"Story of a Bank" Basel II Accreditation through University-Industry Collaboration-Case Study

(Kisah Sebuah Bank: Kajian Kes Mengenai Akreditasi Basel II Melalui Kolaborasi antara Universiti-Industri)

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ABSTRACT

This paper deals with a case study of credit risk scoring models at Industrial Bank. The aim of this research is to investigate how a Malaysian financial institution developed and integrated credit risk scoring models with current organisational needs and evaluation of best practices for university-industry collaboration on this initiative. Attempts were made to categorise the credit risk scoring models initiative according to a variety of statistical techniques from modeling. This is an exploratory study which uses qualitative research methodology. Analysis of document from company annual reports as well as articles from journal, Bank Negara Malaysia, (BNM) regulatory reports as well as working papers and semi-structured interviews were conducted to identify the organisational needs as a result of context and task. A company-wide development system for credit risk scoring model was effectively integrated to provide a direct support to competence management endeavor. The company's credit risk scoring models initiatives have also resulted in managerial implications such as increased effectiveness of risk management through measuring the riskiness of each customer and automated the whole process, thereby leading to significant efficiency improvements. Thus, scoring models help banks to control credit risks. Going forward, credit risk scoring model is to become the best practice approach of the receivables management process and is essential to effective credit risk management.

Keywords: Credit risk rating model; Basel II accreditation; industry – institute collaboration; credit risk management

ABSTRAK

Kertas kerja ini berkaitan dengan sebuah kajian kes mengenai model penilaian risiko kredit di sebuah bank industri. Tujuan kajian ini adalah untuk meninjau bagaimana institusi kewangan Malaysia membina dan mengintegrasikan model penilaian risiko kredit melalui keperluan organisasi semasa dan menilai praktis yang terbaik untuk kolaborasi universiti-industri atas inisiatif ini. Beberapa percubaan telah dilakukan untuk membina kategori untuk inisiatif model penilaian risiko kredit melalui pelbagai teknik statistik seperti pemodelan. Ini adalah kajian eksplorasi yang menggunakan metodologi pengajian kualitatif. Analisis dokumentasi seperti laporan tahunan syarikat, jurnal, laporan regulasi dari Bank Negara Malaysia (BNM), kertas kerja dan temuduga semi-struktur dijalankan untuk menentukan keperluan organisasi dari segi kandungan dan tugasan. Pembangunan sistem yang efektif dan berintegrasi dengan model penilaian risiko kredit secara keseluruhan dalam syarikat telah memberi sokongan terus terhadap usaha daripada pihak pengurusan. Model penilaian risiko kredit adalah inisiatif syarikat yang mempunyai kesan atas implikasi pengurusan seperti meningkatkan tahap keberkesanan dalam pengurusan risiko melalui penilaian risiko pelanggan dan mengautomatifkan proses secara keseluruhan, menuju ke arah meningkatkan efisiensi yang signifikan. Dengan itu, model penilaian membantu bank untuk mengawal risiko kredit. Pada masa hadapan, model penilaian risiko kredit akan menjadi praktis yang terbaik dalam proses pengurusan dan adalah penting untuk pengurusan risiko kredit yang efektif.

Kata kunci: Model penilaian kedudukan risiko kredit; Akreditasi Basel II; kolaborasi institusi – industri; pengurusan risiko kredit

BACKGROUND OF THE STUDY

Tracing back, the bank commenced operations 40 years ago, and in December 1980's it became known as Industrial Bank*, a name by which were well known by Malaysians for over four decades. Industrial Bank has grown into a Group with staff strength of 10,000. With the extensive nationwide branch network, ATMs, and Internet banking services, Industrial Bank Group has enjoyed considerable success over the last three decades

and had built one of the largest financial services group in the country, is only a brick and click away (Industrial Bank's Annual Report 2011).

Industrial Bank has determined its' philosophy namely "The Industrial Bank Way: A Culture of Excellence and Professionalism." It was the first merchant bank to be listed on Bursa Malaysia; the first bank to offer a prepaid credit card; the first investment bank to list an equity exchange traded fund in Malaysia; one of the first banks to offer both conventional and Islamic banking; a bank to issue an

Islamic credit card in the region and an investment bank to list a Syariah-compliant healthcare REIT in the world. Industrial Bank Group is steadily rewarded with industry accolades like "Most Customer-Friendly Services" and the "Most Outstanding Islamic Investment Banking" awards (Industrial Bank's Annual Report 2011).

In Industrial Bank, risk management takes centre-stage during the past few years. The Industrial Bank Group adopts a centralised risk governance model to ensure alignment of business strategies with stakeholders' value creation. To enhance asset quality assessment, it is vital to adopt the best practice approach to enhance probability of default (PD), loss given default (LGD) and exposure at default (EAD) models for retail and non-retail portfolios. Industrial Bank has implemented best-in-class

non retail credit risk scoring models that support risk based pricing application, profit at risk and value at risk methodologies.

The first step in measuring credit risk involves calculating Expected Losses (EL) at the lowest level that the data will support – which is the facility level for many businesses. According to the *Bank Negara Malaysia* (BNM) document, the Expected Loss (EL) on an individual credit is equal to the probability of default multiplied by the bank's exposure in the event of default, further multiplied by the percentage of the exposure which will ultimately be taken as a loss should default occur. These three components are respectively termed Probability of Default (PD), Exposure at Default (EAD), and Loss Given Default (LGD).
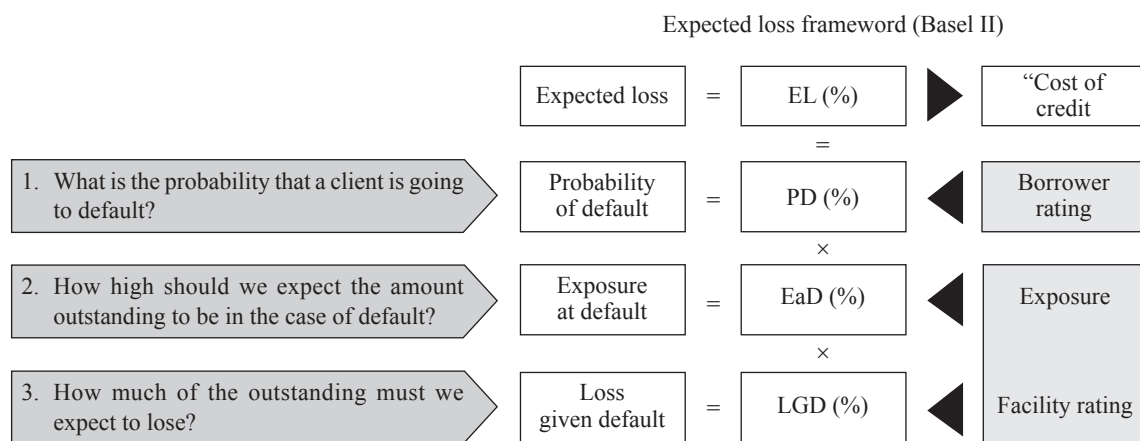
Expected loss frameword (Basel II)

FIGURE 1. Basel II expected loss framework

Each of the three components is defined below:

Probability of Default (PD)   Probability of Default (PD) is simply the probability that a given company will go into default within one year. Default probabilities are differentiated by a bank's internal grading system, as it is the best and most readily available internal measure of a company's financial position. To ensure analytical integrity, default was defined as three months in arrears on loan payments. The definition of default must be consistent for the calculations of default probability, exposure at default and loss given default.

Exposure at Default (EAD)   Exposure at Default (EAD) factors are measured in order to account for the high utilisation of defaulted facilities. The loan equivalence for each facility is the expected outstanding balance if the facility defaults, and is equal to the expected utilisation plus a percentage (the loan equivalency factor) of the unutilised commitments. Facility type and internal grade are the most significant drivers of loan equivalence and are the measures on which loan equivalency factors are calculated.

Loss Given Default (LGD)   Loss Given Default (LGD) represents an estimate of the actual losses incurred on a defaulted loan as a percentage of the outstanding balance

at time of default. Banks seldom lose 100% of the amount outstanding, as collateral can be seized or recovery can be gained through other avenues so that the actual loss caused by a default tends to be significantly less than the bank's total exposure to the borrower. Loss given default rates are formulated to be comprehensive – including the cost of carry, as well as any other source of economic loss to the bank. Loss given default is found to be a function of the type of collateral used to secure a facility.

Effective credit risk scoring frameworks are both quantitatively strong measures of credit risk, and qualitatively effective tools for business use. Best practice risk scoring models feature the following characteristics:

1. Consistent calibration to expected probability of default;
2. A suitable level of granularity and refined scoring definitions;
3. Effective combination of qualitative and financial elements;
4. Transparent and objective process for bank marketing officers and credit approval officers; and
5. Powerful distinction between high and low risk borrowers.

Credit risk analysis, mainly through credit risk scoring models, is becoming prevalent for acquiring new accounts, managing existing accounts, up-selling, cross-selling and predictive analysis such as recovery and collection forecasting. The consistent use of credit risk scoring models help to improve an institution's risk assessment time, speed, accuracy, consistency, bad debt reduction and prioritisation of collections. Credit risk scoring models assure accuracy since the assessment process is mostly free of human error. The net effect is a substantial reduction in risk assessment time and a more systematic approach to collection.

In fact, credit risk is the distribution of financial losses due to unexpected changes in the credit quality of counterparty in a financial agreement. Industrial Bank has developed sophisticated systems in an attempt to model the credit risk. Such models are intended to aid in quantifying, aggregating and managing risk, performance measurement processes, risk-based pricing, active portfolio management and capital structure decisions. The types of credit risk scoring models within Industrial Bank can be illustrated with a segment falls along a spectrum ranging from Non-Data Rich to Data Rich credit risk scoring models, with best practices falling towards the Data Rich credit risk scoring model.

FIGURE 2. Data rich vs. non-data rich credit risk scoring models

In a broad spectrum, it is imperative that the credit risk scoring model development process must be:

1. appropriate to nature, scale and complexity;
2. aligned with the Bank's credit risk strategy and policy;
3. precisely performed to avoid any structural weaknesses in the model;
4. developed based on good quality datasets;
5. tailored to reflect representativeness of the portfolio;
6. consistent with credit sense and economic hypotheses;
7. in compliance with Bank Negara Malaysia (BNM) Guidelines on Risk Weighted Capital Adequacy Framework (RWCAF) (Basel II) issued on 31 December 2009 and Bank of International Settlements (BIS) Guidelines on International Convergence of Capital Measurement and Capital Standards' issued on June, 2006.

The best practices for the management of credit risk and knowledge transfer are no doubt very important and a powerful means discussed by practitioners as well as scholars. Abeda et al. (2011) stated that the evaluation of university-industry collaboration can be accessed through 3 categories of best evaluation metrics which are financial support, cultural development and knowledge sharing. For this purpose, Industrial Bank is involved in the development of skills and knowledge for employment by joining as a member of the Institute of Bankers Malaysia. From the perspective of the industry, the motivation for collaboration is to acquire the source of scientific knowledge and access to qualified human resource from the university. The cooperation between universities and the industry, especially financial institutions in Malaysia needs to be intensified to enhance the credit risk scoring model development for effective risk management, as it is vital that knowledge flows from universities into business and society.

PRESENT CHALLENGES IN CREDIT RISK MANAGEMENT

The business of banking is about managing risks. Increased competition and growing pressures for revenue generation have led credit-granting and other financial institutions to search for more effective ways to attract new creditworthy customers, and at the same time, control losses. The aggressive marketing efforts have resulted in deeper penetration of the risk pool of potential customers, and the need to process them rapidly and effectively has led to the growing automation of the credit scoring and decision making processes. Industrial Bank is now challenged to produce risk adjudication solutions that can satisfactorily assess creditworthiness, keep the per-unit processing cost low, and reducing turnaround times for customers.

In addition, customer service excellence demands that this automated process able to minimise denial of credit

to creditworthy customers, while keeping out as many potentially delinquent ones as possible. At the customer management level, Industrial Bank is striving even harder to keep their existing clients by offering them additional products and enhanced services. Credit risk scoring models are used to help in selecting lower risk customers for these favoured treatments. The present challenge for Industrial Bank particularly credit risk management is to enhance the enterprise risk management infrastructure and credit risk scoring model in order to support the expansion and growth of the business.

OBJECTIVES OF THE STUDY

This research tries to explore the best practice approach for credit risk scoring models developed in a Malaysian financial institution, namely "Industrial Bank" and assess how the credit risk scoring initiatives fit into the organisational needs and tasks as well as evaluation of best practices for university-industry collaboration on this initiative. A case study approach was used to describe the emergence of credit risk scoring initiatives and practice with the managerial implications at Industrial Bank. This study describes the implementation of the best practice of credit risk scoring models in assessing the credit risk of Industrial Bank's business lending portfolio.

The research objectives of this study are:

1. To investigate how a Malaysian financial institution developed and integrated credit risk scoring model initiatives with current organisational needs and tasks.
2. To categorise credit risk scoring models developed within the organisation based on the best practices approach to effective risk management.
3. To evaluate the university-industry collaboration on the credit risk scoring model development and its managerial implications.

WAY THROUGH CONCEPTS

In this section different elements relating to credit risk scoring model are presented. In the beginning, the key concepts are explained in order to grasp a clear view of the credit risk scoring phenomenon. The key concepts that will be covered are:

1. The concept of building a credit risk scoring model that contains predictive variables representing major information categories. This mimics the thought processes of good risk adjudicators, who analyse information from credit applications, or customer behavior, and create a risk profile based on the different types of information available.
2. Collaborative credit risk scoring model development, in which end users, subject matter experts, implementers, modelers, and other stakeholders work in a cohesive and coherent manner, is a best practice approach to get better results.

3. The application of business intelligence to the credit risk scoring model development process, so that the development and implementation of models are seen as an intelligent business solution to a business problem.

Each decision made in the definition of the target variable, segmentation, choice of variables, transformations, choice of cutoffs, or other strategies, should start a chain of events that impacts other areas in the company, as well as to future performance. By tapping into corporate intelligence, and working in collaboration with others, the model developer will learn to anticipate the impact of each decision and prepare accordingly to minimise disruption and unpleasant surprises.

Credit risk scoring models should be viewed as a decision support tool to be used for better decision making, and effective risk management. This means that they must be understood and controlled; credit risk scoring model development should not result in a complex model that cannot be understood in order to make decisions or perform diagnostics.

Finally, it is worth noting that regulatory compliance plays an important part in ensuring that credit risk scoring models used for granting consumer credit are statistically sound, empirically derived, and capable of separating creditworthy from non-creditworthy customers at a statistically significant rate.

ELEMENTS OF AN EARLY WARNING SYSTEM

Credit risk scoring model, as with other predictive models, is a tool used to evaluate the level of risk associated with customers. The model provides statistical odds, or probability, that a customer with any given score will be "good" or "bad." These probabilities or scores, along with other business considerations such as expected approval rates, profit, churn, and losses, are then used as a basis to support the decision making.

In its simplest form, a credit risk scoring model consists of a group of characteristics, statistically determined to be predictive in separating good and bad customers. As a general principle, Industrial Bank must use all relevant information about a customer credit risk scoring model development. Factors used in model development are considered the elements of early warning signal and can be grouped into two categories; continuous factors (mostly financial), and discrete factors (mostly non financial).

CONTINUOUS FACTORS AND DISCRETE FACTORS

The financial factors are, put simply, derived by defining combinations of financial statement positions and ratios based on the financial statement of the customer. Depending on the degree of granularity of financial information available, a large number of potential financial factors can be constructed. These financial factors are usually grouped into "economic clusters" such as:

1. Size and growth
2. Liquidity
3. Profitability
4. Debt service or debt capacity
5. Gearing and leverage

The non-financial information can be obtained internally or externally. Internal non-financial source is derived from the Industrial Bank's customer questionnaires and external information sources can often be purchased from the official credit bureau agency. The non-financial factors are typically grouped into the following clusters:

1. Management background (training, experience),
2. Historical relationship with the bank,
3. Quality of financial reporting, and
4. Market position of the customer.

These types of factors are generally very predictive of default as the behavioral pattern changes when the customer's credit status deteriorates and when they race to default. Therefore, this type of factors can be used as model factor, which is a distinctive characteristic of warning signals. These warning signals have a significant impact on the creditworthiness of the customer and therefore serve as strong predictors of default in the Industrial Bank's credit risk scoring models.

BEST PRACTICE APPROACHES FOR EFFECTIVE RISK MANAGEMENT

Nur Adiana et al. (2008) had compared three methods in model building for predicting the corporate failure of Malaysia's listed companies which are multiple discriminant analysis (MDA), logistic regression and the hazard model. Akbar Pourreza et al. (2012) attempted to predict the bankruptcy of companies using the logistic model. Their research results indicate that there is a significant relationship between financial ratios and bankruptcy prediction of firms listed in the Tehran Stock Exchange (TSE). Logistic analysis is proposed for the prediction of business failure because the dependent variable is binary or dichotomous in nature (Mohd Norfian et al. 2011).

Shuk-Wern et al. (2011) developed a model that can predict financial distress amongst public listed companies in Malaysia using the logistic regression analysis. They claimed that the financial distress prediction model is required to act as a predictor of Malaysian public listed companies' well-being prior to a financial crisis and to gauge the warning signals of the onset of a downturn in order to strategise their survival techniques during this phase. Most research mainly focused on analysing the difference in the financial indicators between companies involved in financial distress and non-financial distress, but paid less attention to the corporate non-financial indicators. Fengyi et al. (2010) have introduced business crisis prediction model based on a combination of both financial and corporate governance related non-financial data. Similarly, Li Jiming et al. (2011) stated that the model

with non-financial indicators can improve the ability of corporate financial distress prediction, and the timeliness and long-run validity of the mix model is much better than the model with only financial indicators.

The prediction of the future financial condition of corporations has attracted the attention of financial researchers, and finding the alerting indexes of financial distress occurrence has turned to be one of the most attractive and significant fields of financial and economic researches (Mirfeyz Fallah et al. 2011). Ben Yap et al. (2010) developed a model to improve the predictive abilities for company failures in lagged time frame with different financial, business and operating conditions in the Malaysian context by using multiple discriminant analysis (MDA).

Mohsen et al. (2012) stated that the ability to predict corporate bankruptcy is one of the areas of risk management that has various social and individual aspects. They demonstrated a comparison between support vector machines and multiple discriminant analysis predictive models. Tomasz (2011) used fuzzy logic to predict company bankruptcy and his results indicate the great potential of this method. He proposed that fuzzy logic is an "open application," which means its structure can be freely modified as opposed to the standard forecasting models, which are "closed applications" – the desire to change even just one parameter is likely to require a re-estimation of the whole model.

June Li (2012) has conducted a prediction of corporate bankruptcy from 2008 to 2011 by using Altman's Z-Score model. He claimed that all models tend to have high type II error of mispredicting a solvent firm as bankrupt. Therefore, there is a need for developing a model for the prediction of solvent firms. Mohammad Hasn et al. (2011) used artificial neural networks to predict corporate financial distress. They concluded that the use of micro-level financial indicators play an important role in financial distress prediction by using artificial neural networks. Martin et al. (2011) have conducted a hybrid model for bankruptcy prediction by using genetic algorithm, fuzzy c-means clustering and multivariate adaptive regression splines (MARS) model. They concluded that the genetic algorithm selects the best factor set and the resultant cluster formed is good by using fuzzy clustering. The hybrid model performs well as the MARS model can classify the organization as bankruptcy or non-bankruptcy.

Credit risk scoring offers a modern alternative to the traditional method of evaluating loans for the businesses. Loans would be approved on the basis of the banker's qualitative judgment, however financial condition is weighted most heavily. Credit risk scoring model, therefore, provides creditors with an opportunity for consistent and objective decision making, based on empirically derived information. Combined with business knowledge, predictive modeling technologies provide the banks with added efficiency and control over the risk management process. In the future, credit

risk scoring is expected to play an enhanced role in large banking organisations, due to the requirements of the new Basel Capital Accord (Basel II). This will also lead to the reevaluation of methodologies and strategy development for credit risk scoring models, based on the recommendations of the final accord.

DEVELOPMENT OF UNIVERSITY-INDUSTRY COLLABORATION

Etzkowitz and Leydesdorff (1997) stated that the three institutional spheres of university, industry and government formed a 'triple-helix' to interact with each other that is better able to form the key to innovation. Universities are an integral part of the skills and the innovation supply chain to business. In line with this reorientation with regard to the role of the university, many governments are beginning to rethink their science and technology (S&T) initiatives and policies (Geoghegan & Pontikakis 2008). The Government of Malaysia has provided a clear vision of achieving the standard of living of industrialised countries by the year 2020. This plan is named Vision 2020 and is set to accelerate Malaysia's shift to high-technology industries by focusing on the development of industry, academic, and government. Based on Heqiang, (2010), stimulating university-industry collaboration, technology transfer and commercialisation of university-born inventions are the most pertinent strategy to achieve Vision 2020. Kusmi (2006) has stated that the mechanisms for the technology transfer and collaboration include jointly organised new technology trainings and seminars, and internship or industrial attachment. The significant benefits of this type of collaboration include fostering expertise in university and industry and enhancing talent pool development.

Nor Idayu et al. (2012) have proposed that mixed skill enhancements and social responsibilities can be achieved through university-industry collaborations. Students develop their managerial knowledge and skills through formal learning environment to increase their employability. Skills developed through extracurricular activities and academic achievements will enable them to meet employer needs. On the other hand, industry players are involved by providing work opportunities through placements and internships. Industrial Bank is changing the recruitment practices by adopting internships and placements within the risk management department to ensure the work-based experience as a formal part of corporate programs.

According to Permsak et al. (2012), the university-industry collaboration is critical in the development of any fields of knowledge. The university is regarded as the source of new knowledge and the industry is generally regarded as the center of professional experts. Universities are viewed as a major supplier of human capital resources with talent and skills to the market that will support business growth and success. Hence, some initiatives have been taken to address the related challenges.

RESEARCH METHODOLOGY

RESEARCH DESIGN

According to Yin (1994), a case study is a preferred research strategy when "how" or "why" questions are being posed, and when the focus is on a contemporary phenomenon within some real-life context. As opposed to a comparative analysis of several firms, this research uses a single organisation approach and focuses on historical records and interviews to achieve the objectives of the study. The primary aim of this study is to analyse the development of credit risk scoring model as a best practice approach for effective risk management in Industrial Bank. The research seeks to understand how the best practice approach being applied through the university-industry collaboration. Therefore, a more open-ended approach is necessary to gain data that provides more in-depth insight into the research inquiry.

SOURCES OF DATA

Both primary and secondary data were used to achieve the objective of this study. The primary data is based on information obtained from interviews conducted with a group of five participants (out of seven staff) of the Risk Management Department of Industrial Bank. The interviewees are at middle management level in Industrial Bank and had shown great concern to work based on a clear standard of excellence and able to understand and appreciate different perspectives on this issue. They are highly engaged with the relevant technical matters and exhibits a very strong understanding of standard operation procedures and policies. Each of the participants was asked a same set of open-ended questions on how the participants' views and responds to the credit risk scoring model initiatives and its development, as well as the evaluation of the university-industry collaboration in Industrial Bank for effective risk management. Interviews were conducted based on semi-structured open-ended questions. The questions were:

1. Does your company have any university-industry collaboration concerning credit risk scoring model development?
2. Does Risk Management Department have an understanding of key credit risk scoring model development issues?
3. Has a credit risk scoring model independent review and audit be done?
4. What is the approach the bank used to develop and integrate the credit risk scoring models?
5. Has credit risk scoring initiatives been matched to the corporate strategy?
6. What are the credit risk scoring initiatives you are involved in?
7. How does it fit into the Industrial Bank's organisational needs and tasks?
8. What are the perceived obstacles?

9. Have strategic credit risk scoring initiatives and practices been developed and integrated with university-industry collaboration?

The secondary data consisted of readings from journals and books, information from Industrial Bank's Annual Report (2011), Bank Negara Malaysia (BNM) documentations, regulatory reports and working papers. In analysing the qualitative data, the findings were then used to clarify all the objectives of the study. This case study design, analysis and interpretation were used by Yin (1994). According to Yin (1994), case study research methods help to provide qualitative data in terms of document design, write up, coding field notes and data display. Nevertheless, an apparent weakness of this research design is the findings are limited to a specific industry, as in this case the financial industry in Malaysia. However, given the difficulties of data accessibility, business secrecy and confidentiality, these issues are judged as acceptable (Easterby-Smith et al. 1993).

BASIC THEORETICAL FRAMEWORK

The most popular theory for bankruptcy prediction is elaborated implicitly from financial measures in contrast to an economic concept being translated into a measure. This notional theory emanates from the perception of financial ratios as indicators of a firm's health. When the firm's indicators are "good," it is perceived as healthy, and if the indicators are poor, it is perceived as unhealthy and at risk of bankruptcy. In the context of Industrial Bank, there are three major categories of indicators used to develop the credit risk scoring model. Three major categories of these measurements are financial factors, non-financial factors and behavioral factors. A positive and high measurement of these three imply a lower risk of bankruptcy. The obvious weakness of this notional theory is its generality. On the other side, this "weakness" actually ensures that the theory does not conflict with, but rather inclusive of other more prescriptive theories.

CONCEPTUAL MODEL

Based on the theoretical framework, the credit risk scoring conceptual model is constructed to measure three key indicators of a company's health based on the popular notional theory of financial indicators.

Probability of bankruptcy = f (financial, non-financial, behavioral)

When building a credit risk scoring model, one seeks to capture indications of a company's general well being. For example, one may look at the financial information from balance sheets, study the quality of the company management and structure, or try to assess the feasibility of a company's business concept. It is important to consider both financial and qualitative aspects (non-financial) of the company in predicting its probability of default.

Argenti (1976) recognises that the process of failure may take several years, and that the signals of failure may be discernible very early on. He postulates a three-step path to default, where general company defects lead to mistakes, which ultimately lead to visible distress symptoms. He concludes that the failure process does not start as a financial phenomenon. Consequently, if one wishes to predict defaults over several years, one needs to consider non-financial variables as well.

FIGURE 3. Three step path to default

Keasey and Watson (1986) have studied the effect of using financial and non-financial variables in an attempt to confirm Argenti's hypothesis. They found that non-financial data are marginally better for predicting defaults in the small business segment. The following factors were studied:

1. Management structure;
2. Submission lags and inadequacy of accounting information;
3. Auditor remarks and reputation/size of auditor;
4. Type of registered secured creditor; and
5. Recent issuing of new share capital.

They conclude that combining non-financial and financial factors significantly enhance the predictive power of a model, as compared to the individual models. Academics have in general supported the combination of financial and qualitative aspects in assessing corporate failure. This is also the approach used in the development of the credit risk scoring models for Industrial Bank.

ANALYSIS

The findings are derived from the interviews of five respondents who are staff of Group Risk Management Department, Industrial Bank. Below are the findings resulted from the semi-structured interview, which is summarised as follow:

Industrial Bank has commenced the university-industry collaboration concerning credit risk scoring model developed through the internships and placement practices in the group risk management department. Undergraduate internship is taken to be a short period of professional experience based on Industrial Bank's internal policy. An emerging new model of placement practice in Industrial Bank provides students with a

variety of working experiences at different departments within Industrial Bank .With the establishment of the Industrial Bank Group Leadership Centre, internal training can be conducted that will promote knowledge transfer among the employees. The training program is also designed to meet the Industrial Bank's organisational goal and needs by developing analytical and employability skills through formal learning environments.

The Risk Management Department has an understanding of key credit risk scoring model development issues as below:

Data Quality Issues   Data is central to model development and as a consequence, the data quality assessment is essential prior to model building. Banks are expected to define internal minimum data quality standards in order to mitigate the risk of incomplete, incorrect or biased data. Industrial Bank has no dedicated data warehouse where modeling data were available. As a consequence, in the course of the model development the data had to be collected manually. Therefore, inconsistency happens in the process of manual data collection and data integrity becomes a critical issue.

Model Performance and Monitoring   Bank Negara Malaysia (BNM) emphasises the need for regular model validation, which includes the monitoring of model performance and stability, review of model relationships and testing of model outputs against outcomes. This procedure is to detect if the credit risk scoring models are not sufficiently predictive and do not distinguish between the risks. Industrial Bank has not yet completely defined its monitoring framework and model performance has not been tested since the model development phase.

Model Validation and Governance   There is currently no internal independent validation team within Industrial Bank to oversee that (1) an initial validation is done prior to the adoption and implementation of the internal ratings and (2) an ongoing validation is performed at least annually. At this point in time, the Internal Audit department has not been involved in reviewing Industrial Bank's compliance with all the applicable minimum requirements of the Internal Rating Based (IRB) approach as well as the independent validation of the ratings system and internal estimates.

Weak Credit Practice and Credit Policy   Sales and underwriter are the same person and the credit policy is incomprehensible due to not being detailed enough to cover all practical issues. At the moment, the Industrial Bank has no model validation team. Therefore, external consultants have been engaged by Industrial Bank to perform an independent validation of Industrial Bank's credit risk scoring models. The model validation was performed in accordance with *Bank Negara Malaysia* (BNM) Basel II requirements, and general market best practices observed by the external consultants.

There are three types of modeling approach adopted by Industrial Bank to develop and integrate the credit risk scoring models as described below:

1. Statistical Method
2. Expert Judgment
3. Expert Overlay on External Rating

The credit risk scoring initiatives have been matched to the corporate strategy as follows:

1. Conduct stress test: Develop clear methodology by using various factors and link to capital allocation, loan monitoring, and credit limits.
2. Data quality improvement: Perform quality dashboard for data entry and enhance system rule to enable data completion (mandatory field, reduce free form format).
3. Enhance data warehouse: To enable real time central database. Implementation of Enterprise Data Warehouse (EDW) project to achieve benefits with value creation as below:

   a. The primary function of EDW is to act as a data repository in a certified data environment.
   b. The EDW will served as a single source of truth that provides customer view from multiple dimension.
   c. To assist in supporting the strategic decision making with a clean, structured and well governance EDW buildup.
   d. Enhance analytical work: Training on basic understanding of the credit risk scoring model.

THE PERCEIVED OBSTACLES IN CREDIT RISK SCORING MODELS

Robust Technology   Technology plays a significant role in enabling active portfolio management, data transparency, growth in the organisation, elimination of manual processes and efficient management of information. In Industrial Bank, system enhancement is required in terms of upgrading the infrastructure and technology to increase the effectiveness and efficiency of the internal system database.

Integration and Standardisation   The centralisation, standardisation, consolidation and timeliness of credit risk management are the key drivers in shaping the banks' approach to effective credit risk management. There are many source systems in Industrial Bank. Industrial Bank has yet to integrate the disparate components of their credit risk systems, for a consistent framework. The key solution is to implement a centralised reporting system.

Challenges of Data Quality Issue   Banks achieve effective credit risk management through deploying a global credit risk management system. The major challenges faced by Industrial Bank include reporting, analytics and data quality issues. Consistent, accurate and reliable data is the foundation of effective credit risk management. Inaccurate or inconsistent data may hinder the banks' ability to understand its current and future business problems.

Current State of Alignment Industrial Bank has encountered some problems with communication, changing culture and legacy set-up on the way to aligning the strategies, policies and business processes through the transformation program. In order to close the existing gaps in alignment, a substantial amount of time is required for Industrial Bank's staff to get used to the new changes from the transformation process.

The strategic credit risk scoring initiatives and practices have been developed and integrated with university-industry collaborations. In Industrial Bank, the recruitment process shows indications of change through the increased use of internships and placements. The new agenda for these work experience opportunities extends beyond skills acquisition; it is becoming an established route to employment. Besides that, the well-known and established knowledge transfer partnerships (KTP) scheme places recent graduates with companies under joint SAS institute and Industrial Bank supervision to undertake a Risk Data Mart project, with the goal of improving the competitiveness of the company. The knowledge transfer program has been carried out in three major ways:

1. Methodology training workshops: A set of methodology training workshops will be held throughout the project to provide a general overview of the theory.
2. Development tool training sessions and handoff: These training sessions will cover the set of development tools used during the project and most of these sessions will be combined together with the methodology workshops described in the section to provide both theory and practical knowledge transfer at the same time.
3. "On the job" training: This is the most effective form of knowledge transfer by replicating key task in the project and to preview all expert discussion material beforehand to ensure that there are fully on-board with the various approaches, assumptions and rationale used for the project.

Industrial Bank's Group Risk department has been implementing a strategic change agenda through its "Advanced Risk Recognition Program." This program is aimed at improving risk recognition skills which incorporate a comprehensive range of initiatives that includes:

1. Developing a more comprehensive risk appetite strategy, execution and monitoring framework;
2. Enhanced risk models and upgrading risk infrastructure.

A more detailed interpretation of the findings from document analysis on credit risk model development in Industrial Bank will be discussed in the subsequent sub-topics.

RESULT AND DISCUSSIONS

The 3 types of modelling approach adopted by the Industrial Bank are described below:

STATISTICAL METHOD

This is the most preferred approach when sufficient internal historical data are available. The model is built based on internal data using statistical method such as logistic regression. Examples of models built using this method are LC, MM and SB models.

EXPERT JUDGEMENT

This method is recommended when the Bank has some data but not sufficient to build the model statistically. The risk factors are chosen judgementally by the experts and then tested their predictive power with limited data available. Examples of models built using this method are OHC, Contractors, CRE-Development, CRE-Investment and CRE-General Recourse models.

EXPERT OVERLAY ON EXTERNAL RATING

This method is usually adopted for externally rated customers of External Credit Assessment Institution (ECAI). They are characterised as low default and with large exposure. The recognised ECAIs are Fitch, Moody's, S&P, RAM and MARC. The external rating can then be adjusted upward or downward based on the consideration of differences in view by the subject matter experts. Examples of models built using this method are Banks model.

Figure 4 summarises the key salient points of the credit risk scoring model methodology to be adopted for Industrial Bank's general model structure.

In developing the credit risk scoring models, the best practice approach is proposed to allow for the combination of financial factors, non-financial factors and behavioral factors. The approach is selected due to the reasons of easy to interpret and maintain and flexible in incorporating subjective overlay by credit experts.

Under the general model structure, a final score is assigned following the steps below:

Financial Factors Ideally, financial information used in model development would be based on a consistent spreading system used by the bank which already includes data cleaning measures and plausibility checks. In the worst case scenario, financial information will have to be captured manually for the model development, if no digitally recorded data exists. Where financial information is already captured in some format within the bank, the extraction relies directly on these systems. The next task is to export all financial statements information that is needed to construct the financial factors that will be considered (at a later step) as candidates for
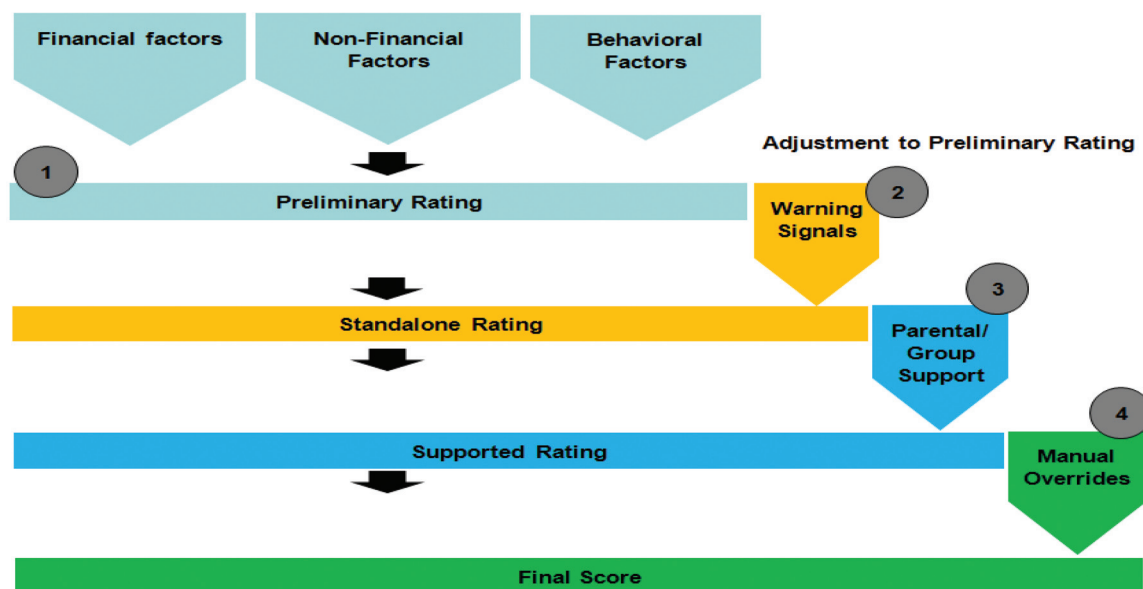
FIGURE 4. General model structure

the final model. A long list of financial factors is, put simply, derived by defining combinations of financial statement positions and ratios. Depending on the degree of granularity of financial information available, a large number of potential financial factors can be constructed. It is required finances to compute the necessary ratios and the weight would be determined based on the weighted average of all the financial ratios.

Non-financial Factors   The assessments on the qualitative aspects of the borrower's creditworthiness in terms of management capability, financial flexibilities, supporting parties, etc with pre-defined descriptions on each of the non-financial factor. Similarly, the overall non-financial weight will be generated based on the weighted average of all the non-financial factors.

Behavioral Factors   Behavioral information is related to the behavior pattern of a borrower. For example, behavioral-type factors include a borrower's delinquency status, credit utilisation and limit breach. These types of factors are generally very predictive of default as the behavioral pattern changes when the borrower's credit status deteriorates and when they race to default.

Preliminary Rating   A preliminary rating is assigned based on the weighted score derived from a set of predictive risk factors such as financial (e.g. EBITDA/ Interest Expense, cash/Current Liabilities), non-financial (e.g. Longer in Business, Industry Growth) and behavioral (e.g. Maximum Months in Arrears in Last 12 Months) risk factors that reflect the risk of a customer.

Warning Signals   Once the preliminary rating is determined, downgrade adjustments (up to 5 notches depending on signal severity) may be applied with any warning signals. They act as an overlay to the Preliminary Rating. Warning signals are adverse signs that happen infrequently but highly predictive of risk such as breach of covenants or loans with overdue payments. It is applicable to all of the models except Rated Bank model.

As one of the components of rating adjustment, apart from the financial, non-financial and behavioral factors, is the warning signals section. Warning signals are events that are rare in occurrence (in contrast to the regular non-financial factors that constitute the core model output) but when they do occur, they have a significant impact on the creditworthiness of the borrower and therefore serve as strong predictors of default. Warning signals can be integrated into the rating model using one or a combination of different approaches. Downgrade by a fixed number of rating grades is the method employed at Industrial Bank. For adjustments with several 'bad' categories with different degrees of severity (maximum 5 notches), downgrades will usually be differentiated by the number of rating grades to be downgraded by.

Parental/Group Support   All rating elements we have presented about so far belonged to the sphere of the borrower itself (i.e. financials, non-financial, behavioral factors and warning signals). Apart from this, there is an outside sphere which is addressed by the group logic overlay. Parental/Group support can be used for a rating upgrade if the parent company is rated better than the borrower and viewed to be able to prevent the borrower from defaulting. The group logic overlay addresses the guarantee that might come from the parent of a corporate borrower.

Manual Overrides   Lastly the rating can be adjusted upward or downward for factors not being considered by the models if justified reasoning is provided. Similar to the rating adjustments discussed above, overrides incorporate infrequent events and other borrower-specific information that is not covered by the regular rating parameters (i.e. the financials, non-financial and behavioral factors) and may lead to a modification of the initial borrower grade.

Overrides may lead to upgrades or downgrades of the borrower grade. Manual override of more than 4 notches upgrade will require management's approval. Downgrades are more flexible in order to enable Industrial Bank to react adequately to negative changes in the borrower's business environment, which is in line with prudent banking practice. In general, discreet handling of overrides is desirable so as to avoid significant deterioration of the discriminatory power of the rating and the subsequent pricing decisions.

Final Score   The final step is to re-map the adjusted rating to the Bank's internal rating based on the standard Rating Master scale and assigned with the relevant mid PD score. The standard Rating Master scale is based on the new Industrial Bank retailMaster scale and has 24 rating grades. Each rating grade has approximately a 1.4x increase in PD moving from one grade to the next.

BEST PRACTICES APPROACH FOR EFFECTIVE RISK MANAGEMENT

Understanding the business and the data is the key for a successful model development. The detail around alternative modeling techniques should be used as a guideline only, and should be used in conjunction with the guidance of the more experienced model developer. As such, employer engagement has become firmly cemented within their academic culture. Industrial Bank has been achieved through innovation in university-industry collaboration; in-company programs, industry designed courses, and placement and internships for students. The evidence that placements, and internships are extremely beneficial and valuable to Industrial Bank, both in terms of producing professions and experienced human capital resources internally and develop a wide scope of recruitment and selection to meet the Industrial Bank's aspirations, or talent or diversity needs of the bank.

The industrial bank group has taken the initiatives to establish the infrastructure and culture of learning by incorporating the Industrial Bank Group Leadership Centre to train the staff internally and promote the knowledge transfer through partnership with the Institute of Bankers Malaysia (IBBM). Each training program is designed to meet the Industrial Bank's need and kite-marking by financial sector skills councils such as *Bank Negara Malaysia* (BNM) and gained the accreditation by professional bodies in Malaysia. This sustainable approach to workforce development is to raise the standards of Industrial Bank's practice towards a learning organization.

IMPLICATIONS OF THE STUDY

The best practice approach developed seeks to ensure the technical and methodological functionality of the credit risk scoring models generated intuitive results to meet the organisational goal. The credit risk scoring models have accomplished two key business oriented implications which are improving approval decisions and allocating risk capital in Industrial Bank.

Improving Approval Decisions   Credit risk scoring models assist Industrial Bank in determining the credit worthiness of an applicant based on his/her characteristics. The applicant's characteristics would include factors such as background information, financial and accounting ratios, and an assessment of the firm's overall financial, management, industry and regulatory risks. The objective of such a credit risk scoring model is to assist in the overall decision making process.

Allocating Risk Capital   As part of the Industrial Bank's risk management strategy, the management has decided to comply with recommendations of the Basel Committee for Banking Supervision. As part of these recommendations, going forward requires providing capital based on the riskiness of each applicant. Thus the credit risk scoring models will assist in measuring the riskiness of each applicant objectively and consistently.

Potential Future Enhancements   Consistent, accurate and reliable data is the foundation of effective credit risk management. Inaccurate or inconsistent data may hinder the banks' ability to understand its current and future business problems. Some of the major issues experienced by banks with regard to data management include data quality and standardisation, assembling accurate data sets with minimum reconciliation and back-testing of credit risk scoring models. By encouraging the bank to adopt a standardised format for all information, the data issues can be mitigated. In terms of technology gaps, most of the technology supports and empowers business alignment to the business strategy. Consequently, banks are driven by business and supported by technology. Industrial Bank needs to enhance the information technology and upgrade the system database to close the gaps with regulatory requirements.

RECOMMENDATIONS

Effective credit risk management has gained an increased attention in recent years, largely due to the fact that inadequate credit risk scoring models are still the main source of serious problems within the banking industry. Managing credit risk thus remains an essential and challenging corporate function within an Industrial Bank. The ultimate goal of an effective credit risk management is to maintain the key components which formed the best practice approach of credit risk scoring models, maintaining a good data quality management and enhancing a robust technology in the Industrial Bank.

RECOMMENDATIONS FOR MANAGERIAL ACTIONS

In addition to achieving the common goals, the recommendations for Industrial Bank's managing action to achieve an effective risk management system should comprise of the following components:

Credit Policy   Credit policy is the foundation on which Credit Risk Management of both portfolio and processes are built. Its aim is to ensure a uniform credit extension to be practiced throughout the bank. A Credit Policy serves as the basis for consistent credit risk management throughout the bank through product, segment, geographic and organisational divisions and should apply to all credit risk scoring models. Credit policies which define appropriate behavior in lending business should support banks' business strategies.

Credit Strategy   Industrial Bank should develop its own credit risk strategy that establishes the objectives in guiding the bank's credit granting activities and adopting the necessary policies/procedures for conducting such activities during implementation of the credit risk scoring models. This strategy should spell out clearly the organisation's credit appetite and define target markets, risk acceptance criteria, credit origination/maintenance procedure and guidelines for portfolio management. The credit strategy should provide for continuity in approach and also take into account the cyclical aspects of the economy and its impact on the composition/quality of the portfolio. It should be viable in the long run and through various economic cycles.

Credit Model Administration   This function is a part of the Risk Management Unit. Its responsibilities would involve monitoring subsequent to the implementation of credit risk scoring models. In the process of managing credit model administration, it is required to have an annual review of all existing credit risk scoring models and a brief semi-annual review of new engagements, periodic reviews of industrial sectors, and undertake at least quarterly reviews of weak (watch list) borrowers.

Organizational Structure   The development and use of credit risk scoring models can be considered a cycle with input from various stakeholders, whose purpose is to ensure that the model performs adequately for the segment in which it is used, and that model performance is acceptable – both on rollout and as it continues to be used. Ideally Industrial Bank should have an independent credit risk department organisational structure, which would be responsible for the following functions in the management of credit risk scoring models.

People   Selection of the staff for the entire process is as important as having a well structured system. The Relationship Manager who initiate the business need to have the correct attitude and drive when they use the credit risk scoring models. Whilst it is their responsibility to make business taking into account the credit policy and target market, they should also be adequately trained to identify and evaluate the risks. As they are rewarded according to the profitability of their respective portfolios, they are also responsible for the timely identification and mitigation of any risk that could end up in a loss. A continuous upgrading of skills is mandatory to motivate staff and to maintain a quality portfolio.

Credit risk is the risk of loss due to the inability or unwillingness of a counter party to meet its payment obligations. Exposure to credit risk arises from lending/financing, securities and derivative exposures. The identification of credit risk is done by assessing the potential impact of internal and external factors of the Industrial Bank Group transactions. The primary objective of credit risk management is to maintain accurate risk recognition, identification and measurement, to ensure that credit risk exposure is in line with the Group's Risk Appetite Framework and related credit policies.

To support credit risk management's observation of disciplines governed by the Basel II Framework and Financial Reporting Standards (FRS), Industrial Bank's rating models pertaining to credit risk (obligor's PD, LGD and EAD) are in the process of being upgraded. These credit risk scoring models are scheduled to be operational continuously and will:

1. improve the accuracy of individual obligor risk ratings and calculation of expected loss;
2. enhance pricing models;
3. facilitate loan/financing loss provision calculation;
4. automate stress-testing; and
5. enhance portfolio management.

CONCLUSION

Despite the rapid transformation in the banking sector, where the traditional interest income derived from lending is changing to fee-based income/business through innovative ancillary products and services, lending will continue to be the core income source for most banks. Hence managing credit risk effectively will continue to be an important area which warrants the attention of Industrial Bank.

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