Analysis of Credit Risks in Bank Loans

(Summary)

This paper constructs and estimates a model to assess the credit risk of the loan portfolio using anonymized data of the financial statements and credit profiles of corporate borrowers from 62 member banks of the Regional Banks Association of Japan. The model provides a general picture of observed historical trends in the default proportion over the past approximately 20 years, and will be used to quantitatively understand the impact of changes in the economic and financial environment on credit risk in the corporate sector, while continuing to be improved.

I. Purpose

Bank loans to the corporate sector play an important role in Japan's financial intermediation, and therefore it is important to understand their trends and risks not only in terms of their impacts on the soundness of each bank but also in terms of the resilience and vulnerability of the financial system as a whole. In recent years, financial authorities in various jurisdictions and international organizations have been enhancing their analyses of the credit risk in bank loans from a macroprudential perspective, by utilizing granular data, such as individual corporate financial data and loan level data, to grasp changes in the risks of individual enterprises in more detail and analyze the impact of such changes on the financial system as a whole.

The purpose of this analysis is to develop a model for estimating borrowers' credit risk in order to quantitatively understand the trend in the financial system. Specifically, this paper modelled the relationship between an individual borrower's probability of default and its financial condition as well as the macro financial environment, using regional banks' loan data. The paper also estimated how changes in economic and financial conditions affect the probability of default of the corporate sector as a whole, using the model developed. It should be noted that the analysis in this paper does not take into account changes in various policies and regulations or differences in each banks' approaches to credit risk management and does not intend to discuss how they should be.

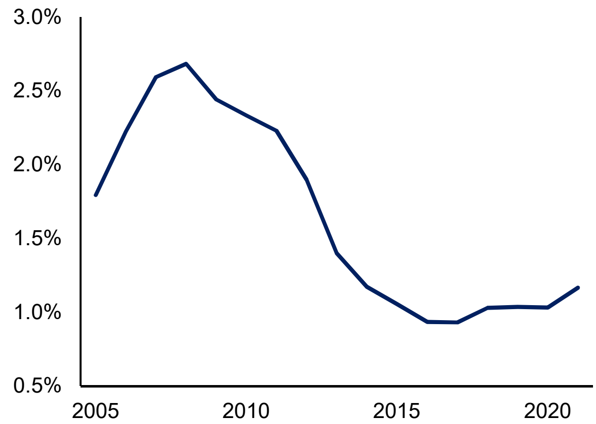
The estimation uses anonymized data of the financial statements and credit profiles of corporate borrowers from 62 member banks of the Regional Banks Association of Japan. The total number of samples for this data is approximately 50 million based on quarterly data from the end of March 2004 to the end of June 2022. Corporate financial information includes basic data such as profits and total assets for each borrower. Credit information includes outstanding loan amounts and borrower ratings by each bank (six categories: "normal," "needs attention," "needs management," "in danger of bankruptcy," "de facto bankrupt," and "bankrupt").

II. Trends in borrowers' financial conditions and defaults

In this paper, “default” is defined as when a borrower with a credit rating between "normal" and "needs management" experiences a downgrade to "in danger of default" or below for the first time within one year after the balance sheet date[3]. Such definition of default based on the borrower ratings is widely used in existing academic research on credit risk models and credit risk management practices in financial institutions.

Figure 1 shows the proportion of borrowers that achieved ratings of "needs management" or higher (non-defaulters) each year but were downgraded to "in danger of default" or lower (defaulters) for the first time in the following year (hereinafter referred to as the "default proportion"). This figure shows that the share of defaulters increased around 2009 and then decreased.

Figure 1 Default proportion (all industries[4])



Defaults of corporate borrowers are affected by various factors; for example, their financial conditions such as interest payment, as well as the business conditions of the sector they belong to

[3] Other definitions may include a requirement that payments be in arrears for at least 90 days. For simplicity, this paper focuses only on borrower rating; however, conditions adding delinquency to the definition of default did not significantly change the overall results of our analysis.

[4] Financial, insurance and public service were excluded (hereinafter the same in this section).

and the macro financial conditions. First, defaults of corporate borrowers increase as the interest payment of each borrower increases. To confirm this point, borrowers were grouped according to the level of interest coverage ratio[5] (ICR), which is generally used as an indicator of the interest payment burden of borrowers. Figure 2 shows the proportion of defaulters in each group. Each blue dot in the figure corresponds to the average ICR and the default proportion of each group. This figure indicates that when the ICR declines below zero (i.e., when the interest payment increases), the default proportion sharply increases.

Next, differences are observed in trends in default proportion among various industries (manufacturing, wholesale and retail, construction and real estate, and all industries) (Fig. 3). For example, the default proportion in the construction and real estate sectors rose sharply around 2009 but has since stayed at a low level compared with other sectors. On the other hand, the increase in the default proportion in the manufacturing sector around 2009 was smaller than that in other sectors, and the decrease thereafter was also smaller. This suggests that borrowers' defaults are affected by industry-specific factors, such as changes in the business conditions of the sector.

In addition, default trends among borrowers are affected not only by funding demand-side factors, such as borrowers' financial conditions, but also by changes in the macro financial environment, including funding supply-side factors. The green and red dots in Figure 2 show the relationship between ICR and default proportion in each ICR level in 2008 and 2016, respectively. This figure indicates that, even at the same level of ICR, the default proportion was higher in 2008 when financial conditions were relatively tight (red dots) than in 2016 (green dots). In particular, such a difference is clearer in the low ICR area (especially where the ICR is zero or less).

The relationship between the financial environment and the default proportion can also be seen in time series. The blue-shaded area in Figure 3 shows the trend in the lending attitude DI[6] for financial institutions, which is used as a proxy variable for the financial environment. There is a certain correlation between the trend of lending attitude DI and that of default proportion: as the lending attitude DI declined (i.e., financial conditions tightened), the default proportion increased. This result suggests that the macro financial environment has a certain impact on borrowers' default trend.

[5] Interest coverage ratio = (operating income + interest and dividend income) / interest and discount expenses

[6] Source: Bank of Japan, "National Short-Term Economic Survey of Enterprises in Japan." This indicator is an index of survey respondents' assessment of financial institutions' lending attitudes. It is calculated by subtracting the percentage of enterprises that answered "severe" from the percentage of enterprises that answered "accommodative" with respect to financial institutions' lending attitude.

The lending attitude DI could be affected by banks' lending decisions as well as domestic and overseas economic and financial developments. Therefore, it should be noted that the estimation formula in this paper does not necessarily indicate a causal relationship in which the default rate changes as a result of changes in the lending attitude of financial institutions.

Figure 2 Relationship between ICR (horizontal axis) and default proportion (vertical axis)[7]

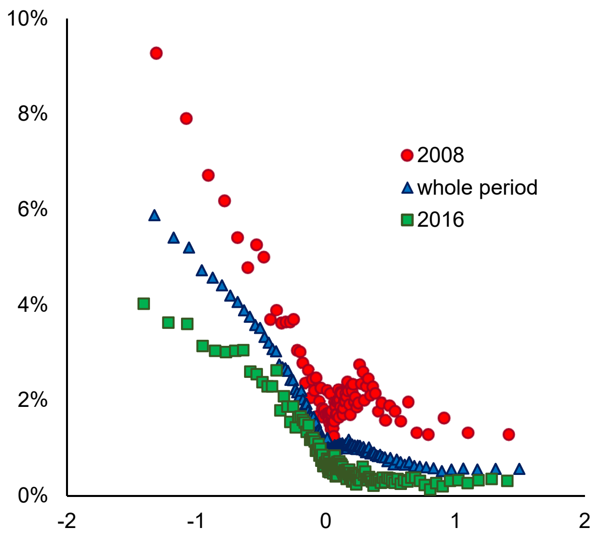
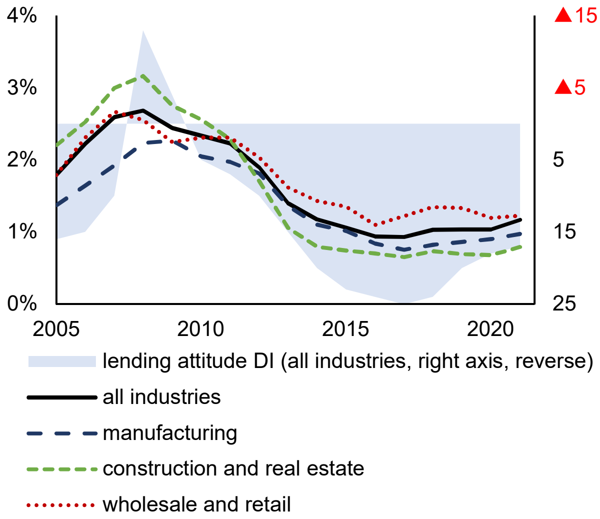


Figure 3 Default proportion by industry and lending attitude DI



III. Models and results

Based on the relationship between borrowers' financial condition, financial environment, and default, this paper develops and estimates a credit risk model. As a modeling policy, the paper tried to make the model as simple as possible while accurately capturing the relationship observed in the previous section. Specifically, the relationship between borrowers' financial variables and financial conditions and defaults was formulated and estimated as the logit model below for each industry group.

$$log\frac{p_i}{1-p_i} = \beta_{0,j}+\beta_{1,j}\cdot ROA_i + \beta_{2,j}\cdot interest_i + \beta_{3,j}\cdot lendingDI_j+\varepsilon_i$$

The dependent variable[8] is the probability that borrower i will default within one year after the balance sheet date (p_i; hereinafter referred to as the "default probability"). As explanatory variables, the following variables are used: operating income ROA (ROA_i), interest rates paid[9] ($interest_i$) which constitutes ICR, and the lending attitude DI (DI for industry group j to which borrower i belongs: $lendingDI_j$) to represent changes in the financial environment. $\beta_{0,j}, \beta_{1,j}, \beta_{2,j}, \beta_{3,j}$, are parameters to be estimated and ε_i represents the error term. The industry types were classified into nine groups: material-related manufacturing, processing-related manufacturing, other manufacturing, construction, wholesale, retail, real estate, services, and infrastructure.

7 For ICR, the refraction ICR was calculated and then exponentiated and neglog transformed.
8 Samples with missing data elements were excluded from the dataset used for estimation.
9 Interest rates paid are calculated as interest and discount expenses divided by loans payable.

Table 4 shows the estimation results for each industry group. Each factor is statistically significant at a significance level of 1% for most of the groups. In addition, the sign of each coefficient implies an increase in the default probability due to a decrease in profitability, an increase in interest rates paid, and a decrease in the lending attitude DI. All of these are consistent with the relationship between default proportion, ICR and financial environment, which was observed from historical data in the previous section. On the other hand, the values of coefficients vary among industry groups. This indicates that the possible effects of operating profits, interest rates paid, and financial conditions on the default probability tend to vary by industry, and the models capture these industry-group specific characteristics.

Table 4 Estimation results for each industry group[10]

	material-based manufacturing	processing manufacturing	other manufacturing	construction	wholesale	retail	real estate	service	infrastructure
ROA	-5.54	-5.45	-4.89	-3.45	-6.10	-4.23	-7.50	-3.02	-6.36
Interest Rates Paid	52.17	45.34	47.69	32.49	44.99	58.77	64.40	42.50	51.11
Lending Attitude DI	-0.018	-0.022	-0.016	-0.024	-0.010	-0.006	-0.032	-0.016	-0.015 ◆
Constant	-5.50	-5.22	-5.28	-4.80	-5.05	-5.36	-6.13	-5.09	-6.15
Pseudo-R-squared	0.102	0.103	0.087	0.085	0.087	0.087	0.106	0.080	0.108

In addition, the estimated models generally capture the actual trend of default proportion. In order to check the accuracy of the estimation, the paper compared the estimated all-firm default probability (average of estimated borrower-level default probability) to the actual default probability (actual default proportion) as shown in Figure 5. Although there are some discrepancies, the estimates generally capture the movement of the past actual default proportion. Figure 6 compares estimates with actual default proportion for each industry group. Similar to Figure 5, the estimates by industry group also capture the movements of past actual default proportion.

10 ◆ indicates significant level of 5%, otherwise 1%.

Figure 5 Actual default proportion and estimated default probability

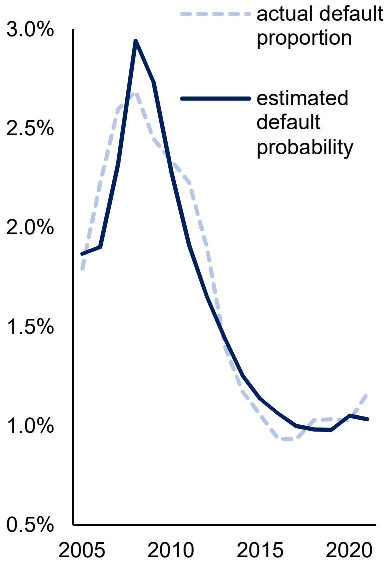
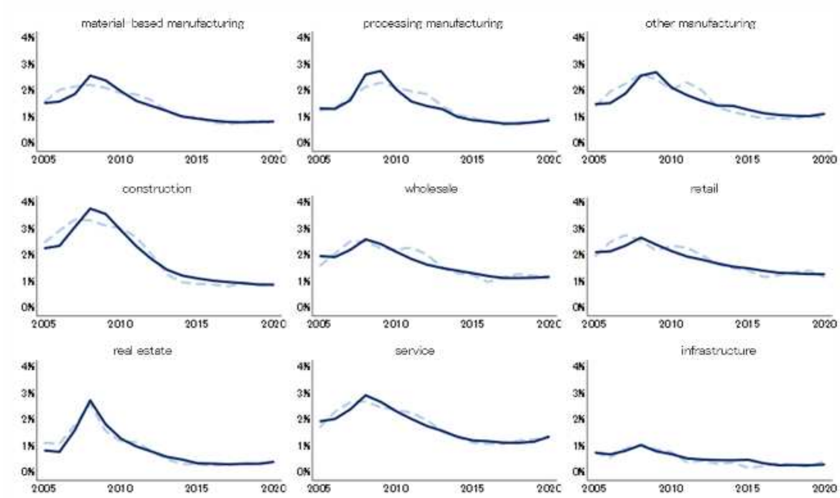
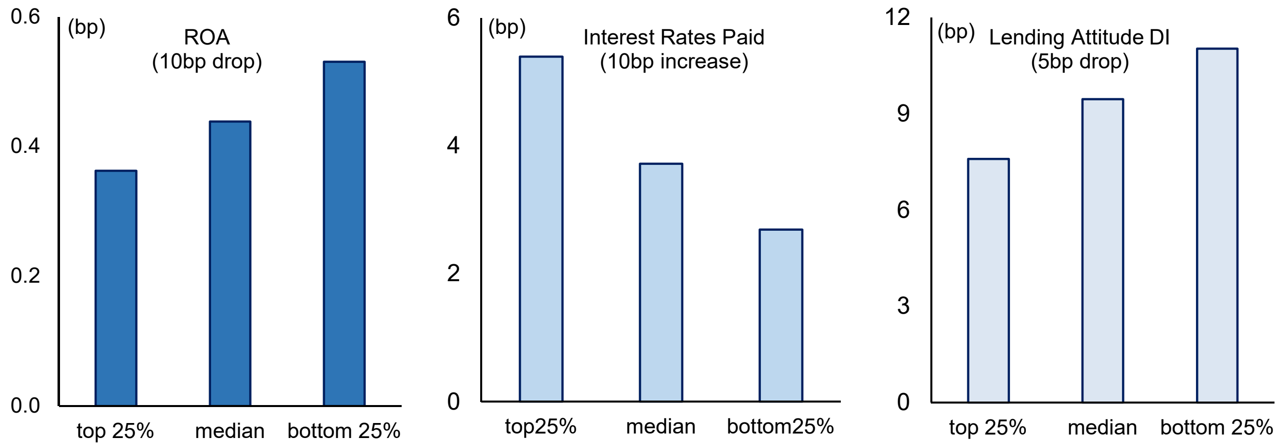


Figure 6 Actual default proportion and estimated default probability (by Industry group)



As the nature of a non-linear model, the degree of increment of default probability with change in each value of an explanatory variable depends on the values of these variables before the change. Figure 7 shows the increase in default probability when the value of each explanatory variable changes to a certain extent starting from the top 25 percentile, median value, and bottom 25 percentile respectively, taking the processing-type manufacturing industry as an example. If the payment rate were at the median level of the sample, a further rise of 10 basis points (bp) in the payment rate would increase the default probability by about 4bp. On the other hand, in the case where interest rates paid are at the top 25 percentile of the sample, a further 10bp rise in interest rates paid increases the default probability for about 5bp, which is slightly larger than the case of the median level. The same tendency can be observed for other variables. It indicates that, as described above, due to the non-linearity of the logit model, the degree of change in default probability may vary significantly among individual borrowers even if they are exposed to the same environmental change.

Figure 7 Sensitivity of default probability to each variable
(by variable level, processing manufacturing)



IV. Impact of changes in economic and financial conditions on default probability

Hereinafter, the paper estimate the impact of changes in economic and financial conditions on the default probability using the model estimated in the previous section. Specifically, this section first uses the model to calculate an estimate of default probability for each borrower based on their financial variables and the lending attitude DI in fiscal year 2021, and then averages these estimates to calculate the overall corporate sector default probability. Then, it estimates the increase in the default probability when financial variables and the lending attitude DI are changed from the 2021 level.

Table 8 shows changes in default probability when each variable (i.e., operating profit, interest rates paid, and lending attitude DI) is changed by the same amount for all the borrowers. In addition to changes in the default probability for all corporate borrowers, the table also shows changes in the default probability by industry group and size of borrower. In case 1, where operating profits decline by 10 percent across borrowers, the default probability for all firms (all industries, all sizes) increases by about 12bp. In addition, the default probability increases by about 56bp in Case 2, in which interest rates paid increase by 1%pt across the board, and by about 19bp in Case 3, in which the lending attitude DI decreases by 10 points.

A breakdown by size reveals that in all cases the increase in default probability is larger for SMEs than for large enterprises. One reason for this is that, since the interest payment burden on SMEs is relatively larger than that on large enterprises in 2021, changes in each variable lead to larger increases in the default probability for SMEs with the nonlinearity of the logit model. On the other hand, a breakdown by industry group shows that the increase in the default probability for non-manufacturers was slightly larger than that for manufacturers, but there was no significant difference between the two.

Table 8 Changes in default probability(unit: bp, incremental from 2021)

		Case 1 operating profits decline by 10%	Case 2 interest rates paid increase by 1%pt	Case 3 loan attitude DI decreases by 10 points
All Industries	all sizes	12	56	19
	SMEs	12	57	19
	Large Enterprises	3	36	12
Manufacturing	all sizes	9	51	19
	SMEs	10	53	20
	Large Enterprises	2	32	12
Non-Manufacturing	all sizes	12	57	19
	SMEs	13	58	19
	Large Enterprises	4	38	12

V. Conclusion

This paper developed and estimated a model to assess credit risk in loan portfolio using data on borrowers of 62 member banks of the Regional Banks Association of Japan. The model provides a general picture of observed historical trends in the default proportion. This model enables to quantitatively assess the impact of environmental changes on credit risk in the corporate sector.

The model and results developed in this paper are expected to contribute to the timely and multifaceted analysis of financial system resilience and vulnerabilities. For example, by using the model, it is possible to capture and analyze the impact of future changes in the economic and financial environment and changes that have already occurred (but not yet reflected in the data) on the corporate sector and the financial system in a forward-looking manner. In addition, it enables to estimate impacts from various perspectives, such as by size of borrowers and by industry. Thus, it becomes possible to understand better which part of the corporate sector would have a relatively large impact from a macro shock.

However, the model and results in this paper are still at the trial phase, and various considerations are necessary for the interpretation of the results, although they provide valuable insights to grasp the quantitative impact. For example, changes in various measures that contribute to the facilitation of corporate financing and their effects are not explicitly considered in the model. In addition, factors such as the liquidity condition of each company, which could affect credit risk, are not included, so there may be bias in the estimates. Given that there remains room for further elaboration from various perspectives, the estimation in this paper needs to be interpreted with certain caution. With these points in mind, the FSA will continue its efforts to enhance financial system risk analyses.