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ESTABLISHMENT OF THE CREDIT RISK DATABASE: CONCRETE USE TO EVALUATE THE CREDITWORTHINESS OF SMES

Satoshi Kuwahara,
Naoyuki Yoshino,
Megumi Sagara, and
Farhad Taghizadeh-Hesary

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Satoshi Kuwahara is president and CEO of the Credit Risk Database (CRD) Association. Naoyuki Yoshino is dean of the Asian Development Bank Institute. Megumi Sagara is a manager at the CRD Association in Tokyo. Farhad Taghizadeh-Hesary is assistant professor of economics at the Faculty of Political Science and Economics of Waseda University in Tokyo.

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Please contact the authors for information about this paper.

Email: farhad@aoni.waseda.jp

Asian Development Bank Institute
Kasumigaseki Building, 8th Floor
3-2-5 Kasumigaseki, Chiyoda-ku
Tokyo 100-6008, Japan

Tel: +81-3-3593-5500
Fax: +81-3-3593-5571
URL: www.adbi.org
E-mail: info@adbi.org

Abstract

The credit risk database (CRD) makes it possible to mitigate the problem of information asymmetry between SMEs and financial institutions and contributes to improving SMEs' access to finance by collecting a large number of financial statements through the mechanism of SME finances and establishing a robust statistical model. In this paper, we use the CRD in Japan, confirm the situation in Japan, and highlight the CRD's contribution to evaluating the creditworthiness of SMEs. We also explain how to establish the CRD as a financial infrastructure, while indicating that the CRD and the scoring model based on it have maintained their quality owing to their operating system. We hope our experience contributes to the introduction of a statistical credit risk database composed of a large number of anonymous financial statement data in other countries and that the CRD helps to improve SMEs' access to finance as a financial infrastructure.

Keywords: credit risk database, CRD creditworthiness, SMEs in Japan

JEL Classification: G21, G28, G32

Contents

1. INTRODUCTION

Asia has been continuously growing, and this growth has alleviated poverty and increased the number of middle-income countries in the region. However, the recent regional and global economic slowdown was caused by several factors, including the limited access of small and medium-sized enterprises (SMEs) to bank credit. It requires new and sustainable models to ease the access of SMEs to finance and boost economic growth and job creation in the region (Yoshino and Taghizadeh-Hesary 2017).

A survey carried out by the Asian Development Bank (Asia SME Finance Monitor (ASM)) on 20 countries from 5ADB regions shows that SMEs accounted for an average of 96% of all enterprises and 62% of the national labor forces across the ASM countries. These countries cover Central Asia, East Asia, South Asia, Southeast Asia, and the Pacific. Meanwhile, the latest data reveal that SMEs contributed an average of 42% of the gross domestic product (GDP) or manufacturing value added in ASM countries (ADB 2015).

Nevertheless, the same survey points out that SMEs' access to finance is highly limited, with bank loans to SMEs making up averages of 11.6% of GDP and 18.7% of total bank lending in ASM countries. Then it suggests that there is a need to promote bankability for SMEs in rapidly changing business environments and global economies through further policy support, and in particular a set of financial infrastructures—1) credit bureaus, 2) collateral registries, 3) sustainable credit guarantee schemes—needs to be developed in low-income countries.

This paper suggests adding 4) a nationwide SME credit risk database and statistical scoring model based on it to such a set of financial infrastructures not only in low-income countries, but broadly in Asian countries that have already established the other three infrastructures.

There is a successful example of such a database and scoring model in Japan: the Credit Risk Database (CRD) of the CRD Association. A CRD is a database that gathers a large number of financial statement data, nonfinancial data, and default data anonymously from member financial institutions. The idea is that collecting large quantities of SMEs' financial statements will introduce a reliable statistical method into evaluating SMEs' credit risk through "the law of large numbers." Statistical accuracy increases with more data, but amount of data that can be collected at one institution is limited. A CRD and a statistical scoring model based on such a huge database certainly work as a financial infrastructure in Japan.

A CRD and scoring model can complement or enhance the functional capabilities of other financial infrastructures as above.

With regard to 1) credit bureaus (or credit registries), a CRD and scoring model complement those because of the differences in data in terms of quality. Databases of credit bureaus (or credit registries), which have the specific names of borrowers and a reference function for identifying unhealthy borrowers, will be effective for estimating a pattern of personal behavior from their own past behavior. On the other hand, a CRD contributes to estimating the creditworthiness of SMEs' ongoing business by evaluating their business prospects through financial analysis. The roles of both are not competitive, but complementary. Different aspects work better in evaluating the creditworthiness of SMEs.

If SMEs have collaterals, or even movable assets, it reduces the credit risk of financial institutions theoretically. However, because it is not easy to evaluate the value of collaterals and to enforce security after bankruptcy, financing based only on this scheme carries unexpectedly high costs and financial institutions might be reluctant to finance. A framework needs to be established to avoid final enforcement of securities, by using preliminary proper evaluation of SME's business and performance risk management.

As regards 3) sustainable credit guarantee schemes, it is necessary to prevent moral hazard problems from occurring. Because financial institutions have extremely low credit risks for credit guaranteed loans, there is incentive for loans to be generated easily even for SMEs with high credit risk in order for them to extend their loans. To cope with this situation, an infrastructure such as a CRD is needed, along with a scoring model that assesses the credit risks of financing loans accurately.

However, it is difficult to forecast the future of SMEs, because even SMEs that maintain favorable growth are likely to experience a sudden deterioration in their business conditions under the influence of an economic downturn. On the other hand, it is possible for SMEs to change their situation owing to the success of new products or new services. In what follows, we use CRD data, confirm the situation in Japan, and highlight the CRD's contribution to evaluating the creditworthiness of SMEs.

Figure 1 describes the composition of SMEs in regard to their financial condition. We divided SMEs into 4 patterns owing to the situation of profit (current profit) and total net worth.

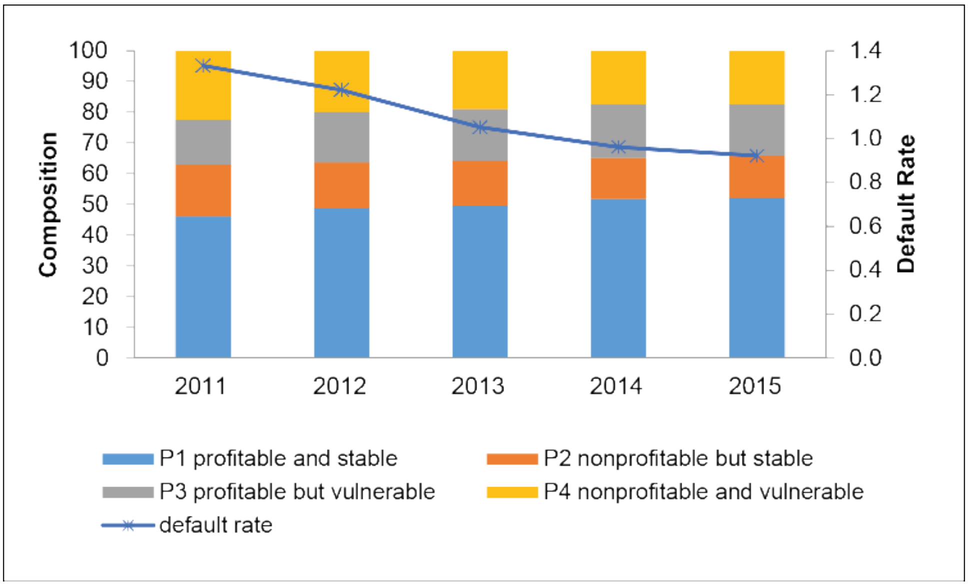
> "Pattern1(P1) profitable and stable": current profit >0 and total net worth >0
> "Pattern2(P2) nonprofitable but stable": current profit =<0 and total net worth >0
> "Pattern3(P3) profitable but vulnerable": current profit >0 and total net worth =<0
> "Pattern4(P4) nonprofitable and vulnerable": current profit =<0 and total net worth =<0

The provision of funds for SMEs in Japan has a very broad base. The CRD collects financial statement data from SMEs that currently have deals with financial institutions. Although about 40% (P3 profitable but vulnerable and P4 nonprofitable and vulnerable) of SME data on the CRD have a negative net worth, financial institutions regard them as customers and have deals with them.

The line shows the default rate, which declines gradually. Default means (a) 3 months past due, (b) de facto bankruptcy, (c) bankruptcy, or (d) subrogation, and default rate means the ratio of SMEs that defaulted within 1 year from account settlement in this paper. The ratio of P1 profitable and stable goes up and the ratio of P4 nonprofitable and vulnerable goes down slightly in response to the decline in the default rate. However, separately from the decline of default and the recovery of the economic environment, the composition regarding patterns as a whole does not change a lot.

Figure 1: The Composition of Four Patterns Regarding Financial Condition

(%)

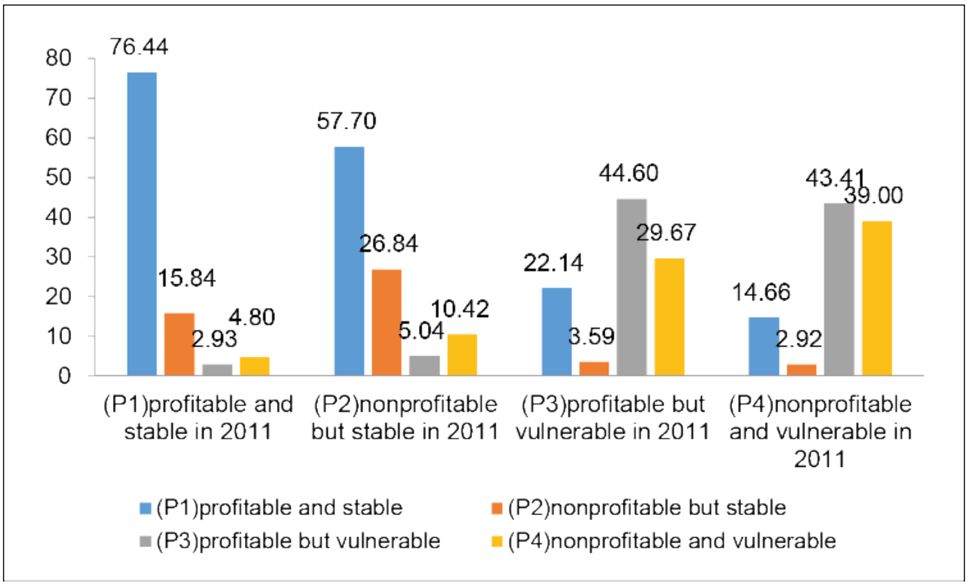


Source: Authors.

In Japan, the composition of patterns 1–4 seems to be relatively stable. Next, we confirm whether the members of each pattern are fixed or not. We check the same SMEs' pattern in 2011 and 2015 and compare those. The object of this comparison is limited to SMEs that have financial statements for both years. The figure below indicates a pattern transition from 2011 to 2015.

Figure 2: Patterns in 2015 (Transition from 2011)

(%)



Source: Authors.

With regard to SMEs that belonged to P1 profitable and stable in 2011, 76.44% still belong to P1, and 15.84% moved to P2 nonprofitable but stable, 2.93% to P3 profitable but vulnerable, and 4.80% to P4 nonprofitable and vulnerable in 2015. Even among those in P1 profitable and stable in 2011, some of them fell into insolvency 4 years later. Conversely, several dozen SMEs that belonged to P3 profitable but vulnerable or P4 nonprofitable and vulnerable in 2011 resolved their insolvency and many of them bounced back to P1 profitable and stable. Now because the economic environment is stable, a relatively large proportion of pattern1 did not move. However, this is the exception rather than the rule. It is difficult for many SMEs to keep the same condition in a positive or even a negative way.[1]

Although the composition of patterns does not change much as a whole, it seems that SMEs individually move backward and forward among some patterns in a relatively short period of time. Because the business situations of SMEs are likely to be transient, it seems to be difficult to forecast the financial condition of each SME. However, evaluation through a financial analysis is still effective. It would be possible to estimate the creditworthiness of SMEs if we could create a large number of databases and make use of statistical methods with them.

In this paper, we explain the effectiveness of the CRD for estimating the creditworthiness of SMEs and how to establish the CRD as a financial infrastructure. The CRD and the CRD scoring model have maintained their quality owing to their operating system and provide an adequate function as a financial infrastructure.

2. OUTCOME FROM THE CREDIT RISK DATABASE (CRD)

We indicate easy-to-understand examples to certify the effectiveness of financial analysis regarding SMEs. One is an example of financial information and the next is an example of a statistical scoring model made from the CRD.

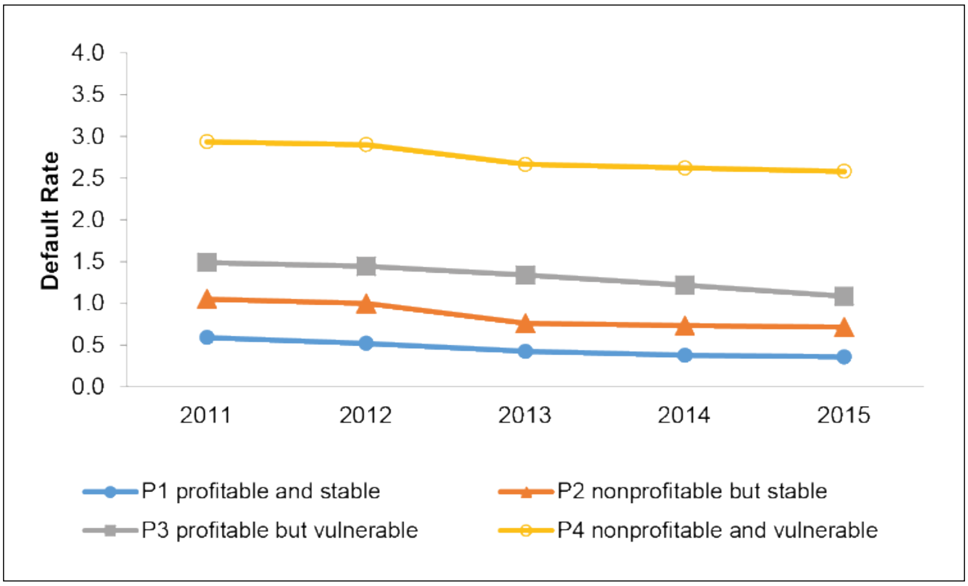
2.1 Statistical Information

Financial information about SMEs contributes to grasping the typical figure of SMEs in specific categories. We divide SMEs into 4 categories regarding the situation of profit and loss statements and balance sheets: P1 pattern1 profitable and stable; P2 pattern2 nonprofitable but stable; P3 pattern3 profitable but vulnerable; and P4 pattern4 nonprofitable and vulnerable. With regard to financial conditions, P1 is first and P2, P3, and P4 follow Because, basically, losing profit will become detrimental to the balance sheet, i.e. the continuation of negative profit can be the reason for producing capital deficit, we determine that the situation of P3 is much more serious than that of P2. Figure 3 shows the default rate within 1 year of each pattern.

1 This fluctuation in business of SME is one of the striking outcomes presenting reality of the SME situation by data analysis since the establishment of the CRD. Outcome from the analysis comparing 1997 with 2001 (CRD Association 2003) has been the same since then.

Figure 3: The Default Rate of Each Pattern

(%)



Source: Authors.

The default rate of all patterns declines gradually. After the Lehman shock, the default rate peaked in 2008 (default observing period from February 2008 to December 2009) and kept declining after that due to the government's financial measures such as the SME Financing Facilitation Act, the Emergency Guarantee Program, and so on.

Although we evaluate the order of 4 patterns regarding financial condition, the order as we ranked it remained consistent from 2011 to 2015. The default rate of P1 subsequently remained at low levels and that of P4 shifted to a high level.

By confirming with data, we can recognize the actual situation in an objective way, the extent to which SMEs belonging to P1 are secure or the extent to which SMEs belonging to P4 are at risk. If we gather 200 SMEs in each pattern, it can be estimated that one SME from P1 (200*0.5%) and 5 SMEs from P4 (200*2.5%) default within 1 year. It is effective to grasp the difference in risk degree in each category objectively.

As we explained, financial information can indicate the condition of SMEs in specific categories objectively by using large and wide-ranging data. The CRD database contains information on both incorporated and sole-proprietor SMEs. Currently there are more than 3 million SME borrowers (debtors) in the database. Because borrowers provide financial statements covering several years, the number of financial statements in the CRD is more than 20 million.

The CRD is rich in content, in addition to being large in scale. The CRD members submit data composed of up to 59 items from the balance sheet (minimum 26) and up to 26 items from the profit and loss statement (minimum 9) and nonfinancial data such as the type of corporate entity, industry sectors, region, year of establishment, owning or not owning real estate, successor or no successor, number of employees, and birth year of president. In the analysis, we compare the situations between small and mid-sized enterprises, among industry sectors, among several regions, between urban and rural areas, between start-up and well-established companies, and so on. Thus, it is possible to analyze the characteristics in specific categories in accordance with members' needs.

2.2 Statistical Scoring Model

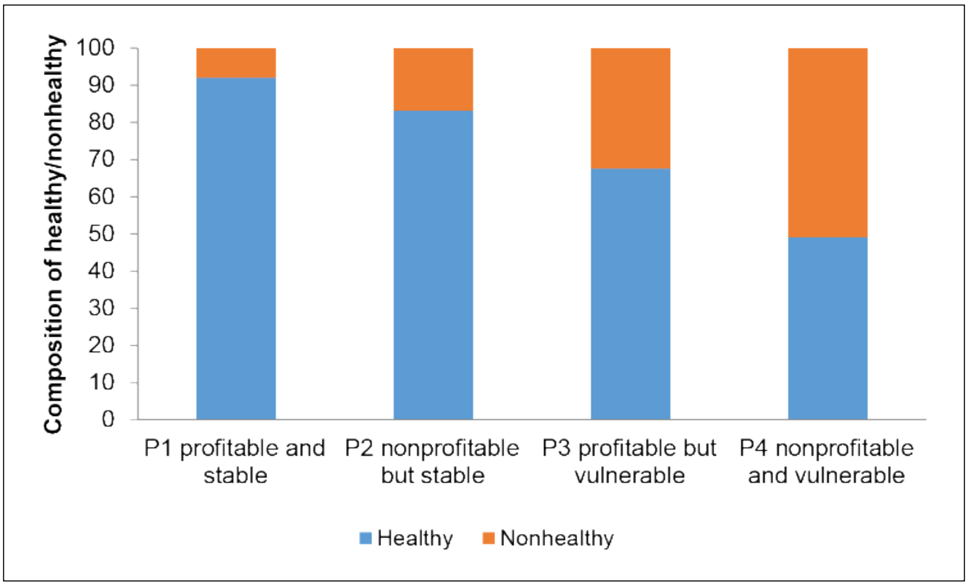
Next is an example of a statistical scoring model that combines many financial indexes made from the CRD. A scoring model has various aspects in estimating the creditworthiness of SMEs and can distinguish correctly between healthier SMEs and less healthy SMEs.

A scoring model calculates the probability of default (PD) for each SME by using its financial statements and gives a lower PD to healthier SMEs and a higher PD to less healthy ones. For our example, we define the PD for healthy SMEs as being under 1.0% (PD=<1.0%) while for nonhealthy SMEs it exceeds 1.0% tentatively. We choose 1% as a threshold that was an average PD from 2011 to 2015. “PD 1%” means that if 100 SMEs in similar financial conditions gather together, one of them will default.

We use 4 patterns combining current profit and total net worth again. Although P1 profitable and stable is very good and P4 nonprofitable and vulnerable is very bad seemingly, there are some SMEs from P1 defaulting and some from P4 recovering sharply in the short term. If we use a scoring model to forecast the financial condition of SMEs, the scoring model can calculate PD from each detail condition and estimate the future status of each SME.

The ratio of healthy to nonhealthy in each pattern is as follows.

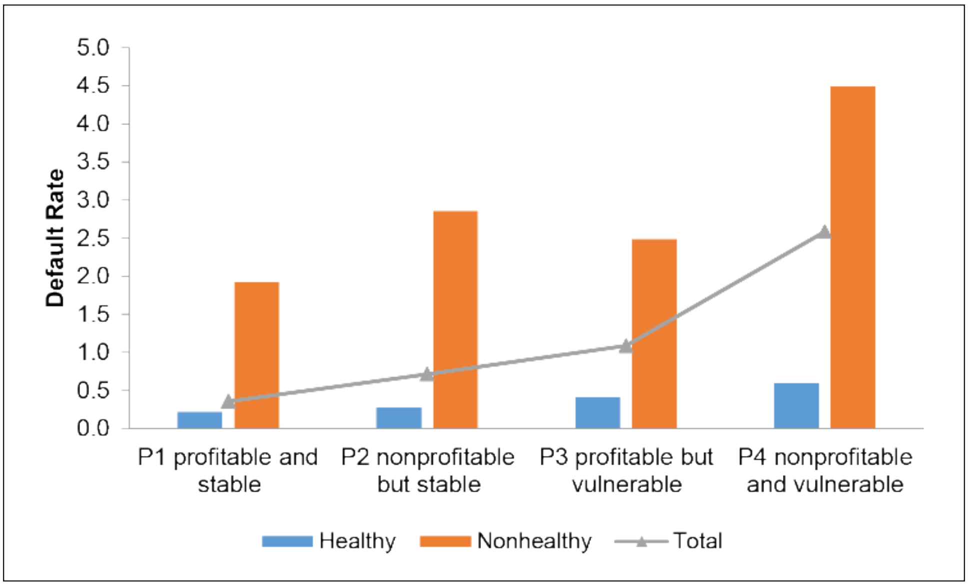
Figure 4: Categorization of SMEs based on Their Healthiness
(%)



Source: Authors.

Naturally, the ratio of healthy SMEs is highest in P1 and that of nonhealthy SMEs is highest in P4. At the same time, it is clear that the majority of SMEs in P2 and likewise in P1 are healthy. Then we confirm the default rate in each pattern regarding financial statements in the 2015 accounting year. The shaded bar chart shows the default rate of the nonhealthy group in each pattern and the painted bar chart refers to that of the healthy group.

Figure 5: Default Rate of Healthy and Nonhealthy SMEs in Each Pattern
(%)



Source: Authors.

Although the appearance of current profit and total net worth are similar in some patterns the shaded bar chart surpasses the painted one significantly in all patterns. The default rate of the healthy group in all patterns is low, even in P4. Although P1 earns profit and its own capital steadily, the nonhealthy group's default rate in P1 is quite high, at almost 2%, against all expectations. The SMEs in P2 categorized as nonhealthy by the scoring model are at more risk than those in P3, although the SMEs in P2 have a positive total net worth and SMEs in P3 have negative ones.

If we use the scoring model to evaluate creditworthiness and divide the SMEs in each pattern into two categories (healthy or nonhealthy), we can capture more detailed results and can improve our skill in regard to evaluation. Proper evaluation can mitigate credit risks and expand the provision of funds to SMEs, by not avoiding credit risks but controlling them. As just described, a scoring model is a reliable tool for evaluating the creditworthiness of SMEs as well as SMEs' fluctuation in management. Next, we explain the method for establishing a scoring model.

3. ESTABLISHMENT OF SCORING MODEL BASED ON THE CRD

3.1 Financial Analysis

We think that people are more familiar with financial analysis regarding an evaluation using financial statements. As with a financial analysis, a scoring model uses effective financial indexes made from financial statements regarding the aspects of the profitability, stability, growth potential, efficiency, and so on of a business operation.

As for profitability, a scoring model evaluates financial indexes like return on asset (ROA), gross margin, current margin, and so on, which estimate SMEs' earning capacity, especially from profit and loss statements. A scoring model evaluates capital ratio, dependency on borrowing, fixed ratio, and so on, in order to confirm the stability of the financial structure of enterprises from the balance sheet side. A scoring model also evaluates revenue growth rate, capital expenditure, and so on, which check the growth potential and evaluate capital turnover ratio, inventory turnover, and so on, which analyze the efficiency of financial management.

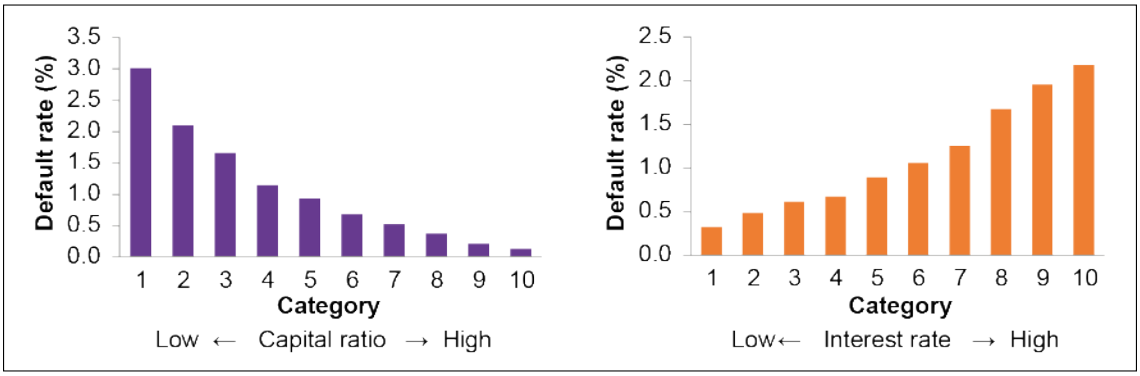
In financial analysis, people find the proper level for each financial index from their experience or customs, compare the financial index of an SME with such a level, and evaluate that financial index. It is helpful to form an impression; however, it is difficult to explain their evaluation in a comprehensive, systematic, and objective way. Although a scoring model uses financial analysis in the same way, it can analyze many financial indexes synthetically in connection with default data.

3.2 Creating Candidates for Variables of Scoring Model

Although we basically create financial indexes that are traditionally used for financial analysis of management, we try to mix financial items from P/L and B/S of the CRD exhaustively, create a large number of financial indexes, and analyze the relationship with default. Financial indexes that have a relationship with default will be candidates for explanatory variables for the scoring model. We explain the relationship with default through the figure below.

There are some financial indexes we can easily identify and can detect the possibility of default. We show such examples; the capital ratio shows the stability of capital and the interest rate shows the borrowing situation.

Figure 6: Relationship between Financial Index and Default Rate



Capital ratio = Net Asset / (Liabilities and Net Assets).

Interest rate = Interest expenses / Liabilities.

Source: Authors.

We divide the data set into 10 groups according to the value of financial indexes. This is a very simple way to discretize data sets and puts the extremely low data into category 1 and the extremely high data into category 10. Figure 6 shows the default rate in each group. We can easily find a strong relationship between these two financial indexes: If the capital ratio goes lower or the interest rate goes higher, the default rate goes up, and vice versa. Financial indexes like these can be candidates for variables of a scoring model.

We need to mention that creating financial indexes as candidates of variables for a scoring model is not straightforward. First, we need to consider the most suitable data type for financial indexes such as continuous variables, discrete variables, transformed variables such as logarithmic transformation, box-cox transformation, neglog (negative logarithmic) transformation, or something else. Financial indexes sometimes distribute around zero intensively, take negative values or extreme outliers, and they cannot be candidates for variables as they are.

To create an accurate scoring model, it is necessary to consider proper data handling owing to the distribution characteristics of the financial index. Miyamoto et al. (2012) examined and compared methods of data handling such as box-cox transformation, neglog transformation, general neglog transformation, and so on using the CRD. The data handling procedure is not attention-grabbing in general, but is indispensable work.

Usually we create many financial indexes from the CRD for creating a scoring model and investigate the relationship between financial indexes and default by performing a single logit regression. Significant financial indexes in a single logit regression become candidates for variables of a scoring model.

We indicate a simple exercise for finding candidates. We performed a single logit regression where the dependent variable was default and the independent variables were (1) capital ratio, (2) interest rate, (3) return on asset (ROA), (4) account payable turnover ratio, and (5) revenue growth rate against default. We used financial statements in the accounting year 2015 and excluded outliers (we define here that they exceed by 3 times the standard deviation from the mean). It turned out that coefficients of (1), (2), (3), and (4) are statistically different from zero at below the 1% significance level and have a strong relationship with default.

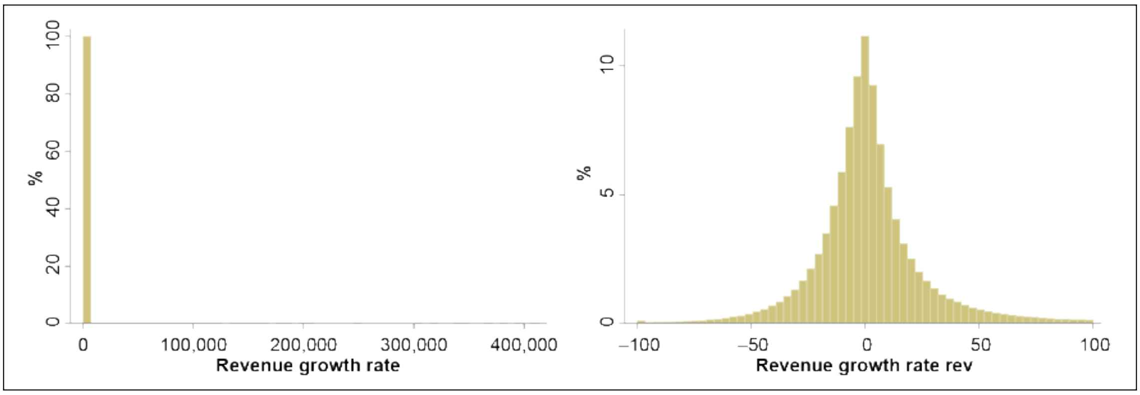
$$p = \frac{1}{1 + exp^{-(\beta_0 + \beta_1 \cdot X)}}$$

$P = 1\ if\ default$ and $P = 0\ if\ nondefault$

$\beta_0: constant\ \beta_1: coefficient\ X: financial\ index$

However, (5) revenue growth rate is not significant. Generally, the revenue growth rate is regarded as an effective financial index in evaluating the growth potential of SMEs. We check its distribution. The figure on the left-hand side is a distribution of the revenue growth rate. It has a long tail at the upper end. Although we exclude outliers, this is not enough for the upper end. The figure on the right-hand side is a distribution of revenue growth rate under the value of 100%. It seems to distribute properly and outliers created an adverse result for a single logistic regression.

Figure 7: Distribution of Revenue Growth Rate



Source: Authors.

In order to exclude the impact of outliers for certain, we used a very simple method. We categorized revenue growth rate data by dividing into 10 groups according to the value and allocated a score to each group.

Table 1: Threshold of Revenue Growth Rate in Each Group

Rank	1	2	3	4	5	6	7	8	9	10
Value	<-22.69%	<-12.5%	<-6.83%	<-2.85%	<0.34%	<3.75%	<8.47%	<16.18%	<33.92%	>=33.92%

Source: Authors.

Thus, bigger data were absorbed in the highest group. We tried again to perform a single logistic regression of the categorized revenue growth rate and confirm that the revenue growth rate is adequately significant as we expected.

Although the CRD is made from relatively clean and consistent data by cleansing, we need to manage data handling under the distribution of data to create candidates for the scoring model. Moreover, sophisticated data-handling skill can contribute fully to increasing the accuracy of the scoring model.

3.3 Model Building and Validation

Next, we fix the model structure and perform an estimation of significant financial indexes. We can make up financial indexes in order according to the significance level individually. However, putting the financial indexes sequentially into a model in accordance with the level of significance does not necessarily succeed in creating a good scoring model from the statistical and practical viewpoints.

From the statistical viewpoint, a combination of financial indexes is very important because there are some financial indexes that are correlated or complementary. It is certainly important that a scoring model has high explanatory power and stability even without correlation and being complementary.

From the practical viewpoint, it is also very important that a scoring model is composed of a combination of unbiased financial indexes covering the stability, profitability, efficiency, and growth potential of the ongoing business, and for the users to be familiar with the financial analysis, that it is easy to use practically.

Generally, the entire data set is not used to create the scoring model and part of the data set is set aside. Though it is understandable that a scoring model fits the dataset from which it was made, i.e. in-sample data, it is not clear whether it definitely fits in actual use. Therefore, we need to confirm the fitness of the scoring model against out-of-sample data before concluding the operation. It is important to perform a validation with out-of-sample data. If a scoring model can get a high accuracy ratio even against out-of-sample data, we will find that this scoring model is accurate and stable and will be sustainable in actual use.

4. MAINTAINING THE QUALITY

We explain three schemes the CRD established to maintain the quality of the CRD and the scoring model based on it.

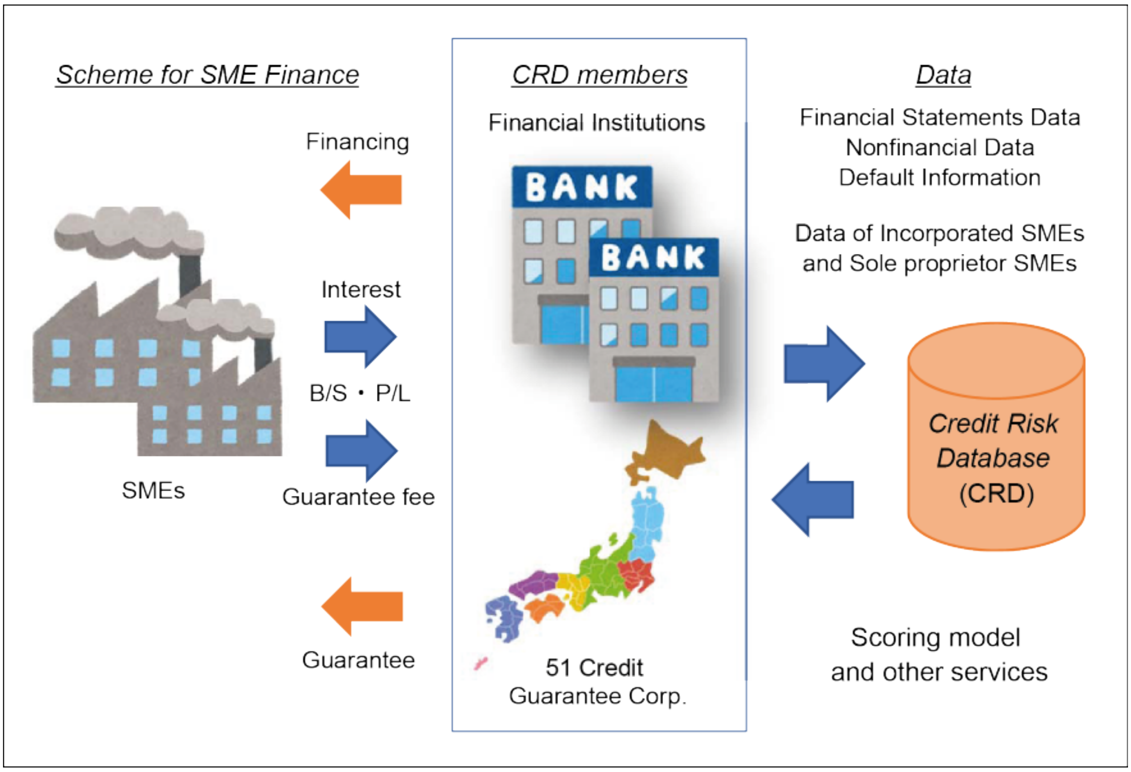
4.1 Data through the Scheme for SME Finance

The CRD does not collect financial statements from SMEs directly but through the mechanism of SME finances. When SMEs borrow money from financial institutions, they submit their financial statements to those financial institutions. If SMEs are guaranteed by the Credit Guarantee Corporations (CGCs), the financial institutions pass the financial statements over to the CGCs. Throughout the loan and guarantee period, financial institutions and CGCs ask SMEs to submit their financial statements so that they can monitor the SMEs' business situation and confirm the certainty of repayments.

Collecting data through this scheme helps maintain the high quality of the database besides making it easy to collect abundant financial statements. There are many financial institutions that require 3 consecutive-year financial statements for the initiation of a deal. This enhances not only the quality of screening, but also the exclusion of window dressing because it is difficult to make noncontradictory financial statements over 3 years fictionally.

Before putting the SMEs' financial statements into the CRD, these are screened and corrected by financial institutions or CGCs as part of their examining process, enhancing the accuracy of the database and the effectiveness with a view to better evaluating the SMEs' creditworthiness (Figure 8).

Figure 8: Circulation of Data and Services



B/S = balance sheet, P/L = profit and loss statement, SME = small and medium-sized enterprise.

Source: Authors.

4.2 Data Cleansing

The second scheme for maintaining the quality of the CRD is data cleansing. The submitted data are cleaned and consolidated before being put into the CRD. Data cleansing is conducted twice, which means that the CRD performs basic cleansing and more rigorous cleansing. When the CRD receives the data from member institutions, first, cleansing as a basic cleansing is performed. The CRD creates each member's database after this operation. We describe part of the cleansing methods as an example (Table 3).

Before the CRD consolidates a member's database, a second, more rigorous cleansing is performed. This process is more rigorous than the previous one in order to unify each member's database into one database. After these cleansings, the database needs to consolidate the data of the same borrowers.

These processes enable us to create a high-quality database and we monitor the quality of data continuously.

Table 2: Examples of Cleansing

An Example: 1st Cleansing	An Example: 2nd Cleansing
• Check the condition as follows • Current assets ≦ Assets • Fixed assets ≦ Assets	• Check the condition as follows • Asset ≒ Current assets + Fixed assets + Deferred assets Summing up details (making few allowances)

Source: CRD Association of Japan.

4.3 Validation Framework

The CRD Association established a scheme that evaluated the CRD models objectively in order to maintain the quality of the models and to acquire reliance on its services. They formulated the guidelines on the model development, model operation, and model validation over a decade ago. In accordance with the guidelines, they organized the Third-Party Evaluation Committee, composed of prominent scholars and bankers with expertise in this field. The committee assesses the outcome of regular validation performed by the CRD Association, identifies problems, and gives suggestions for the improvement of accuracy.

The CRD Association performs a structured validation menu yearly, which the Third Party Evaluation Committee discusses and determines in consultation with the SME Credit Insurance Act and the Financial Service Agency's notification of requirements for banks selecting an internal rating approach of Basel standards.

The checkpoints on the validation are as follows:

(1) To check the transition of actual data as compared with the data that the current models are based on

If the tendency of data has changed considerably since their construction, it is necessary to check the necessity of the modification of models.

(2) To check the accuracy ratio (AR) of the models

This validates whether enterprises given low evaluations (high PD) did indeed default. AR is an index to measure the accuracy of the model that takes a value from 0 to 1. If the accuracy of the scoring model is higher, the value is closer to 1. We can find the concrete calculation and statistical background in the Basel Committee's working paper (2005).

(3) To compare PD with the actual default rate

This method separates data into groups according to the value of PD and compares the average PD with the actual default rate in each group. We can validate whether PD as a predicted value differs or not from the default rate as an actual value.

(4) To check the stability of the model

This validates the result of (2), (3), and so on over time and confirms the stability.

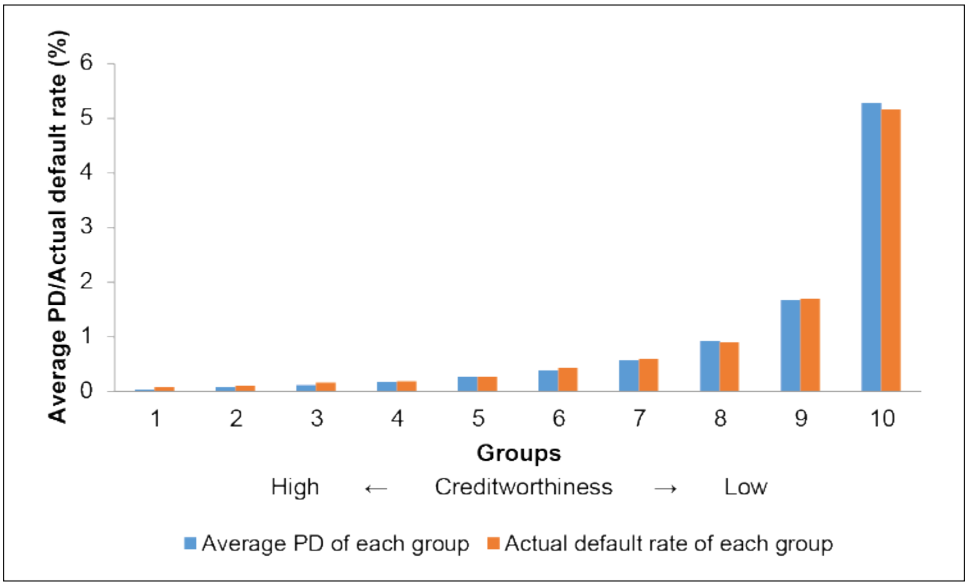
(5) To check the explanatory ability of the variables to detect default

This validates the discriminatory power of variables in accordance with the structure of the model.

The figure below compares the scoring model's estimations with actual results. We indicate it as an example of checkpoint (3).

As you can see, we divided the SMEs into 10 groups based on the outcomes of the scoring model, by probability of default (PD), with group 1 being the most creditworthy and group 10 the least creditworthy. The average PD of each group almost corresponds to the actual default rate in each group.

Figure 9: Conformity between PD and Actual Default Rate

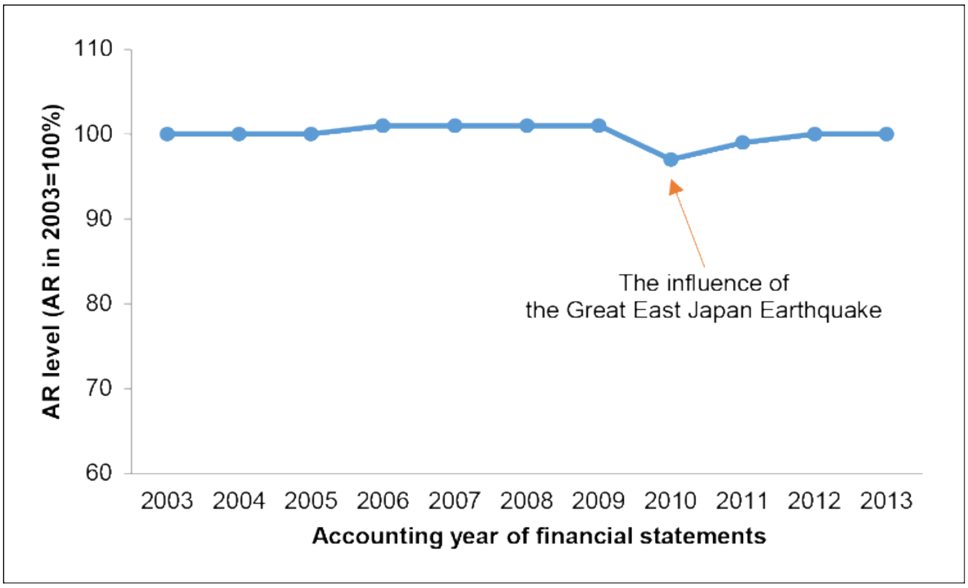


Source: CRD Association of Japan (2016).

The next figure shows the transition of the accuracy ratio (AR) for the CRD model. We indicate it as an example of checkpoint (2). A higher AR value means more accuracy. The AR value is normalized to the value in 2003 in Figure 11. AR is a statistical method for evaluating the accuracy of a model, i.e. whether the model could identify nonhealthy SMEs and estimate low scores (high PD) for the default borrowers beforehand from their financial statements. As shown in the figure below, the AR value for the CRD model has been consistently stable.

Figure 10: Transition of Accuracy Ratio (AR)

(%)



Source: Authors.

The model cannot handle the situation for a natural disaster like the Great East Japan Earthquake, because all the SMEs, regardless of the evaluation of the model, would be influenced by the disaster. But this is an exception, a very rare case, and went back to the former level of AR briefly.

At the time of the Lehman shock, although the accuracy of the CRD model did not deteriorate, even the relatively large banks revised their in-house models due to lowering of the accuracy. The CRD model is very robust because of having been created from a large number of data and having many variables.

With regard to checkpoint (5), we would like to mention the need to disclose the model structure to users. Explanatory variables are validated individually. If some variables are ineffective in predicting defaults over time and the accuracy of the scoring model has declined because of this, it is preferable to consider replacing them and reconstructing the scoring model.

If the scoring model is a black box, we cannot perform a causal analysis. If the AR has declined, we need to break down the reason into its basic components. If we recognize the structure of the model, we can try to improve the accuracy of the model by replacing ineffective variables with alternative ones. It is very important to grasp the details of the scoring model's structure in order to maintain its quality.

5. ACTUAL USE OF FINANCIAL INFORMATION AND THE CRD SCORING

Next we explain the actual use of financial information and the CRD scoring model from the functioning aspect, as in 5-1, Base of evaluation; 5-2, Benchmark; and 5-3, Mutual yardstick. Kuwahara et al. (2016) introduce a variety of the CRD services to members and the overall usage of such services. We cover some of them and add another relevant fact in this chapter.

5.1 Base of Evaluation

We can define the usage of the CRD model in the internal rating system of financial institutions as a base of evaluation. Because the evaluation of an internal rating system relies heavily on the financial evaluation, the accuracy of the internal rating system is affected by the accuracy of financial evaluation. It is necessary for financial institutions to use a highly accurate and stable scoring model for their internal rating system.

First, they group customers into categories in accordance with the degree of estimated PD based on the CRD scoring models. Then they develop their internal rating systems taking other attributes such as qualitative items into account.

As we described earlier, if we can use a very large number of data to create a scoring model, we can acquire an eminent scoring model. The model made from the CRD corresponds precisely to it. Small-scale financial institutions do not have many customers and cannot accumulate a large number of data for creating a model by themselves.

The same applies to medium-scale financial institutions. Even for large-scale financial institutions, using the CRD model for their internal rating system has an advantage. Because the CRD model was made from a much bigger data set than those of a single financial institution, the accuracy of the model can be robust even at a time of economic change. Some large-scale financial institutions seemed to remodel their in-house model after the Lehman shock due to the deterioration of their model. Although the CRD pulled up the level of PD for its scoring model in accordance with the rise of the actual default rate in the recession after the Lehman shock, the CRD did not need to change its model structure because the accuracy of the CRD model was maintained.

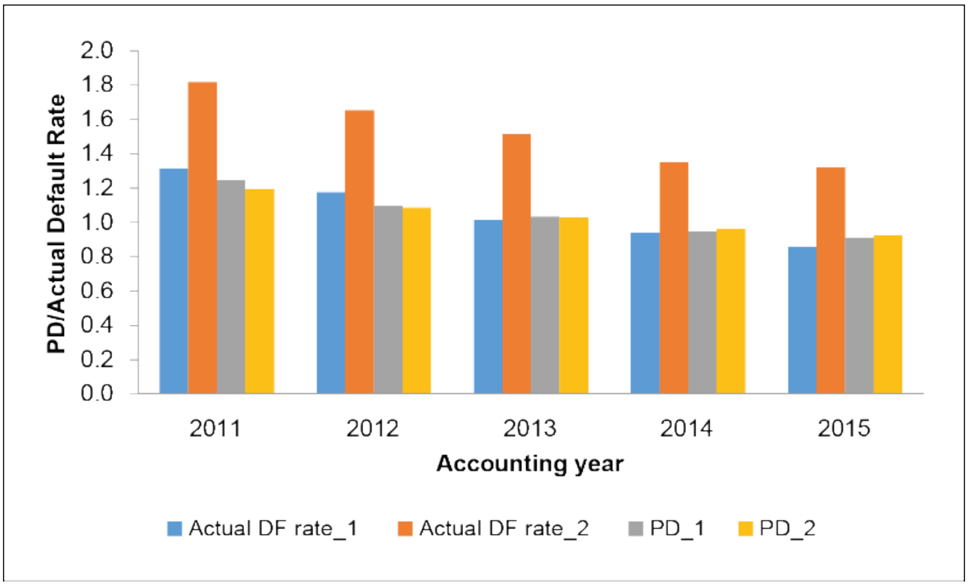
Another actual usage for an internal rating system is to use a sample data service. Members can use random sampling data of financial statements when they do not have sufficient financial statement data in order to create their in-house model and to validate the accuracy of their model with out-of-sample data. The CRD provides members with anonymous data of various industries in each region to meet the needs of members. It can contribute to enhancing the quality of members' internal rating system.

This is an important reminder for financial institutions to establish the proper internal rating system. Evaluation by the CRD model is effective and a robust base, however it is not versatile. It is dangerous that evaluation of an internal rating system relies only on the outcome of a scoring model. A scoring model naturally cannot evaluate the conditions excluded from variables and cannot take in all the conditions of SMEs. If the scoring model is made only from financial statements, it should be complemented by adding other risk factors outside the model.

The CRD scoring model for incorporated SMEs is made from only financial statements. Here we indicate some examples and hope to draw readers' attention through concrete examples using qualitative data of the CRD.

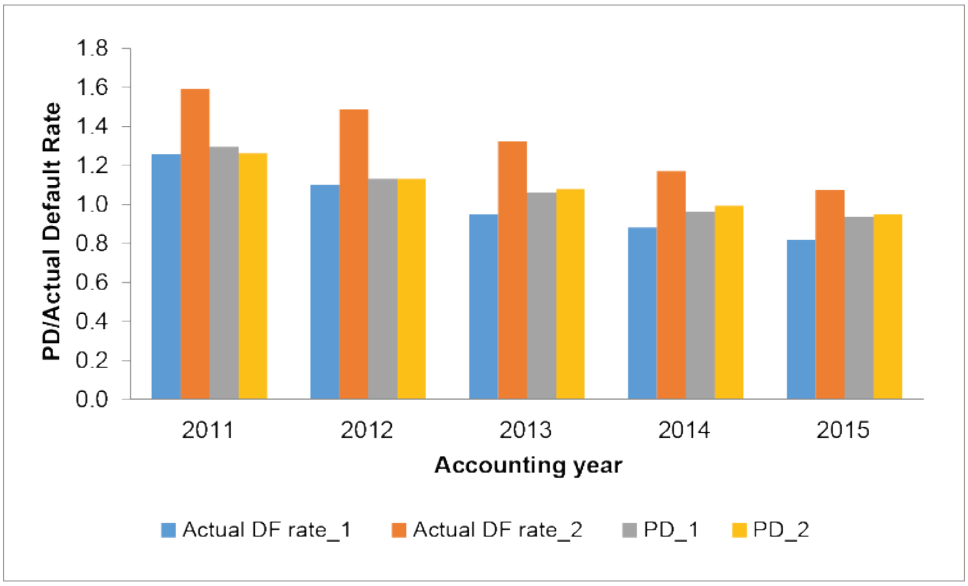
The first example is the difference in the actual default rate between SMEs that have real estate and those that don't. It includes real estate not only in a company's name, but also in a personal name.

Figure 11: To Have or Not to Have Real Estate
(%)



Note: 1 = SMEs having real estate, 2 = SMEs not having real estate.
Source: Authors.

Figure 12: To Have or Not to Have a Successor
(%)



Note: 1 = SMEs having a successor, 2 = SMEs not having a successor.
Source: Authors.

Although the PD in both categories shifts in a similar way, the actual default rate of not having real estate shifts to a high level. Not having real estate becomes an indication of heightening of default.

The next example is the difference in the actual default rate between the SMEs that have a successor and those that don't have one. Although the PD in both categories shifts in a similar way, the actual default rate of not having a successor shifts to a high level. Not having a successor also becomes an indication of heightening of default.

We are not sure whether these examples are always true in various countries. However, it is necessary to supplement a scoring model made from financial statements with nonfinancial attributes, such as industry trends, business base, qualification of management, operation action, and so on, in an internal rating system. Each financial institution needs to take in nonfinancial aspects fitting to its customers.

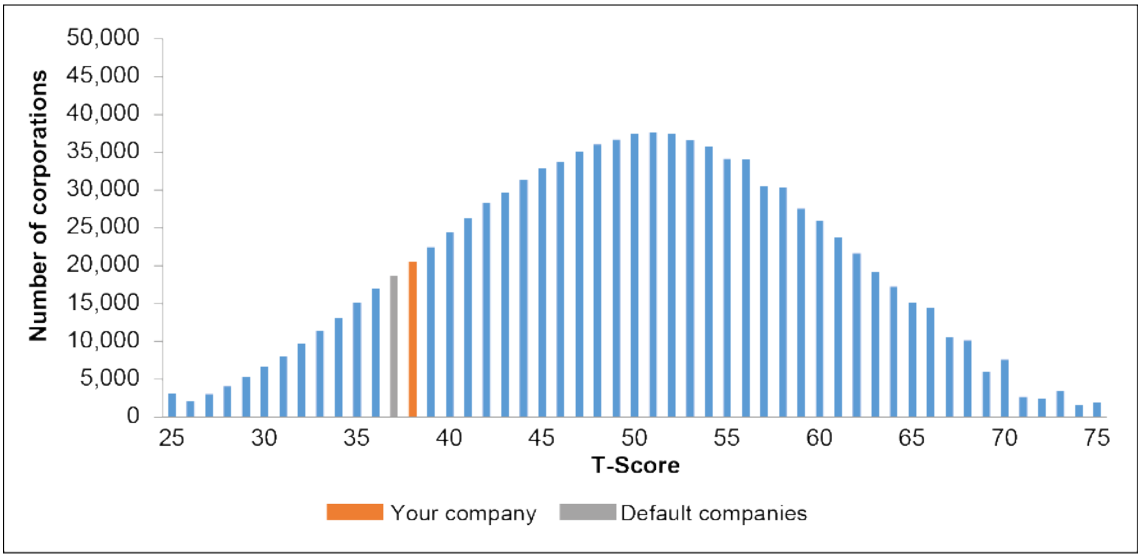
5.2 Benchmark

Next is the usage of the scoring model and financial information of the CRD as a benchmark. Although a scoring model can evaluate the creditworthiness of each SME, it is not easy to grasp the extent of goodness or badness of each SME's condition compared to that of all SMEs. The CRD provides members with a Management Consulting Support System (McSS), which evaluates the financial conditions of borrowers using the CRD model and shows their relative creditworthiness compared with accumulated data in the CRD. There are almost one million financial statements for one accounting year in the CRD. The figure below shows the distribution of about one million scoring results of financial statements in the CRD, which are converted to a T-score. Users can grasp the relative evaluation of an SME ("Your company") compared to one million SMEs. "Your company" is placed at 38 (dotted bar chart) near the mean of default companies (37) and is not relatively creditworthy. McSS also rank "Your company" within a subgroup, its prefecture (ex. Tokyo), the same industry sector (ex. manufacture of transportation equipment group), and similar firm size (ex. same scale of sales, $1million-$3million).

Users can also perform a "future simulation (for improved management of client SMEs)." Users simulate increase in sales, cost-cutting, reduction of repayment and so on as a remediation plan and create estimated balance sheet and profit and loss statements. The CRD model in McSS evaluates creditworthiness of this estimated financial statements. Users can grasp the extent of improvement compared to the evaluation of one million SMEs. The figure below indicates the relative position of "Your company" in the future when the plan has been accomplished well. If the future plan is accomplished, "Your company" will improve its financial condition fully and move up to a T-score of 53 within 5 years.

Members' financial institutions can share the future image with their clients by using the CRD model and data as an evaluation benchmark. This will contribute to improving communication between them.

Figure 13: Sample of Evaluation in McSS

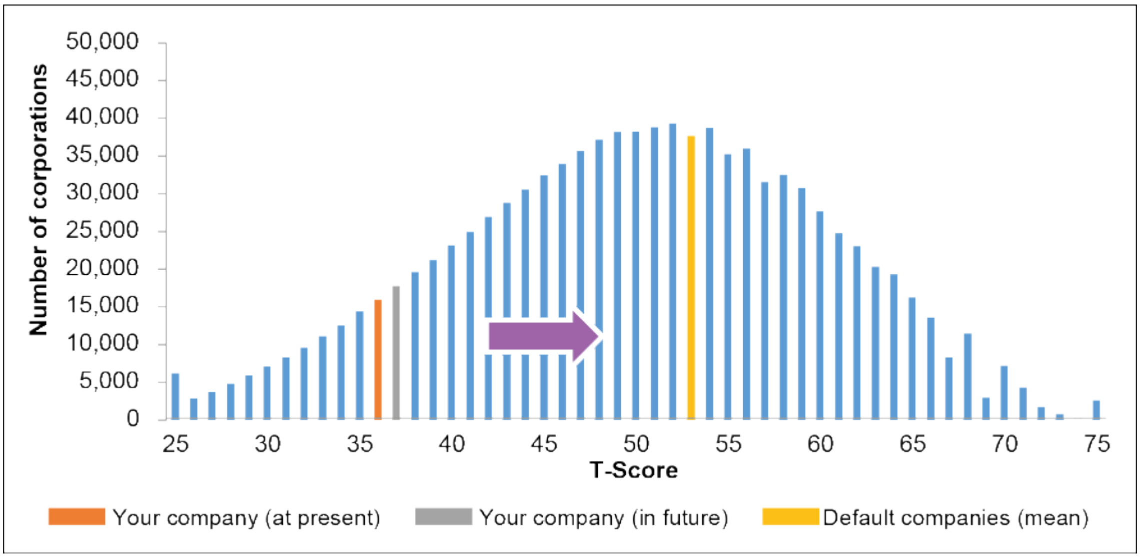


Fiscal Term	CRD Rank (A～E)	Your Company T-Score	Default Companies T-Score (Mean)	Ranking in the "Manufacture of Transportation Equipment" Group	Ranking in Tokyo	Ranking in the Same Scale of Sales	
						Category	Ranking
March, 2017	D	38	37	7,200 (in 8,000)	120,000 (in 140,000)	$1 to $3 million	220,000 (in 250,000)
March, 2016	C	45	37	6,000 (in 8,000)	91,000 (in 140,000)	$1 to $3 million	175,000 (in 250,000)
March, 2015	C	46	37	5,700 (in 8,000)	85,000 (in 140,000)	$1 to $3 million	165,000 (in 250,000)

*These numbers are imaginary. The same hereinafter.
Source: CRD Association of Japan.

McSS also includes the function of evaluating the reasonability of the plan. Under the plan, it prepares the forecast financial statements and calculates the increase rate of main items such as revenue, account payable, and so on. Then it assesses this increase rate to be excessive or undervalued compared to the average rate of the CRD data and gives a warning in such cases. The large number of the CRD data contributes to creating a proper plan as a benchmark.

Figure 14: A part of the future evaluation in McSS



Fiscal Term	CRD Rank (A～E)	Your Company T-Score	Default Companies T-Score (Mean)	Ranking in the "Manufacture of Transportation Equipment" Group	Ranking in Tokyo	Ranking in the Same Scale of Sales	
						Category	Ranking
March, 2016	C	45	37	6,000 (in 8,000)	91,000 (in 140,000)	¥100 to ¥300 million	175,000 (in 250,000)
March, 2017	D	38	37	7,200 (in 8,000)	120,000 (in 140,000)	¥100 to ¥300 million	220,000 (in 250,000)
One year later	C	45	37	6,000 (in 8,000)	91,000 (in 140,000)	¥100 to ¥300 million	175,000 (in 250,000)
2 years later	C	48	37	6,000 (in 8,000)	91,000 (in 140,000)	¥100 to ¥300 million	175,000 (in 250,000)
3 years later	C	48	37	6,000 (in 8,000)	91,000 (in 140,000)	¥100 to ¥300 million	175,000 (in 250,000)
4 years later	C	49	37	6,000 (in 8,000)	91,000 (in 140,000)	¥100 to ¥300 million	175,000 (in 250,000)
5 years later	B	53	37	3,800 (in 8,000)	55,000 (in 140,000)	¥100 to ¥300 million	125,000 (in 250,000)

Source: CRD Association of Japan.

5.3 Mutual Yardstick

As regards the usage of a credit scoring model as a mutual yardstick in some financial system, we can cite a case of a credit supplementation system. When SMEs borrow money from financial institutions, they can be guaranteed by credit guarantee corporations because of paying a credit guarantee fee to the regional credit guarantee corporation.

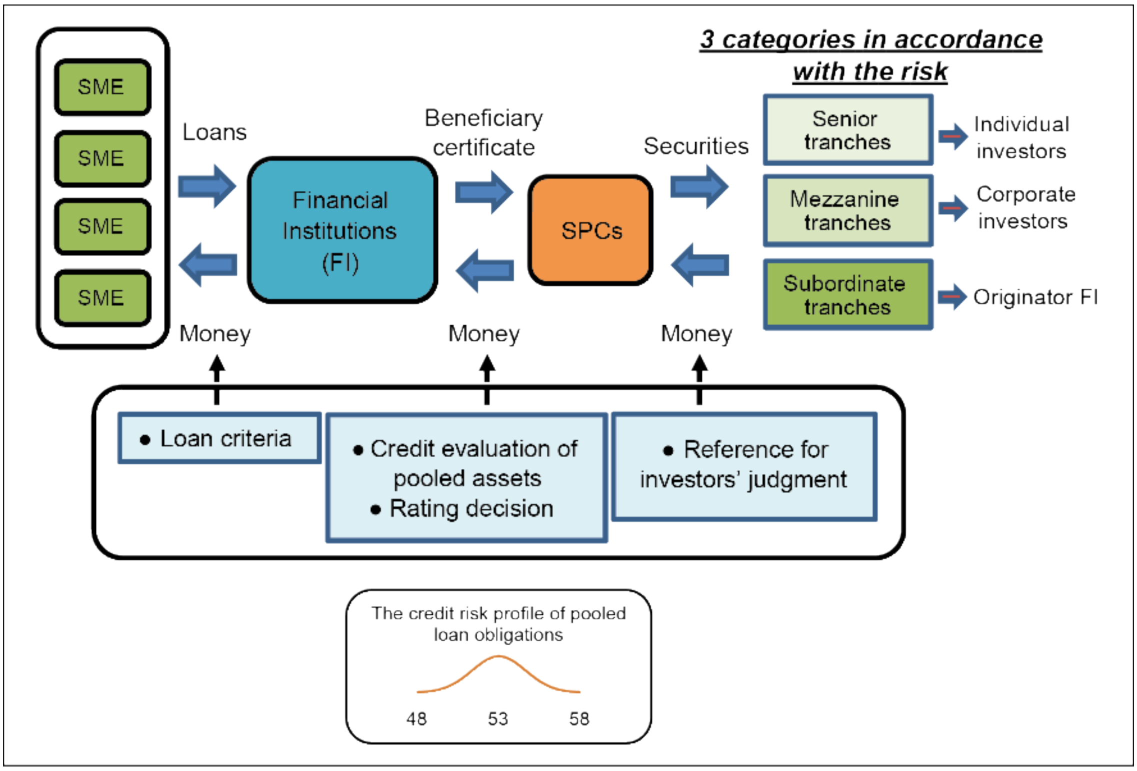
Table 3: Credit Guarantee Fee Rate
(%)

Classification	Uniform
Credit guarantee fee rate	1.35

Classification	1	2	3	4	5	6	7	8	9
Credit guarantee fee rate	2.20	2.00	1.80	1.60	1.35	1.10	0.90	0.70	0.50

The credit guarantee fees were uniformly 1.35% before April 2006. These changed to a risk-based fee. The classification of the credit guarantee fee was divided into 9 according to SMEs' creditworthiness, i.e. PD by the CRD scoring model. It brought fewer burdens than before for healthier SMEs and more financing opportunities for less healthier SMEs. Each regional credit guarantee corporation and financial institution as the CRD members can share the credit information of client SMEs, evaluate by using the same CRD model, and can facilitate providing funds to SMEs more easily.

Figure 15: CLO Scheme



Source: Authors.

Besides the use of a scoring model in a credit supplementary system, we can refer to usage in a supervisory agency as a mutual yardstick. Evaluating borrowers in different institutions by the same model is effective in comparing the situations among them. The supervisory agency does not have a mutual yardstick except for this.

Another example is usage in a collateralized loan obligation (CLO) scheme. CLO is a kind of asset-backed security and a way of fundraising from the capital market through securitization of pooled loans. The figure shows a very brief sketch of a CLO scheme. A bank extends traditional loans to each SME, then bundles the SME loans and transfers them to the SPC. The SPC issues securities backed by the said pool of loans to investors. In this way, investors provide funds to the SMEs through the SPC and the bank.

In the process of the CLO scheme, the risk evaluation of bundled loans is indispensable: first, loan criteria for selecting loans to be bundled; second, credit risk evaluation of pooled assets; third, reference for investor judgement. When the originator bank bundles SME loans into a pool, the CRD scoring of each SME loan is employed as a criterion for the selection of loan obligations. The originator indicates the holistic risk profile of the pooled loan obligations.

The arranger classifies CLOs into several tranches, usually senior, mezzanine, and subordinate. After the classification of CLOs, the senior tranches and the mezzanine tranches are sold to investors, while the subordinate tranches are generally taken back to the originator banks. Investors can refer to the credit risk profile and external ratings of rating agencies for their investment judgement.

The recent extremely low level of the interest rate has made it difficult to cover the issuance and servicers' management cost of CLO in Japan. In Asian countries, interest rates are higher than in Japan, so it is possible to hold a sufficient margin and develop SME CLO markets. Therefore, we suppose that the securitization of SME loans is still a hopeful measure for broadening fund provision to SMEs in Asian countries. The establishment of credit risk databases and a scoring model based on the CRD is almost indispensable for its development.

6. CONCLUDING REMARKS

In the 1980s in Japan, financial institutions relied heavily on the land collateral to avoid information asymmetry between lenders and borrowers with rising land price as a backdrop. However, a collapse of the bubble economy occurred and the land price started to decline drastically in 1992. Financial institutions were forced to change their lending methods based on land collateral. Due to the long-lasting dependency on land collateral, financial institutions lost their ability to screen and monitor borrowers. As a result, credit withdrawal and a credit crunch have occurred. To cope with this situation, the Small and Medium Enterprise Agency of the Ministry of Economy, Trade, and Industry allocated funding for the development and demonstration of the systems required for the CRD. The number of the CRD members was 58 at the time of establishment in 2001. First, credit guarantee corporations throughout Japan became the core of the membership system. Then, many financial institutions followed in joining and the number of members has now expanded to 180.

Similarly, in other Asian countries, SMEs with little collateral have difficulty in gaining access to enough funding, and the implementation of risk-based pricing is difficult to achieve due to the information asymmetry problem and the lack of a proper risk evaluation tool. As we mentioned at the beginning, the Asia SME Finance Monitor (ADB 2015) suggests developing financial infrastructures, credit bureaus, collateral registries, and sustainable credit guarantee schemes to improve SMEs' limited access to finance. We propose adding the CRD and the scoring model based on it to such a set of financial infrastructures in order to ensure the broadening of SMEs' financial access. Yoshino and Taghizadeh-Hesary (2014, 2015) and Yoshino et al. (2016) actually developed credit scoring models based on different samples of SMEs' financial statement data in other countries. These models are applicable to financial institutions for reducing the information asymmetry. They showed that the use of a comprehensive scoring model by financial institutions will not only help them to reduce the nonperforming loans but will also help them to find new lending sources and increase the flow of funds to the SME sector, which can secure the growth of this sector and contribute to economic growth in developing Asia.

The CRD maintains the qualities of its database and scoring model through the use of some methods. The CRD collects many financial statement data through the mechanism of SME finances. Financial institutions require SMEs to provide financial statements for their screening and monitoring of SMEs. The CRD collects financial statements from financial institutions after financial institutions exclude manipulated and inconsistent financial statements. This collecting scheme contributes to enhancing the quality of the database. In addition to that, the submitted data from members are cleaned and consolidated before being put into the CRD. This process contributes to further enriching the quality of the database. Also, there is a scheme that evaluates scoring models objectively in order to maintain the quality of the scoring model and to acquire reliance from members. Generally, the scoring model tend to deteriorate over time. The scoring model is validated once a year and the quality of the scoring model has been maintained. Methods like these are needed for the CRD to operate soundly.

Because of their transience in business, it is difficult to foresee the future of SMEs. Nevertheless, we explain the effectiveness of establishing the CRD in this paper. Although each financial institution or credit guarantee corporation has a limited number of data, members can take advantage of consolidating their data. Statistical information about the CRD contributes to grasping the characteristics of SMEs, and the statistical scoring model based on the CRD is a reliable tool for evaluating the creditworthiness of SMEs.

A scoring model works as a base of evaluation, a benchmark, a mutual yardstick, and so on. We illustrate ways of making use of the CRD and the scoring model through some examples. We expect that the introduction of actual uses will be sufficient to awaken the interests of readers and help to deepen their understandings of the CRD. We hope our experience contributes introduction of the CRD composed of a large number of anonymous financial statement data in other countries and the CRD helps to improve SMEs' financial access as a financial infrastructure.

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