we can know predict power of current scorecard.

3.2.3 Step 2: Determine the Shape of the Power Curve Using Reference

Due to low AR of current scorecard and lacking of defaults in the available data, we do not have full information to get a power curve with a continuous and smooth shape even though we have the AR information for the scorecards.

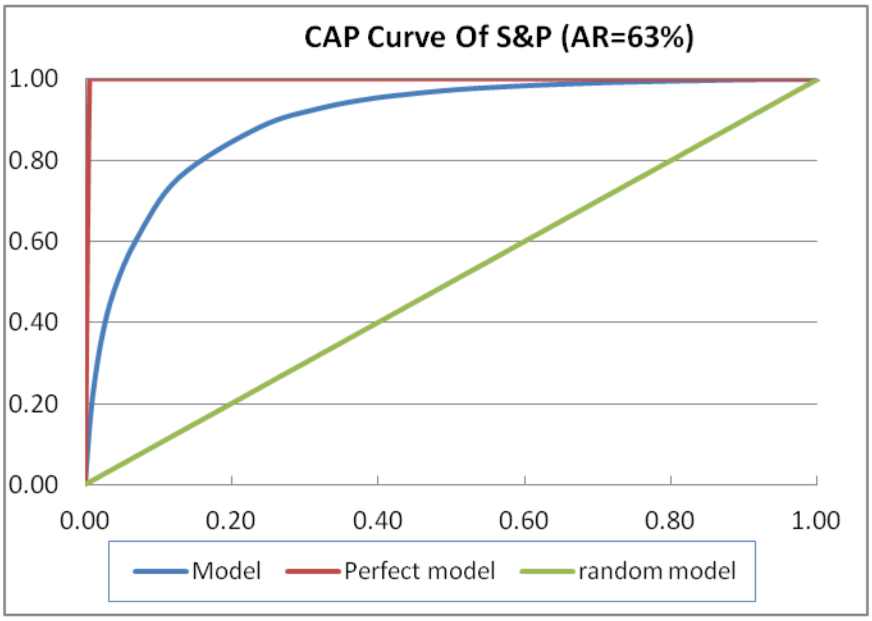
By having AR information only, there is no unique Power curve that gives the same AR. As illustrated in Figure 6 below, there are 2 Power curves (pink line and dark blue line) that yield AR equal to 27.5%. Therefore, in order to obtain more reasonable PD estimates, we need to firstly use a reference Power curve so that we may obtain a reasonable "shape" of the Power curve (shown as Blue line in Figure 6 below) at the first place as the starting point. The reference Power curve will be adjusted to a new Power curve (which have reasonable "shape") and reflect the AR of internal model.

Figure 6. Illustration of the needs of having a reference Power curve



In this project, S&P's rating and default data which provide high AR and enough default cases are adopted as reference. As can been seen from Figure 7 below, the reference power curve is very smooth with AR equals 63%. From this reference Power curve, we can reduce the AR to fit to our internal model's AR to get a reasonable power curve for our internal model.

Figure 7. CAP curve of S&P

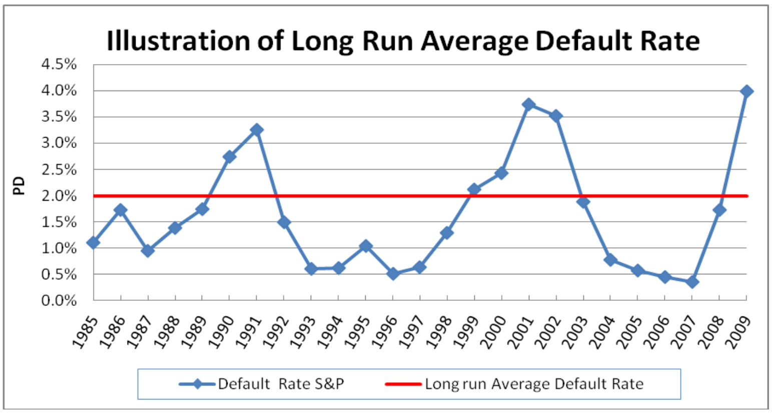


3.2.4 Step 3: Determine the Long Run Average Default Rate

In order to obtain accurate PD estimate, we need to estimate the level of the PD where the default rates in different years fluctuate around. This is necessary to avoid underestimating or overestimating the PD due to short time period of sample data.

The red line in Figure 8 below, illustrates the long run average default rate of S&P rated companies. The long run average default rate is around 2%, and this is the level where the actual default rate fluctuated around in the last 25 years.

Figure 8. Illustration of long run average default rate



There are four ways to estimate the long run average default rate or central tendency:

1. Actual default rates (count based)
2. Write-off data (write-off based)
3. Loan loss provisioning data (provisioning based)
4. External Data

The actual default rate can be calculated as:

$$\text{Actual default rate} = \frac{\text{No. of customers become default in the next year end}}{\text{No. of customers is non default in the next year end}} \text{......(12)}$$

Write-off data and loan loss provisioning data can be used as:

$$\text{Default Rate} = \frac{\text{Volume of write off or Provisioning}}{\text{Volume of Loans} * \text{LGD}} \text{......(13)}$$

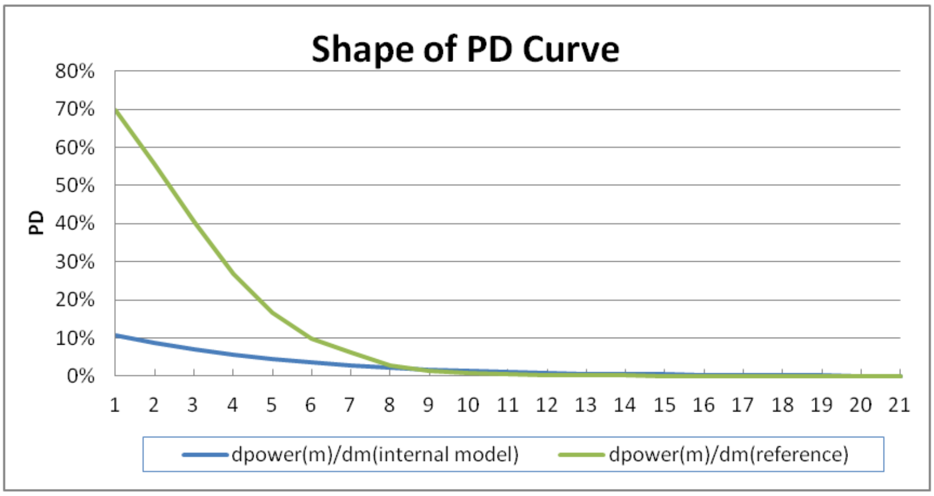
Where LGD can be estimated by using actual loss experiences data (the one for LGD model development). LGD model, however, has not been developed in VietinBank , default rate is just a approximate value which highly relies on the LGD assumption.

Actual default rates of VietinBank only covers four years period, where is not long enough to cover a full economic cycle. Although downturn adjustment can be made, we still need to obtain external default rate as comparison benchmark or references. This is required as an additional information that we can take into account before making the final decision regarding the long run average default rate for each segment.

3.2.5 Step 4: Determine the Shape of the PD Curve

Once we get a reasonable Power Curve which gives desired AR (obtained from Step 2), we can easily obtain its first derivative by using formula (3). PD curve of internal model can be derived by feeding the results of reference curve, AR and CT of internal model to formulas (2) to (4). Below figure shows two PD curves, one with AR=63% and one with 27.5%. Obviously, the higher accuracy one will have steeper curve.

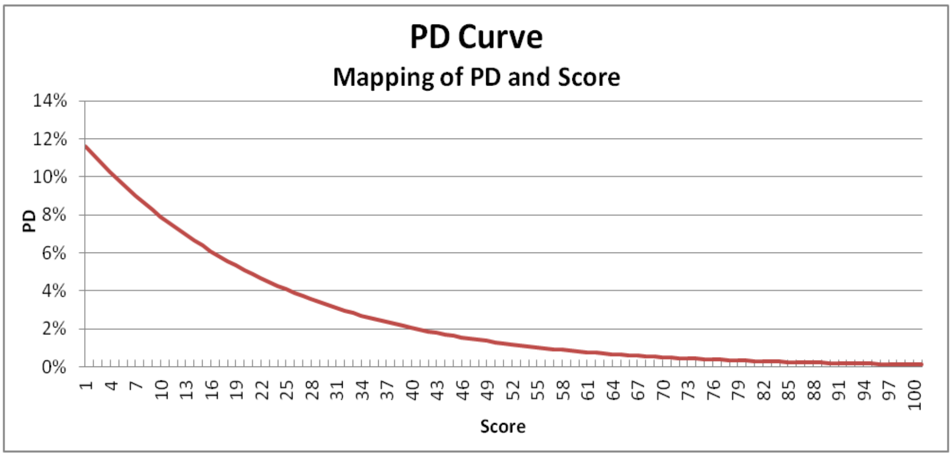
Figure 9. Sample: Shape of PD curve



3.2.6 Step 5: Obtaining the PD Estimate

After completion of the above steps, we can apply the obtained CT's and minimization specification as shown in equation (7) to derive two parameters, α and β. These two parameters will be used to estimate PD of a customer through specification as shown in equation (5).

Figure 10. Sample: PD curve (mapping of PD and score)



4. Result and Analysis

4.1 Accuracy Ratio of Scorecard

As mentioned in section 3.2.2, there are two ways to calculate the predictive power of scorecard: actual default cases and expert ranking.

4.1.1 AR Estimated Using Actual Default Cases

One of the methods to obtain AR of a scorecard is to use actual default cases. Table 8 below shows AR result of each of the segment of VietinBank's scorecards calculated using scores of customers as of December 2009 and their default/non-default performance in 2010. The AR result of scores of all scorecard combined is shown in Figure 11 below.

We may observe that the AR of total score of each segment ranges from 0.67 (Retail/Wholesale segment) to 0.97 (Real Estate segment) and the AR of all scorecards together is 0.80. These AR results are extremely high. These are even higher than the AR of S&P data (0.63, refer to section 3.2.3).

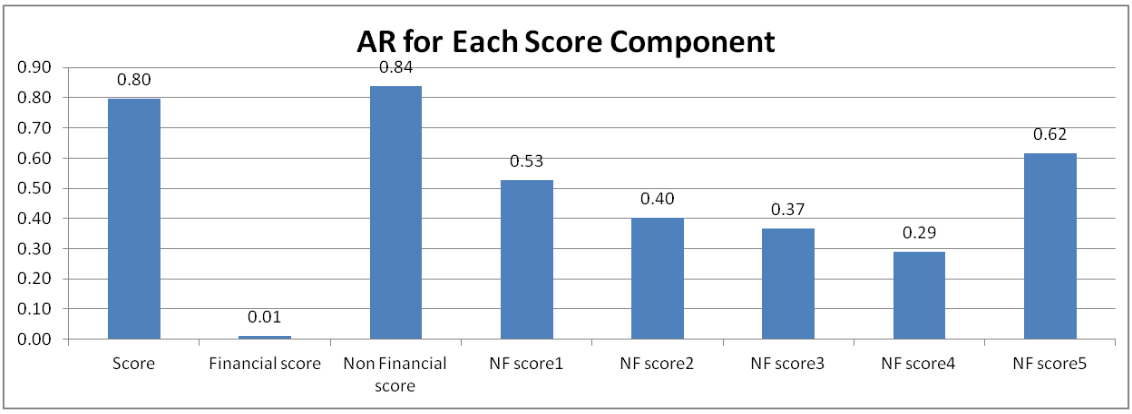
When we analyzed in more details, we found that the high AR's are the results of high AR for non-financial components, which range from 0.65 to a perfectly accurate 100%. As discussed in section 2.1.2, the high AR for non-financial component is not reliable due to the known status of customer when we were doing "back scoring" in the second half of 2010 (when the scorecards are firstly implemented).

In order to obtain more reliable AR using default/non-default data, we need total score assigned to customers prior to the performance window. In other words, the scores assigned in Oct 2010 may be a good data for obtaining a more reliable AR after a complete 12 months performance window is reached (by end of September 2011). Obviously, it is impossible to perform this calculation at the time of this project.

Table 8. AR of seven segments

Segment	Segment Name	AR		
		Overall Score	Financial Part	Non-Financial Part
1	Capital intensive manufacturing	0.86	0.28	0.90
2	Light manufacturing	0.88	0.10	0.94
3	Retail/Wholesale	0.67	0.01	0.65
4	Transportation and communications	0.85	0.02	0.86
5	Services	0.93	0.00	0.99
6	Real estate	0.97	0.03	1.00
7	Construction	0.77	0.00	0.86

Figure 11. AR for each score component



Note: NF Score1- NF Score 5 means non-finical score 1 to non-finical score 5. For the detail scorecard information, please refer related scorecard document.

The Financial scores, which are derived from financial statement, have less issue for "back scoring" (as discussed in section 2.1.2). We may observe that the AR for this component is very low, ranging from 0 to 0.27 with AR for overall 0.01 only. Nevertheless, we need to be very cautious in interpreting this result.

First of all, the default cases are fairly limited for each segment. Number of default cases for each segment is shown in Table 9 below. Due to limited number of default cases, the AR fluctuation is very large, and it is very sensitive to extreme observation/outliers; one or two defaulted customers assigned with high score will lead AR suddenly drop.

Table 9. Number of default accounts in each segment

Segment	Segment Name	No. of Default
1	Capital intensive manufacturing	10
2	Light manufacturing	12
3	Retail/Wholesale	17
4	Transportation and communications	19
5	Services	3
6	Real estate	1
7	Construction	11

Secondly, the AR for all financial scores combined is based on the assumption that the scores from different scorecards are comparable. However, in reality they are not comparable (as discussed in section 1.1). To avoid comparability issue, it is better to analyze the AR of financial scores by segment. The AR of financial score for segment 1 (capital intensive) is promising, as it reaches 28%.

In order to show how large influence of such extreme cases make, we performed sensitivity analysis by excluding default accounts with highest financial score one by one in the remaining sample for each segment to see how the AR estimate may change.

As can been seen from Table 10 below, AR of segment 3 (Retail/Wholesale), 4 (Transportation) and 7 (Construction) are still not well performing, nevertheless but the AR's have increased significantly after deleting 1 or 2 extreme default cases in each segment.

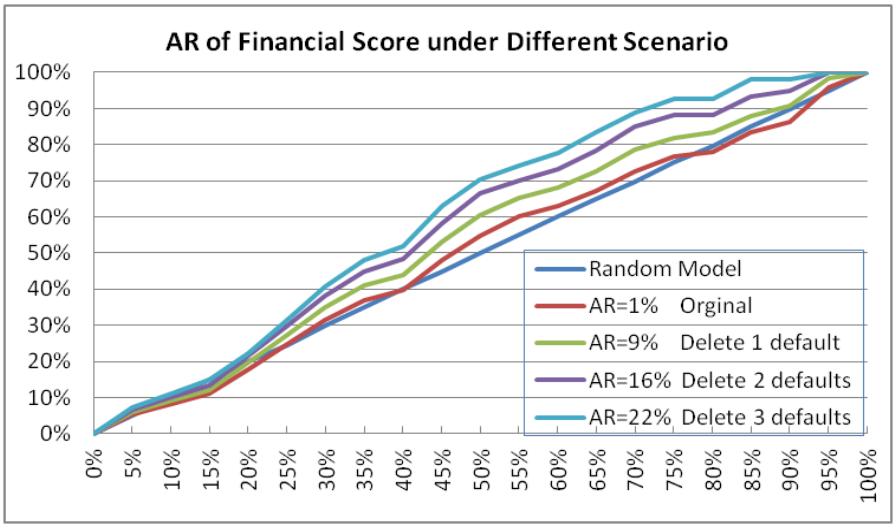
This is a promising result, where the financial score indeed has some predictive power. We do believe that it is unlikely to have expert judgment models that are totally not predictive (will elaborate more on this point in section 4.1.2).

Moreover, financial score just accounts for 30%-35% in the total score of VietinBank's corporate scorecards, deriving conclusion regarding AR of the Total Score based on the AR of financial component only is not appropriate. We do believe that the inclusion of non-financial part would improve AR.

Table 10. AR for each segment under different scenario

Segment	Segment Name	AR of Financial Score		
		Delete one Default	Delete two Defaults	Delete three Defaults
1	Capital intensive manufacturing	0.35	0.38	0.41
2	Light manufacturing	0.20	0.31	0.44
3	Retail/Wholesale	0.05	0.11	0.17
4	Transportation and communications	0.07	0.13	0.16
5	Services	0.08	0.56	N/A
6	Real estate	N/A	N/A	N/A
7	Construction	0.00	0.08	0.17

Figure 12. CAP curve of financial score under different scenario



4.1.2 AR of Expert Ranking

As mentioned in the previous section, it is unlikely to have expert judgment models that are totally un-predictive. Table 11 below shows Somer's D rank correlation (as a proxy of AR) of the scorecards output and expert judgment ranking.

Based on our experiences, the predictive power of the expert judgment scorecard is commonly around 30% to 35%. From Somer's D rank correlation result, we can observe that the proxy AR of current scorecards is 33%. This is well within expectation. The proxy AR of each segment is also close to or slightly beyond this range, except the segment 5 (Services) which has slightly lower Somer's D than that for other segments.

The Somer's D rank correlation result also validates our proposition that expert judgment scorecard that is totally un-predictive is unlikely. We need to believe that VietinBank's credit experts should have a sense to tell which customer is better than the others, especially for the sample that we have chosen that are quite significant range in the credit worthiness. From the rank correlation, we may observe that the alignment between ranking from scorecards and ranking from internal credit experts are within acceptable range (mostly above 30%, with minor exceptional cases).

Table 11. AR of expert ranking

Segment	Segment Name	AR
1	Capital intensive manufacturing	43%
2	Light manufacturing	36%
3	Retail/Wholesale	34%
4	Transportation and communications	39%
5	Services	21%
6	Real estate	27%
7	Construction	34%
Total		33%

Due to the limitation in the AR derived by suing default/non-default status (discussed in section 4.1.1 above). In this PD estimation project, we use proxy AR (Somer's D rank correlation) as the basis to perform PD calibration.

4.2 Long Run Default Rate

For PD calibration, we analyzed VietinBank historical default experiences as well as external benchmarks in order to obtain long run average default rate for VietinBank corporate credit portfolio.

As mentioned in section 3.2.4, there are four ways to calculate the long run default rate: actual default rates (count based), write-off data (write-off based), loan loss provisioning data (provisioning based) and external benchmark. Each of these will be elaborated in the sub-sections below and at the end we come up with a conclusion on Central Tendency (CT) that will be used in the PD calibration.

4.2.1 Actual Default Rates (count based)

The default counts are obtained based on 5 loan categories (Current, Special mentioned, Substandard, Doubtful and Loss). The default cases are defined as customers who were in current and special mentioned in the end of the year and become non-performing in the next year end. For the non-default accounts in the end of year 2009, the performance window is only up to the end of Oct 2010, therefore the number of default cases is annualized. The industry classification used in the calculation is based on the 20-industries classification, which were mapped into 7 major segments as discussed in section 2.2. We should note that there is no separation between real estate and construction in this classification, and therefore the default rate figures for construction segment include real estate and construction.

Table 12. Actual default rates (count based)

Segment Name	2006	2007	2008	2009	Average
Capital intensive manufacturing	0.70%	0.64%	0.61%	1.32%	0.82%
Light manufacturing	1.60%	1.89%	1.00%	1.51%	1.50%
Retail/Wholesale	1.56%	0.90%	1.08%	1.47%	1.25%
Transportation and communications	1.00%	0.77%	2.18%	3.53%	1.87%
Services	1.05%	1.97%	1.30%	1.47%	1.45%
Real estate	N/A	N/A	N/A	N/A	N/A
Construction	2.80%	2.45%	1.37%	1.59%	2.05%

Due to government stimulus program and liquidity available in the market, the current financial tsunami is not considered as downturn in credit cycle. Therefore, the average default rate calculated using this approach, as shown in Table 12 above, based on our option is too low to represent long run average PD.

4.2.2 Loan Loss Provisioning Data (provisioning based)

Loan loss provisioning is the product of volume of loan, default rate and LGD, hence it can be used to calculate the default rate. But default rate derived from provision is an approximate estimation which is highly relied on the LGD assumption.

The following formula is used to calculate the default rate using provisioning data:

$$\text{Default Rate} = \frac{\text{Volume of provisioning}}{\text{Volume of Loans} * \text{LGD}} \text{......(14)}$$

Although there's no LGD model of corporate customers in VietinBank, there are two alternative choices to get LGD value:

- Use 45%: which is the LGD value of senior unsecured loans under Basel II FIRB approach. This is assuming that we do not have information about eligibility of collateral to make LGD reduction.
- Use 39%: which is the result of roughly calculating the LGD under FIRB by using VietinBank's financial report.

There's no actual LGD figure derived from the model and 39% is a rough calculation result using summary figures from financial report. Based on our discussion with VietinBank, it was decided to use 45% as the LGD assumption.

Considering that the bank usually writes off bad debt in December, for the conservative reason, both November and December data are used for calculation. As can be seen from below tables, the default rates estimated by using provision figures as of the end of November are higher than those obtained using year-end provisioning data.

Table 13. Provision rate (Year End)

Provision Rate (Year End)					
Segment Name	2006.12	2007.12	2008.12	2009.12	2010.10
Capital intensive manufacturing	0.96%	0.88%	0.76%	0.75%	0.78%
Light manufacturing	1.61%	1.30%	0.97%	0.93%	1.06%
Retail/Wholesale	0.87%	0.85%	0.96%	0.85%	1.08%
Transportation and communications	0.88%	0.81%	0.87%	0.98%	2.30%
Services	1.11%	0.88%	0.98%	0.99%	1.11%
Real estate	N/A	N/A	N/A	N/A	N/A
Construction	2.54%	1.10%	1.09%	0.88%	0.93%

Table 14. Default rate derived from provision (Year End)

Default Rate Derived from Provision(Year End)						
Segment Name	2006.12	2007.12	2008.12	2009.12	2010.10	Average
Capital intensive manufacturing	2.13%	1.95%	1.70%	1.67%	1.74%	1.84%
Light manufacturing	3.58%	2.89%	2.17%	2.06%	2.35%	2.61%
Retail/Wholesale	1.94%	1.90%	2.14%	1.88%	2.41%	2.05%
Transportation and communications	1.96%	1.79%	1.94%	2.18%	5.10%	2.59%
Services	2.46%	1.96%	2.18%	2.20%	2.46%	2.25%
Real estate	N/A	N/A	N/A	N/A	N/A	N/A
Construction	5.65%	2.44%	2.42%	1.95%	2.07%	2.91%

Table 15. Provision rate (November)

Provision Rate (November)					
Segment Name	2006.11	2007.11	2008.11	2009.11	2010.10
Capital intensive manufacturing	1.00%	0.80%	0.88%	0.76%	0.78%
Light manufacturing	2.01%	1.99%	1.56%	1.09%	1.06%
Retail/Wholesale	0.89%	1.16%	1.25%	1.07%	1.08%
Transportation and communications	0.88%	0.88%	0.89%	1.83%	2.30%
Services	1.13%	0.97%	1.17%	1.23%	1.11%
Real estate	N/A	N/A	N/A	N/A	N/A
Construction	3.30%	3.10%	1.25%	0.89%	0.93%

Table 16. Default rate derived from provision (November)

Default Rate Derived from Provision (November)						
Segment Name	2006.11	2007.11	2008.11	2009.11	2010.10	Average
Capital intensive manufacturing	2.21%	1.78%	1.95%	1.68%	1.74%	1.87%
Light manufacturing	4.46%	4.42%	3.47%	2.42%	2.35%	3.42%
Retail/Wholesale	1.98%	2.59%	2.77%	2.37%	2.41%	2.42%
Transportation and communications	1.95%	1.95%	1.98%	4.07%	5.10%	3.01%
Services	2.52%	2.15%	2.60%	2.74%	2.46%	2.49%
Real estate	N/A	N/A	N/A	N/A	N/A	N/A
Construction	7.34%	6.90%	2.78%	1.98%	2.07%	4.21%

The estimated default rate is higher than its derived from count based approach, however it also suffers the same limitation where it does not cover downturn period. In addition, the default rates obtained using this method are affected by LGD assumption.

4.2.3 Write-off Data (write-off based)

As provision, write-off rate can also be used as a proxy to calculate the default rate. LGD is assumed to be equal to 45% in the calculation.

The following formula is used to calculate the default rate using write-off data:

$$\text{Default Rate} = \frac{\text{Volume of write off}}{\text{Volume of Loans} * \text{LGD}} \ldots\ldots(15)$$

Table 17. Write-off rate

Write-off Rate					
Segment Name	**2006**	**2007**	**2008**	**2009**	**2010**
Capital intensive manufacturing	0.00%	0.00%	0.11%	0.09%	0.06%
Light manufacturing	0.97%	1.03%	1.13%	0.59%	0.38%
Retail/Wholesale	0.04%	0.20%	0.23%	0.37%	0.21%
Transportation and communications	N/A	0.01%	0.01%	0.86%	0.63%
Services	0.10%	0.07%	0.09%	0.24%	0.02%
Real estate	N/A	N/A	N/A	N/A	N/A
Construction	1.61%	1.08%	0.30%	0.10%	0.17%

Table 18. Default rate derived from write-off rate

Default Rate Derived from Write-off Rate						
Segment Name	**2006**	**2007**	**2008**	**2009**	**2010**	**Average**
Capital intensive manufacturing	0.01%	0.00%	0.25%	0.20%	0.13%	0.12%
Light manufacturing	2.16%	2.29%	2.50%	1.31%	0.84%	1.82%
Retail/Wholesale	0.08%	0.45%	0.52%	0.83%	0.47%	0.47%
Transportation and communications	N/A	0.01%	0.03%	1.91%	1.40%	0.84%
Services	0.23%	0.15%	0.19%	0.53%	0.04%	0.23%
Real estate	N/A	N/A	N/A	N/A	N/A	N/A
Construction	3.58%	2.40%	0.67%	0.22%	0.37%	1.45%

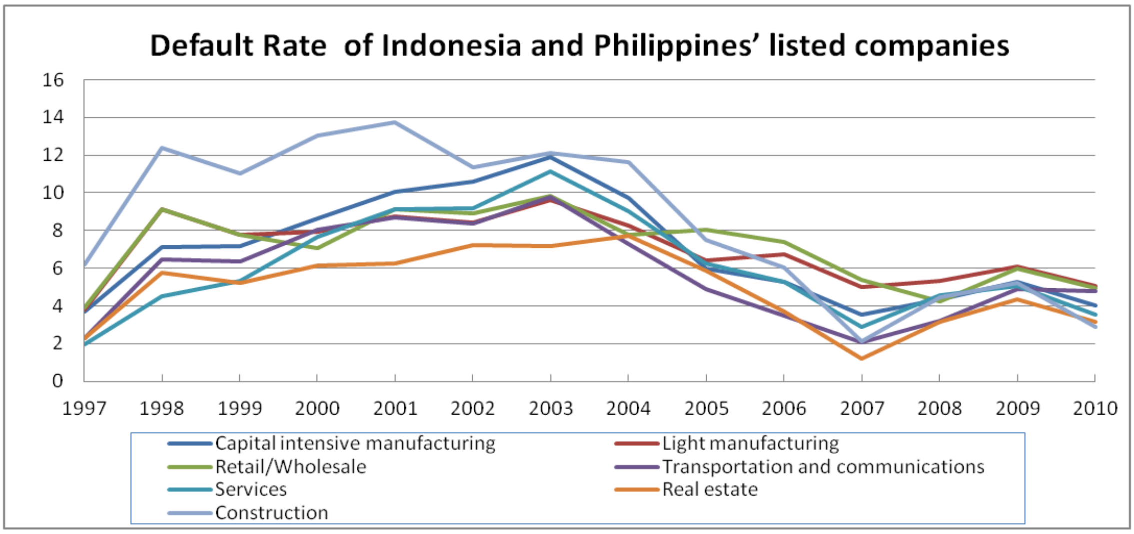
We understand from VietinBank that writing-off is a lengthy procedure, where it needs to go through a long approval process. Therefore, using write-off data for CT estimation is likely to underestimate. In addition, the same issue as using provision data, default rate derived from write-off also suffers the same limitation where it does not cover downturn period and affected by LGD assumption.

4.2.4 External Data

In the three sub-sections above, we have analyzed the average default rate by using internal data. However, all of these three approaches suffer the same limitation where the internal data is not long enough to cover a complete cycle. In this sub-section, we will analyze external benchmark data in order to get another perspective of what the most appropriate long run average PD is.

Based on EY's past projects, we have the default rate of Indonesia and Philippines' listed companies. Both countries have the same country rating and are in the same region as Vietnam. The default series is from 1997 to current, which covers three economy crisis period (1998 Asian Financial crises, 2001 global economy crises and 2008 financial tsunami) and one pandemic episode (2003 SARS).

Figure 13. Default rate of Indonesia and Philippines's listed companies



As can be seen from the above chart, due to Asia financial crisis and SARS, the first downturn lasted from 7 years from 1997 to 2003, and the default rate of this period is much higher than that of 2007 financial tsunami which was benefited from large government's stimulus plan. Since it covers 4 economic downturns, long run default rate derived from external data may be overestimated.

Table 19. Default rate of external data

Segment Name	Average
Capital intensive manufacturing	5.78%
Light manufacturing	5.62%

Segment Name	Average
Retail/Wholesale	5.55%
Transportation and communications	4.56%
Services	4.07%
Real estate	5.14%
Construction	5.48%

4.2.5 Determination of Long Run Average Default Rate

In the above sub-sections, we have calculated average default rates by using four different approaches. However, none of them can be regarded as final ones since each has its own limitation. In order to obtain the appropriate long run average PD, we need to perform further analysis.

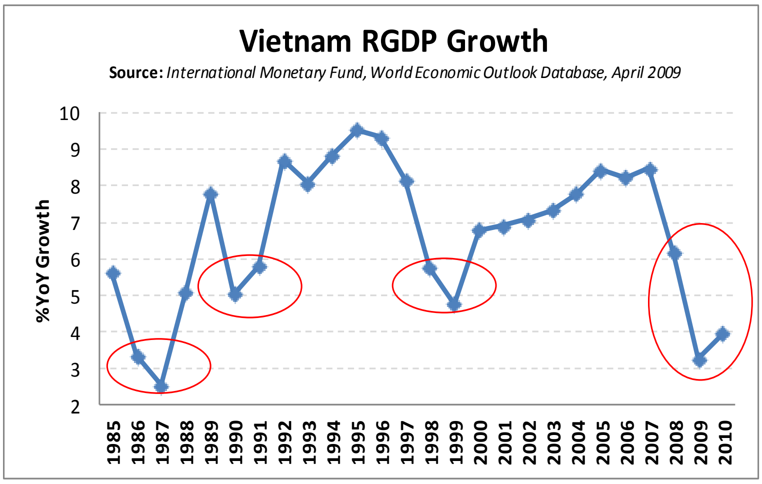
Adjustment to include downturn economy period's default rate

In order to include the impact of the downturn economic cycle to obtain long run average PD, we need to find the answer for the following questions:

1. How frequent the downturn economic cycle may happen
2. If it does happen, what would be the default rate comparing to non-downturn period default rate

To calculate the probability of downturn economy happening, we use GDP growth rate as a starting point to analyze how many times the downturn happened in the Vietnamese history. As can been seen from below Figure 14, a total of four sessions of downturn happened in last 25 years from 1985 to 2010 in Vietnam. A new economic cycle occurred right after a recession period. The first recession in the last 25 years happened in 1986-1987, therefore a new cycle started in 1988. From 1988 till 2010, i.e. 22 years period, there were 3 recession periods: 1990-1991, 1998-1999 and 2009-2010. Vietnam has experienced approximately 14% likelihood of downturn (i.e. 3/22). To be conservative, we round it up to 20% as those indicated by Basel II requirement (at least 5 years data to calculate long run average PD, or it uses assumption that one downturn in 5 years time).

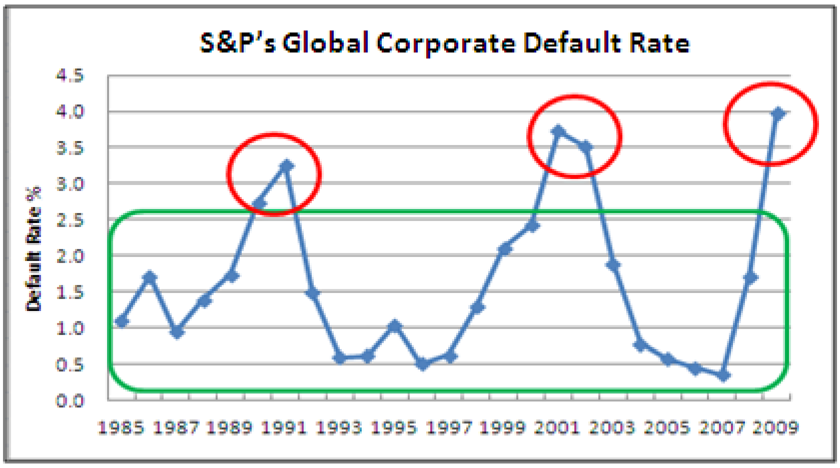
Figure 14. GDP growth rate of Vietnam



To get a reasonable estimate for the ratio of default rate between the good years and bad years, we need a long time series of default rate which covers several downturns. A lot of countries, including Vietnam, do not have long enough historical default time series data. As a common practice, we use S&P's global corporate default rate[5] as a reference. There are three downturns from 1985 to 2009. The average default rate for the downturn (red circle) periods and non-downturn (green box) periods are 3.45% and 1.17% respectively. Therefore, the default rate during downturn is approximately 3 times (=3.45%/1.17%) higher than that of non-downturn period.

[5] References: S&P's publication on February 2010: "2009 Annual Global Corporate Default Study & Rating Transition"

Figure 15. S&P's global corporate default rate



By combining the probability of downturn happening and ratio of default rate between downturn and non-downturn period, we propose to use formula below for obtaining downturn adjusted default rate, where average default rates from VietinBank historical data in the last 4 years are assumed to be the non-downturn default rates.

Downturn Adjusted Default Rate = 80% * (Default Rate of non-downturn) + 20% * (3* Default Rate of non-downturn) ……(16)

Table 20. Summary of default rate and downturn adjusted default rate

Segment Name	External	Count *	Provision (Year end)	Provision (November)	Write Off	Count *	Provision (Year end)*	Provision (November)*	Write Off*
Capital intensive manufacturing	5.78%	0.82%	1.84%	1.87%	0.12%	1.14%	2.57%	2.62%	0.16%
Light manufacturing	5.62%	1.50%	2.61%	3.42%	1.82%	2.10%	3.65%	4.79%	2.55%
Retail/Wholesale	5.55%	1.25%	2.05%	2.42%	0.47%	1.75%	2.88%	3.39%	0.66%
Transportation and communications	4.56%	1.87%	2.59%	3.01%	0.84%	2.62%	3.63%	4.21%	1.17%
Services	4.07%	1.45%	2.25%	2.49%	0.23%	2.02%	3.15%	3.49%	0.32%
Real estate	5.14%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Construction	5.48%	2.05%	2.91%	4.21%	1.45%	2.87%	4.07%	5.90%	2.03%

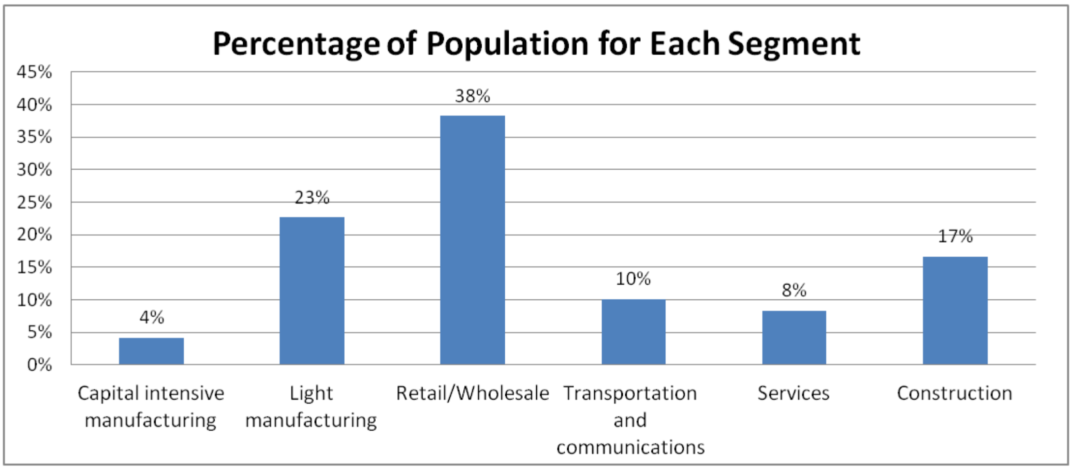
*Note: * indicates downturn adjusted PD*

Another external rating information that we need to consider is the country rating. Vietnam's sovereign rating is BB+. Based on our estimate, the rating distribution on S&P rating scale should be concentrated in B+ where the PD level is approximately 4%.

Long run average default rate of 4% is also well supported by downturn adjusted long run average PD derived from provision data (November). Therefore, we are comfortable to propose setting long run average PD equals to 4%.

Considering the population distribution, where there are more than 60% customers concentrated in segment 2 (Light Manufacturing) and Segment 3 (Trading). In order to let overall PD is at approximately 4%, the long run default rate of these two segments are assigned as 4%. This is close to those indicated by downturn adjusted figure (using provision data by end of November) for these 2 segments, i.e. 4.79% and 3.39% respectively. The reason of setting the same level of long run average PD for these 2 segment is that by default count, the average PD for these 2 segments are close to each other, i.e. 2.10% and 1.75% respectively.

Figure 16. Percentage of population for each segment



In the capital intensive segment, there are a lot of state owned companies. This is one of the reasons why the internal data shows that the CT is lower than those in the external data (using Indonesia and Philippines as proxies). We use the number suggested by "Provision*" but add a conservatism to that figure. It is rounded up to the closest quarter point from 2.62% to 2.75%.

For services sector the figure from "Provision*" shows that the CT is higher than light manufacturing and lower than trading. We use the number same as there two segments.

For the transportation segment, the result is similar to light manufacturing and it also highly related to light manufacturing, then we set the CT at 4%.

As Table 20 above shows that construction segment exhibits higher risk than other segments. It is nearly 30% higher than the others by comparing the default rate deriving from the external, account based and provision based data. Therefore, we assigned CT=4.75% for construction segment. Real estate segment is highly correlated with construction segment, however it is less risky than the latter by 10% by comparing the external benchmark. Therefore, we assign 4.25% as the CT.

Table 21. Summary of long run default rate

Segment Name	Long Run Default Rate
Capital intensive manufacturing	2.75%
Light manufacturing	4.00%
Retail/Wholesale	4.00%
Transportation and communications	4.00%
Services	4.00%
Real estate	4.25%
Construction	4.75%

4.3 Result of PD Estimation

After having the AR and reference power curve and determining the long run default rate for each segment, we can get the PD estimates by using the approach in section 3. Figure 17 and Figure 18 below show the CAP curve result for each segment and their estimated PD respectively.

Figure 17. CAP curve for each segment

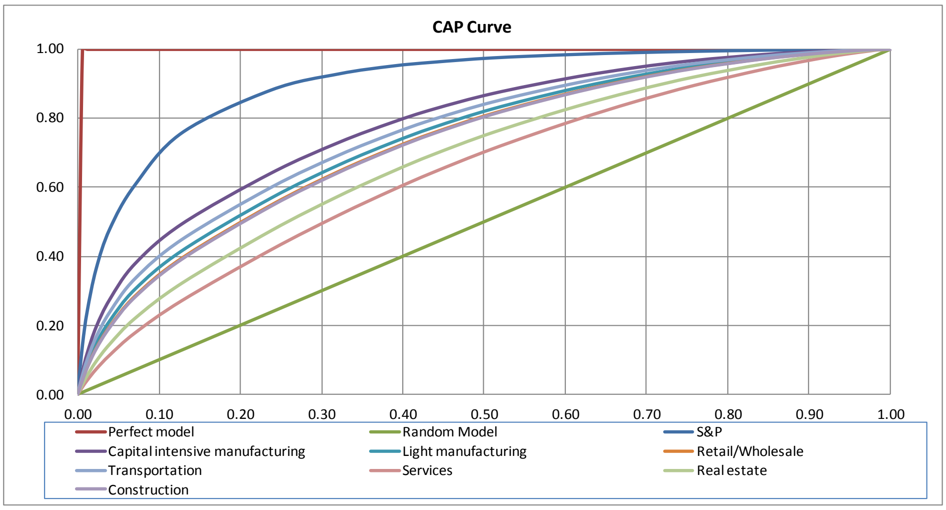
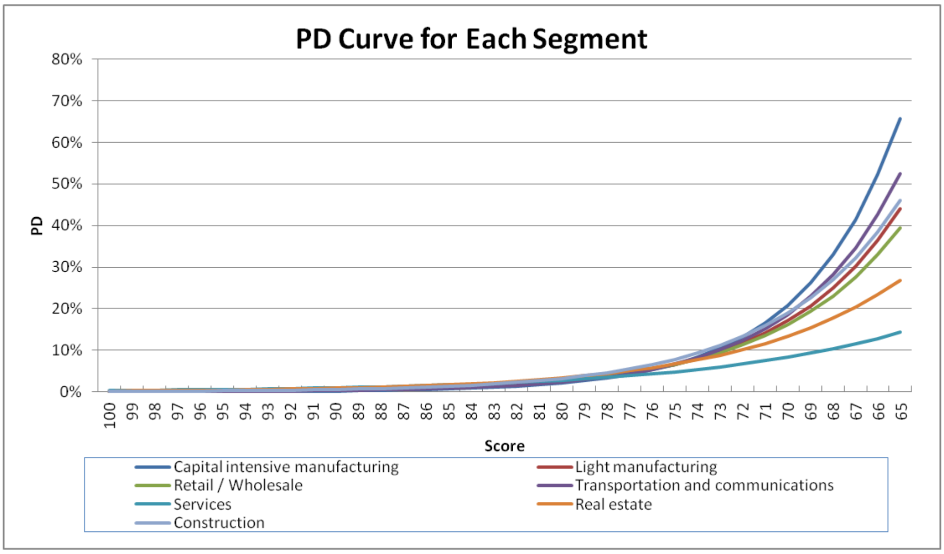


Figure 18. PD curve for each segment



Note : Detail score and PD mapping for each segment, please refer appendix

Since Services segment has the lowest AR (21%), the 'Score & PD mapping ' curve is more flat than others. The more flatter PD curve will lead to higher rating concentration, higher PD on the good end customers and only have lower PD at the bad end customers. As can be seen from Figure 18, PD of services segment will be less than others if score is below 78. Although Services industry is using the same CT level as light manufacturing and retail/wholesale, the customers from Services industry will not obtain the same rating distribution as of these two industries because of lower accuracy of the model.

On the other hand, Capital intensive segment which have AR=43% have steeper PD curve at the low end. Combined with lower CT for this industry, we will expect customers from this segment will have better ratings comparing to the others.

From this PD estimation exercise, we can see that the PD estimates for customers are not merely affected by the long run average PD, but it is also affected by the accuracy of the model. This is one of the key incentive provided by Basel II IRB framework where banks with more accurate model will have more capital saving comparing to the ones that have lower accuracy models.

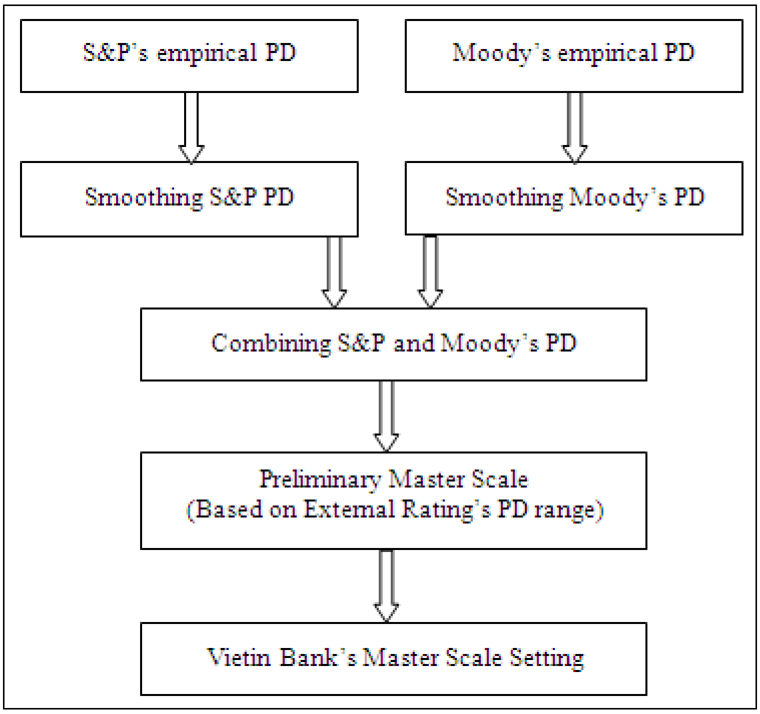
The AR of current scorecards are just merely close to an acceptable level, we strongly urge VietinBank to move forward to utilize statistical method to develop internal rating models so that it may obtain more accurate models.

By having more accurate models, we will be able to set more conservative CTs without scarifying the rating results. This practice will let banking supervisor feeling more comfortable with the conservatism in the overall PD level, in the mean time it will not lead to much higher capital requirement.

5. Master Scale Development

Rating master scale will act as a "ruler" that provides consistent rating definition across various scorecards and it can also provide an objective mapping to external rating agencies' rating. It is designed to become a consistent default risk measure across credit portfolio in VietinBank. The following flow chart shows the approach used in designing VietinBank's rating master scale. Each of the activities will be elaborated in the following sections:

Figure 19. Steps of determining master scale



5.1 Historical PD of external rating agencies

External rating agencies empirical PD can be used as a starting point of the VietinBank's master scale design. By benchmarking to external rating's PD, the internal master scale can be easily associated with external ratings.

The following table shows the historical PD of S&P and Moody's[6]. The empirical PD's of the external rating agencies are calculated by using a static pool of rated companies in the last more than 20 years. The static pool means that all companies in the whole time series with the same rating will be pooled and the empirical default rate can be calculated. The same companies may be counted more than once in the calculation.

The length of the data used is not the same for S&P and Moody's. The S&P PD's are based on data from 1981 to 2009 while Moody's PD's are based on data from 1983 to 2009. Given the long data coverage, 29 years and 27 years for S&P and Moody's respectively, the changes on the PD values are fairly limited. The inconsistency on the data period used is merely because of the availability of the data in their publication.

Table 22. PD of S&P and Moody

S&P Rating	S&P's PD
AAA	0.000%
AA+	0.000%
AA	0.020%
AA-	0.040%
A+	0.070%
A	0.090%
A-	0.090%
BBB+	0.170%
BBB	0.240%

Moody's Rating	Moody's PD
Aaa	0.000%
Aa1	0.000%
Aa2	0.000%
Aa3	0.050%
A1	0.062%
A2	0.060%
A3	0.048%
Baa1	0.134%
Baa2	0.174%

[6] References:
Moody's publication on February 2010: "Corporate Default and Recovery Rates, 1920-2009"
S&P's publication on February 2010: "2009 Annual Global Corporate Default Study & Rating Transition"

S&P Rating	S&P's PD
BBB-	0.410%
BB+	0.530%
BB	0.820%
BB-	1.340%
B+	2.700%
B	6.260%
B-	9.860%
CCC/C	27.980%

Moody's Rating	Moody's PD
Baa3	0.299%
Ba1	0.738%
Ba2	0.783%
Ba3	1.844%
B1	2.561%
B2	3.965%
B3	7.941%
Caa1	10.179%
Caa2	18.497%
Caa3	29.097%
Ca-C	36.207%

There are 3 issues that need to be resolved before using external PD benchmark as the starting point to design the internal PD master scale:

1. The empirical PD's of the several best rating grades are zeros, as indicated by red color fonts on the table above. It is well acknowledged that the PD should not equal to zero even for the AAA rated companies.
2. There are some rating grades which have empirical PD's that violates the strictly monotonic property of the PD curve. This is indicated by blue color fonts on the table above, i.e. A- for S&P rating, A2 and A3 of Moody's rating. This observation is most likely due to statistical noises on the empirical default rates rather than the discriminatory power of the external ratings.
3. The last PD figure (green fonts) shown on the table above is the number of issuers' weighted average of few rating grades. For S&P, the empirical PD figure of 27.98% is the PD for companies rated as CCC+ to C. For Moody's, the last PD figure of 36.207% is the PD for companies rated as Ca to C.

In order to use the external rating's empirical PD as the starting point in designing a PD master scale, all 3 issues above need to be resolved first. The common method used is to perform a smoothing to the empirical default rates. In the next section, the smoothing process will be elaborated further.

5.2 Smoothing Empirical PD curves

The smoothing of the empirical PD curve can be conducted by fitting two exponential curves. One exponential curve cannot provide a good fir to the empirical PD given the steepness of the curve on the worst rating grades.

The two-exponential curves fitting is conducted by finding 2 set of parameters which can give best fit to the log-odds curve of the empirical default. Since the fitting is based on the log-odds, the empirical PD's which are zeros need to be excluded first. The following table depicts the historical PD of S&P and Moody's rated companies after smoothing.

Table 23. Adjusted PD of S&P and Moody

S&P Rating	S&P's PD
AAA	0.01%
AA+	0.01%
AA	0.02%
AA-	0.03%
A+	0.04%
A	0.07%
A-	0.10%
BBB+	0.16%
BBB	0.24%
BBB-	0.37%
BB+	0.57%
BB	0.88%
BB-	1.34%
B+	3.14%
B	5.55%
B-	9.62%
CCC+	16.17%
CCC	25.90%
CCC-	38.77%
CC	53.43%
C	67.52%

Moody's Rating	Moody's PD
Aaa	0.01%
Aa1	0.01%
Aa2	0.02%
Aa3	0.03%
A1	0.05%
A2	0.07%
A3	0.10%
Baa1	0.16%
Baa2	0.24%
Baa3	0.36%
Ba1	0.54%
Ba2	0.82%
Ba3	1.24%
B1	2.58%
B2	4.23%
B3	6.87%
Caa1	10.96%
Caa2	17.03%
Caa3	25.52%
Ca	36.38%
C	48.83%

5.3 Combining S&P and Moody's PD

From the final results after smoothing, we may observe that the PD for each rating grade of each rating agency may differ substantially. Nevertheless, we need to emphasize that the empirical PD are subject to statistical noises. In combining the PD of both rating agencies, we need to consider the confidence interval of the PD in each rating grade.

Utilizing the results from the smoothing and also the number of companies in each rating grade, we may calculate the standard deviation of the PD for each rating grade. The standard deviation of PD can be calculated by assuming binomial distribution of default rate, of which under large sample the distribution of the default rate would be normally distributed with distribution parameters: $\mu = \overline{p}$ and

$$\sigma = \sqrt{\frac{\overline{p}(1-\overline{p})}{N}}.$$

The following is the result for the empirical PD of each rating agency:

Table 24. Empirical PD of S&P and Moody

S&P				Moody			
Rating Grade	PD	N	σ	Rating Grade	PD	N	σ
AAA	0.01%	889	0.03%	Aaa	0.01%	3487	0.02%
AA+	0.01%	494	0.05%	Aa1	0.01%	1643	0.03%
AA	0.02%	1668	0.03%	Aa2	0.02%	5549	0.02%
AA-	0.03%	2012	0.04%	Aa3	0.03%	6693	0.02%
A+	0.04%	3274	0.04%	A1	0.04%	7025	0.03%
A	0.07%	4481	0.04%	A2	0.07%	9615	0.03%
A-	0.10%	3882	0.05%	A3	0.10%	8330	0.04%
BBB+	0.16%	4329	0.06%	Baa1	0.16%	6251	0.05%
BBB	0.24%	5011	0.07%	Baa2	0.24%	7236	0.06%
BBB-	0.37%	3882	0.10%	Baa3	0.36%	5606	0.08%
BB+	0.57%	2652	0.15%	Ba1	0.54%	3348	0.13%
BB	0.88%	3477	0.16%	Ba2	0.82%	4390	0.14%
BB-	1.34%	4467	0.17%	Ba3	1.24%	5640	0.15%

S&P				Moody			
Rating Grade	PD	N	σ	Rating Grade	PD	N	σ
B+	3.14%	5845	0.23%	B1	2.58%	9244	0.17%
B	5.55%	3086	0.41%	B2	4.23%	4881	0.29%
B-	9.62%	1638	0.73%	B3	6.87%	2591	0.50%
CCC+	16.17%	892	1.23%	Caa1	10.95%	1694	0.76%
CCC	25.90%	583	1.81%	Caa2	17.03%	1107	1.13%
CCC-	38.77%	305	2.79%	Caa3	25.52%	579	1.81%
CC	53.43%	312	2.82%	Ca	36.38%	593	1.98%
C	67.52%	13	12.99%	C	48.82%	25	10.06%

To combine the empirical PD of S&P and Moody's, we need to consider the confidence interval of the PD in each rating grade. The combined PD is calculated by weighting S&P PD and Moody's PD:

$$PD_{Combined} = w\,PD_{S\&P} + (1-w)\,PD_{Moody's} \;\ldots\ldots\textbf{(17)}$$

The PD*combine* becomes a new mean estimate of PD for each of the rating grade of both rating agencies. While the standard deviation of the new PD estimate is calculated assuming both N of each rating agency would enlarge the sample, so that:

$$\sigma_{PD_{Combined}} = \sqrt{PD_{Combined}(1-PD_{Combined}).\left(\frac{1}{N_{S\&P}} + \frac{1}{N_{Moody's}}\right)} \;\ldots\ldots\textbf{(18)}$$

The remaining parameter that need to be solved for is the weight (w) for PD of each rating agency. In order to find the optimal w, we set up an optimization problem. The objective is that to find a weight so that the new confidence interval obtained from $PD_{Combined}$ and $\sigma_{PD_{Combined}}$ can optimally cover the confidence interval of both $PD_{S\&P}$ and $PD_{Moody's}$. In other words, given a "w", we may calculate the Confidence Interval of the $PD_{Combined}$:

$$PD_{Combined\_Low} = PD_{Combined} - Z_{\alpha/2}.\sigma_{PD_{Combined}} \;\ldots\ldots\textbf{(19)}$$

$$PD_{Combined\_High} = PD_{Combined} + Z_{\alpha/2}.\sigma_{PD_{Combined}} \;\ldots\ldots\textbf{(20)}$$

And the distribution coverage for the PD of each rating agency can be obtained by:

$$\%Coverage(S\ \&\ P) = F\left(PD_{Combined\_High}, PD_{S\&P}, \sigma_{PD\ S\&P}\right) - F\left(PD_{Combined\_Low}, PD_{S\&P}, \sigma_{PD\ S\&P}\right)$$

……(21)

$$\%Coverage(Moody's) = F\left(PD_{Combined\_High}, PD_{Moody's}, \sigma_{PD\ Moody's}\right) - F\left(PD_{Combined\_Low}, PD_{Moody's}, \sigma_{PD\ Moody's}\right)$$

……(22)

Where F is the Cumulative Normal distribution function with mean $PD_{S\&P}$ (or $PD_{Moody's}$) and standard deviation of $\sigma_{PD\ S\&P}$ (or $\sigma_{PD\ Moody's}$).

The objective to be optimized is the average of the %Coverage (S&P) and %Coverage (Moody's) with constraints:

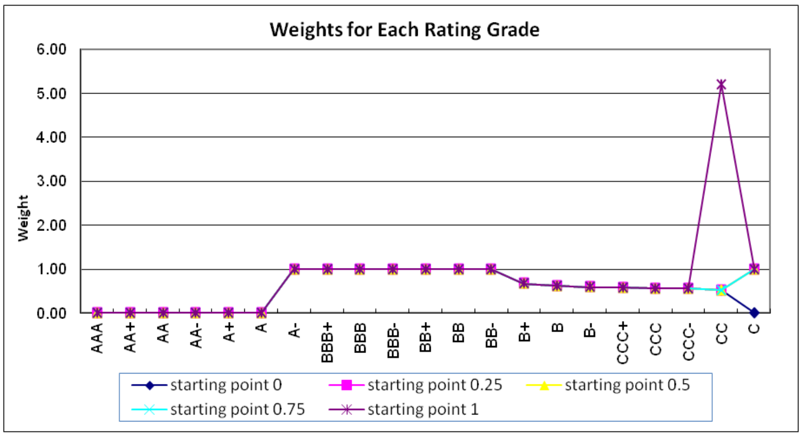
- $0 \le w \le 1$
- %Coverage (S&P)= %Coverage (Moody's)

Second constraint above is set in order to have a balance precision toward both S&P and Moody's rating.

The optimization is solved numerically using Excel Solver. As it is the case for other optimization problem, solving an optimization using numerical method is rather sensitive to the initial parameters. Therefore, we have tested several initial parameters: 0, 0.25, 0.5, 0.75 and 1.

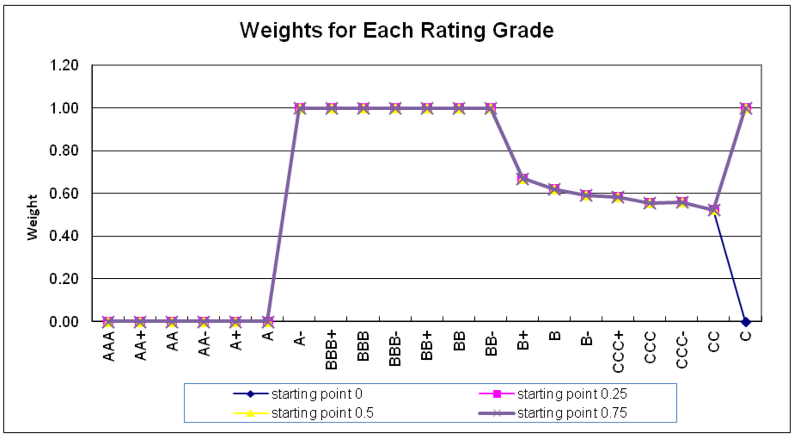
The resultant weights for each rating grade are shown in the following chart:

Figure 20. Weights for each rating grade (1)



We may observe that using initial parameter of 1 give negative weights for few rating grades although we have applied a constraint that the weight should ranged from 0 to 1. Therefore, the results by using this initial values are not acceptable. Ruling out the starting point of 1, the results are very consistent with an exception for the last rating grade ("C")[7].

Figure 21. Weights for each rating grade (2)



The finally chosen weights are the one using initial parameter of 0.5. The optimum PD distribution coverage of each rating grade is shown in the following chart:

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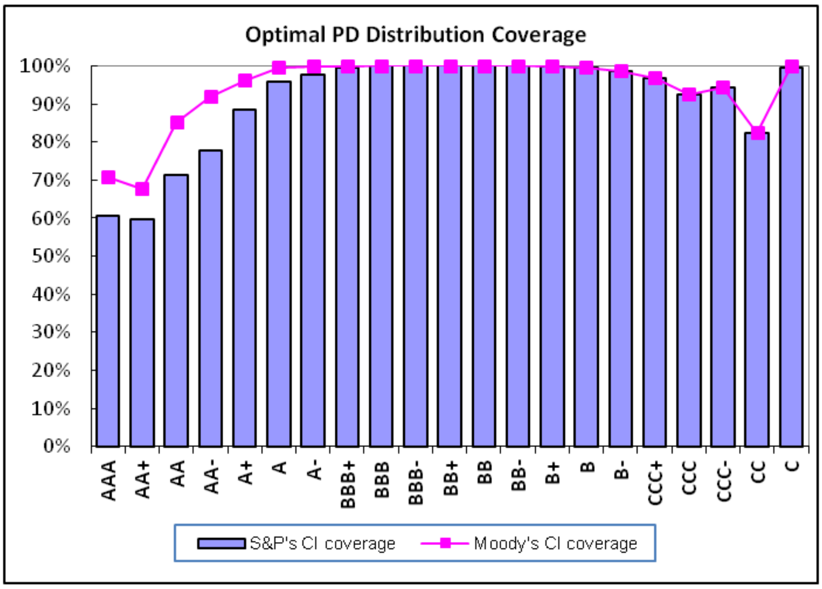
[7] The sample size for rating C is very small, i.e. 13 observations and 19 observations for S&P and Moody's, respectively.

Figure 22. Optimal PD distribution coverage



As can been seen from the above chart, the coverage percentage of S&P and Moody are higher and very close to 1 below the A- rating. Given that most of VietinBank's customers will have external rating equivalent of lower or equal to S&P's BB+, we think that the result above is encouraging.

Using the optimal "w" obtained above; the "Preliminary" Master scale would have the following PD range:

Table 25. PD range of external rating grade

S&P Rating	Moody's Rating	PD-Low	PD-Mid	PD-High
AAA	Aaa	0.0000%	0.0084%	0.0104%
AA+	Aa1	0.0104%	0.0128%	0.0158%
AA	Aa2	0.0158%	0.0194%	0.0239%
AA-	Aa3	0.0239%	0.0295%	0.0363%
A+	A1	0.0363%	0.0447%	0.0550%
A	A2	0.0550%	0.0678%	0.0839%
A-	A3	0.0839%	0.1039%	0.1287%
BBB+	Baa1	0.1287%	0.1594%	0.1974%
BBB	Baa2	0.1974%	0.2444%	0.3025%

S&P Rating	Moody's Rating	PD-Low	PD-Mid	PD-High
BBB-	Baa3	0.3025%	0.3745%	0.4634%
BB+	Ba1	0.4634%	0.5735%	0.7093%
BB	Ba2	0.7093%	0.8773%	1.0843%
BB-	Ba3	1.0843%	1.3400%	1.9902%
B+	B1	1.9902%	2.9559%	3.8633%
B	B2	3.8633%	5.0493%	6.5505%
B-	B3	6.5505%	8.4981%	10.9067%
CCC+	Caa1	10.9067%	13.9979%	17.5317%
CCC	Caa2	17.5317%	21.9576%	26.8860%
CCC-	Caa3	26.8860%	32.9207%	38.6164%
CC	Ca	38.6164%	45.2976%	55.3038%
C	C	55.3038%	67.5204%	100.000%

PD-Mid is the one obtained from the weighted average of S&P PD and Moody's PD, while PD_Low and PD_High are obtained from a geometric mean of 2 consecutive PD_Mid.

5.4 Master Scale of VietinBank

After applying the above master scale to the result of PD estimate, we get below rating grade distribution as shown in Figure 23 and Figure 24 below.

The overall population in each rating grade is less than 30%, where meets the Basel II requirement. And there are less than 2 percent of the population which rating is better than BB+(sovereign rating of Vietnam). Hence this master scale with 21 rating grade can be used for VietinBank's corporate portfolio. For further using, some grades in the low end and high end side can be merged together or rating of B+ and B can be further split.

Figure 23. Customer rating distribution on master scale

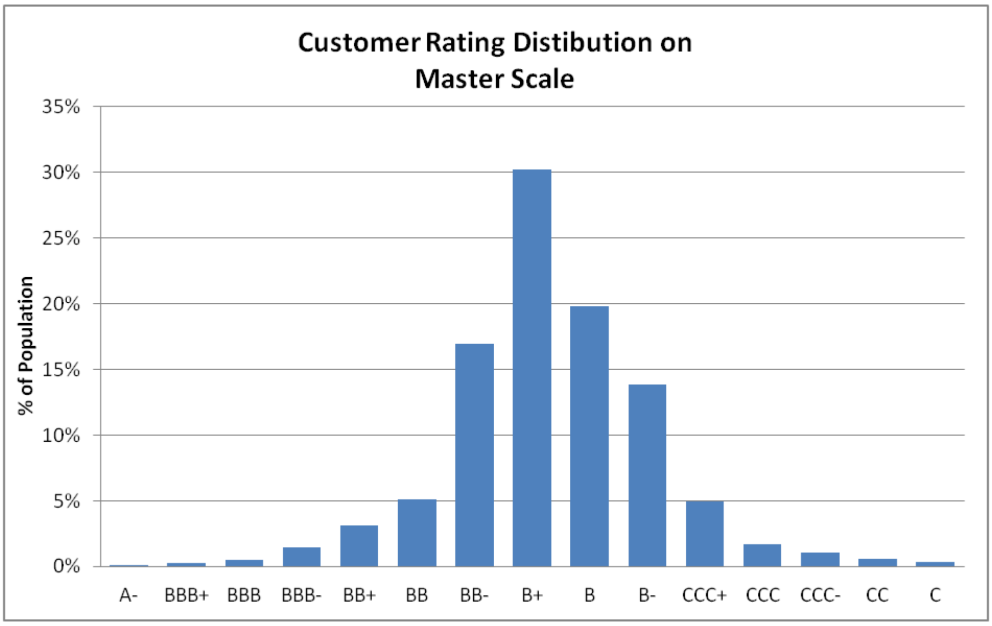
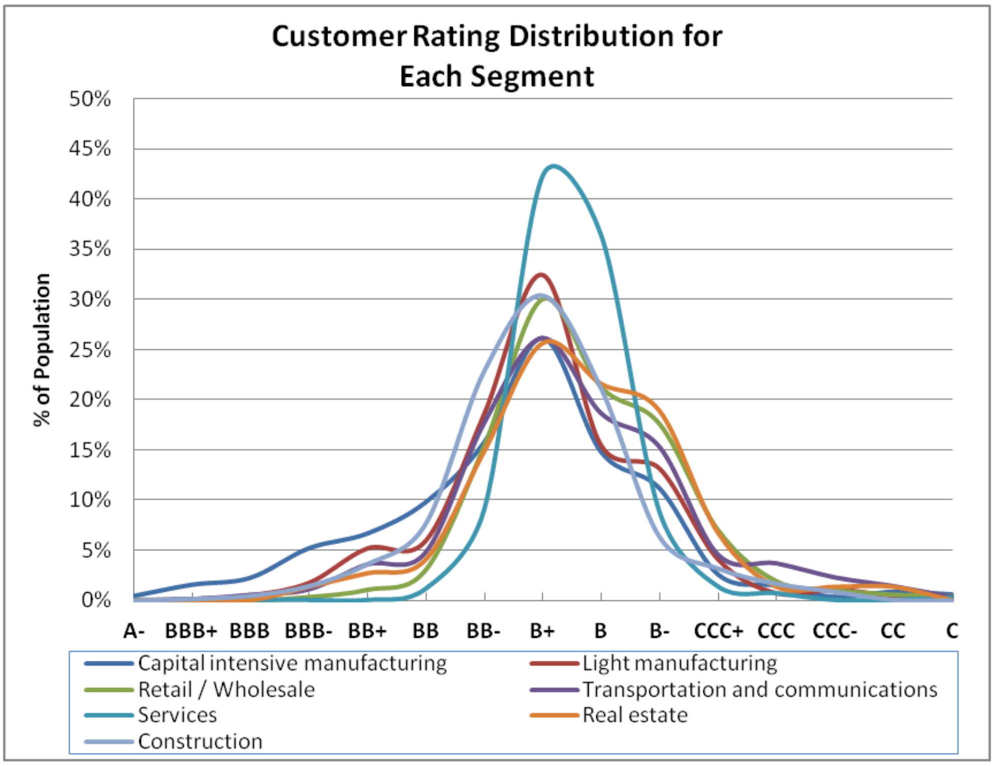


Figure 24. Customer rating distribution for each segment



In this project, we have not yet decided to make a Rating Grade "name" of each internal rating scale and has not decided how many internal rating grades that VietinBank would like to use.

The following is an illustration on how the internal rating scale may look like when we are using alphanumeric as the rating grade title as in the practice in leading bank. The alphanumeric grading name is in order to avoid confusion with external rating names. There are 10 non-default rating grades are used in this example.

Table 26. VietinBank's rating master scale

VietinBank Rating	S&P Rating	Moody's Rating	PD-Low	PD-Mid	PD-High
1	AAA to BB+	Aaa to Ba1	0.00%	0.57%	0.71%
2	BB	Ba2	0.71%	0.88%	1.08%
3	BB-	Ba3	1.08%	1.34%	1.99%
4	B+	B1	1.99%	2.96%	3.86%
5	B	B2	3.86%	5.05%	6.55%
6	B-	B3	6.55%	8.50%	10.91%
7	CCC+	Caa1	10.91%	14.00%	17.53%
8	CCC	Caa2	17.53%	21.96%	26.89%
9	CCC-	Caa3	26.89%	32.92%	38.62%
10	CC or below	Ca or below	38.62%	45.30%	100.00%

We should stress here however, although the master scale can be constructed we do not regard this as the "final" one that is recommended to VietinBank to be implemented **for the time being**. We recommend that VietinBank is still using existing rating grades for SBV requirement.

This recommendation is based on the consideration that **very soon**, VietinBank will initiate a project where a more advanced method will be used, and more accurate internal rating models will be developed. By then, the internal rating master scale may need to be revised by taking into consideration the rating distribution of new rating models.

Since the new project will be initiated very soon, therefore we are of opinion that it is unwise to implement something that will be revised in 18 months time in the future. Implementing a new rating master now will lead to a confusion where in 18 months time when users just started to be familiar with rating master scale, there is going to be a change in place.

6. Appendix

6.1 Score and PD mapping

Table 27. Score and PD mapping

Score	Capital intensive manufacturing	Light manufacturing	Retail / Wholesale	Transportation and communications	Services	Real estate	Construction
100	0.02%	0.06%	0.08%	0.04%	0.32%	0.21%	0.09%
99	0.03%	0.07%	0.09%	0.05%	0.36%	0.24%	0.11%
98	0.03%	0.08%	0.11%	0.06%	0.40%	0.27%	0.13%
97	0.04%	0.10%	0.13%	0.07%	0.44%	0.31%	0.16%
96	0.05%	0.12%	0.15%	0.09%	0.49%	0.36%	0.19%
95	0.07%	0.15%	0.18%	0.11%	0.55%	0.42%	0.23%
94	0.08%	0.18%	0.22%	0.13%	0.61%	0.48%	0.27%
93	0.11%	0.22%	0.26%	0.16%	0.68%	0.55%	0.32%
92	0.13%	0.26%	0.31%	0.20%	0.76%	0.63%	0.38%
91	0.17%	0.32%	0.38%	0.25%	0.85%	0.72%	0.46%
90	0.21%	0.39%	0.45%	0.30%	0.94%	0.83%	0.55%
89	0.27%	0.47%	0.54%	0.37%	1.05%	0.96%	0.65%
88	0.34%	0.56%	0.64%	0.45%	1.17%	1.10%	0.78%
87	0.42%	0.68%	0.77%	0.56%	1.31%	1.26%	0.93%
86	0.53%	0.82%	0.92%	0.69%	1.46%	1.45%	1.11%
85	0.67%	0.99%	1.10%	0.84%	1.63%	1.67%	1.33%
84	0.84%	1.20%	1.31%	1.04%	1.81%	1.91%	1.59%
83	1.06%	1.45%	1.57%	1.28%	2.02%	2.20%	1.89%
82	1.33%	1.75%	1.88%	1.57%	2.25%	2.53%	2.26%
81	1.67%	2.12%	2.25%	1.93%	2.51%	2.90%	2.70%
80	2.10%	2.56%	2.69%	2.37%	2.80%	3.34%	3.22%
79	2.64%	3.10%	3.22%	2.91%	3.12%	3.83%	3.85%
78	3.33%	3.74%	3.85%	3.58%	3.48%	4.41%	4.59%
77	4.18%	4.53%	4.60%	4.40%	3.88%	5.06%	5.48%
76	5.26%	5.47%	5.50%	5.41%	4.32%	5.82%	6.55%
75	6.62%	6.61%	6.58%	6.65%	4.82%	6.68%	7.82%
74	8.33%	8.00%	7.88%	8.18%	5.37%	7.68%	9.33%
73	10.48%	9.66%	9.42%	10.05%	5.99%	8.82%	11.14%
72	13.18%	11.68%	11.27%	12.36%	6.68%	10.14%	13.30%

Score	Capital intensive manufacturing	Light manufacturing	Retail / Wholesale	Transportation and communications	Services	Real estate	Construction
71	16.58%	14.12%	13.48%	15.19%	7.45%	11.65%	15.88%
70	20.86%	17.07%	16.12%	18.67%	8.30%	13.39%	18.96%
69	26.25%	20.64%	19.28%	22.95%	9.26%	15.39%	22.64%
68	33.02%	24.95%	23.06%	28.22%	10.32%	17.68%	27.02%
67	41.54%	30.15%	27.58%	34.68%	11.50%	20.31%	32.26%
66	52.26%	36.45%	32.99%	42.64%	12.82%	23.34%	38.52%
65	65.75%	44.06%	39.46%	52.41%	14.30%	26.82%	45.99%
64 and below	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%