FSA Analytical Notes

June 2025 vol.2

Analysis on Credit Risk Management Practices in Regional Banks
— Investigation on Credit Risk Mitigation for Loans and Study on Rating Transition Prediction Models —

(Summary)

This paper presents an analysis of credit risk mitigation (loan coverage) and an examination of a rating transition prediction model, using loan-by-loan data collected through the Common Data Platform. While this paper does not assess the appropriateness of loan coverage—given that it should vary depending on factors such as borrower size, characteristics, and purposes of funds—the analysis revealed a tendency for lower coverage ratios particularly among shared borrowers (borrowers with loans from multiple banks) and prefecture-wise cross-border loans (loans extended to borrowers outside the bank's home region). In the verification of the rating transition prediction model, it was suggested that the model predicting downgrades from "needs attention or above" to "in danger of default or below" performs with relatively high accuracy using financial information alone, compared to models predicting other transition patterns.

I. Introduction

As part of its efforts to enhance the understanding of financial institutions' credit risk management practices based on quantitative data, the Financial Services Agency (FSA) published FSA Analytical Notes (2025.1) vol.2: Analysis of Borrower Classifications Assigned to Shared Borrowers, which analyzed borrower classifications using granular loan-level data collected through the Common Data Platform. Building on this initiative, this paper conducts further analysis by utilizing loan-level data from regional banks[1], focusing on loan coverage and the validation of a borrower classification transition prediction model. Regarding the former, the actual status of loan coverage was examined

[1] "Regional banks I" refers to Saitama Resona Bank and members of the Association of Regional Banks. "Regional banks II" refers to members of the Second Association of Regional Banks. "Regional banks" refers to both regional banks I and regional banks II.

from multiple perspectives, including whether the borrower is a shared or single-bank borrower[2], and whether the loan is cross-border or within the home region[3]. Regarding the latter, in order to assess the extent to which financial information contributes to the determination of borrower classifications—an effect that may vary by classification category—machine learning techniques were applied to develop prediction models for multiple transition patterns using financial data alone, and the predictive accuracy of these models was compared.

[2] A "single-bank borrower" refers to a borrower that has loans from only one bank, whereas a "shared borrower" refers to a borrower that receives loans from multiple banks. This classification is determined based on the lending relationships with regional banks and major banks (i.e., Mizuho Bank [including Mizuho Trust & Banking], MUFG Bank, SMBC, Sumitomo Mitsui Trust Bank, Resona Bank, Aozora Bank, and SBI Shinsei Bank). Other types of institutions such as credit associations (shinkin banks) are not taken into account. While there are some credit associations with relatively large lending volumes in certain regions, their impact on the overall results of this analysis is considered to be limited.

[3] In this paper, cross-border lending is determined based on the location of the borrower relative to the head office of the lending bank, using prefectures as the unit of reference. It should be noted, however, that the actual business areas of banks may vary, and lending to borrowers located outside the prefecture of a bank's head office does not necessarily constitute cross-border lending from banks' business perspective in all cases.

II. Current trends in loan coverage

This section provides an overview and analysis of current trends in loan coverage. The analysis focuses on corporate borrowers (excluding local governments) for which coverage-related information is available, based on loan-level data as of the end of March 2024[4]. These borrowers represent approximately 50% of the total outstanding corporate loans (excluding local governments) held by regional banks. It should be noted that this analysis is intended to capture the actual state of coverage, with the understanding that coverage levels may vary depending on borrower size and characteristics, and each bank's credit policy. In other words, the purpose is not to assess the appropriateness of the loan coverage itself.

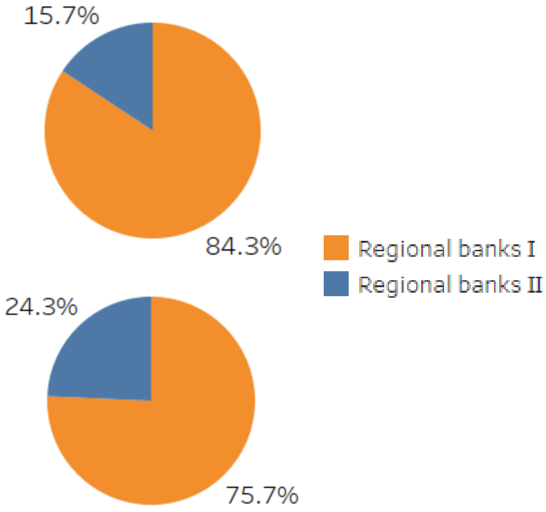
1. Basic Profile

Figures 1 and 2 show the profile of analysis samples by bank type and by borrower classification, respectively. Regional banks I account for 84.3%, regional banks II account for 15.7% of analysis samples. By borrower classification, 85.3% is rated as "normal," 12,3% as "needs attention," and 2.4% is "in danger of bankruptcy or below[5]."

[4] Full-scale data collection through the Common Data Platform is scheduled to begin from March 2025. The data used in this paper were collected during the preparatory phase, when efforts were still underway to improve data quality ahead of the official launch. As a result, not all financial institutions participating in the Common Data Platform are included in the aggregation presented in this paper.

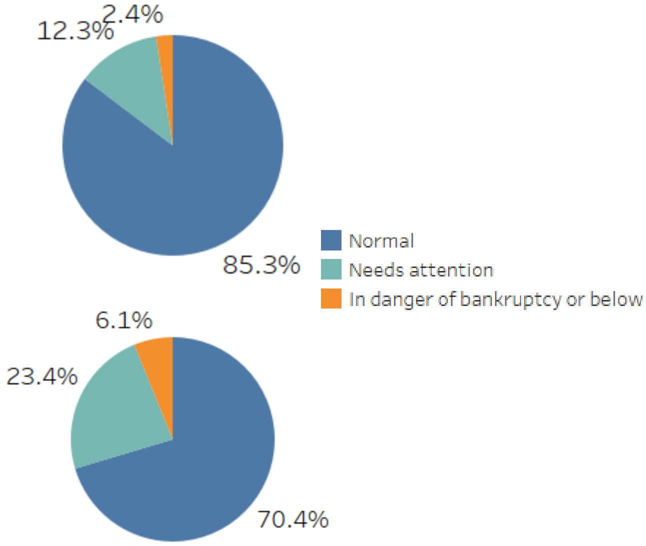
[5] In this paper, the term "needs attention" refers to a combined category comprising both "other needs attention" and "needs special attention" classifications as reported in the Common Data Platform. Similarly, the term "in danger of default or below" includes the classifications "in danger of bankruptcy," "de facto bankrupt," and "bankrupt".

Figure 1: Share by bank type
Upper chart: loan amount basis, lower chart: borrower count basis



Regional banks I	Loan (1 T yen)	82.0
	n	456,725
Regional banks II	Loan (1 T yen)	15.2
	n	146,518

Figure 2: Share by borrower classification
Upper chart: loan amount basis, lower chart: borrower count basis

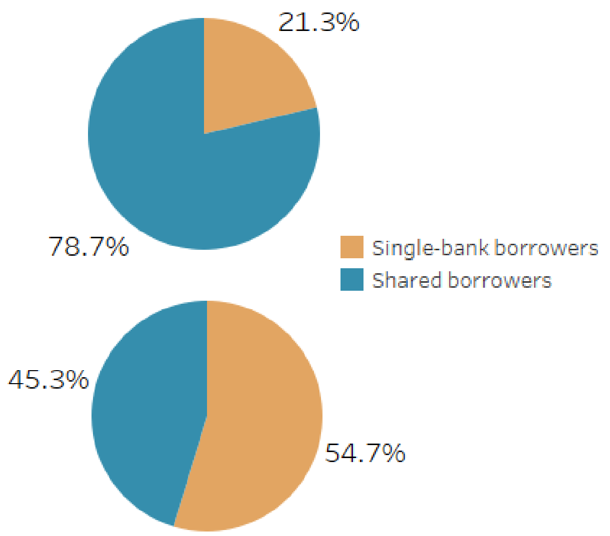


Normal	Loan (1 T yen)	82.9
	n	424,778
Needs attention	Loan (1 T yen)	11.9
	n	141,385
In danger of bankruptcy or below	Loan (1 T yen)	2.4
	n	37,080

Figure 3 shows the breakdown by single-bank and shared borrowers, while Figure 4 presents the breakdown by cross-border classification. In both cases, the proportion based on loan amounts is higher for shared borrowers and cross-border loans, whereas the proportion based on the number of borrowers is higher for single-bank borrowers and within-the-home loans. This discrepancy is likely due to the fact that the average loan amount per borrower tends to be larger for cross-border shared borrowers[6].

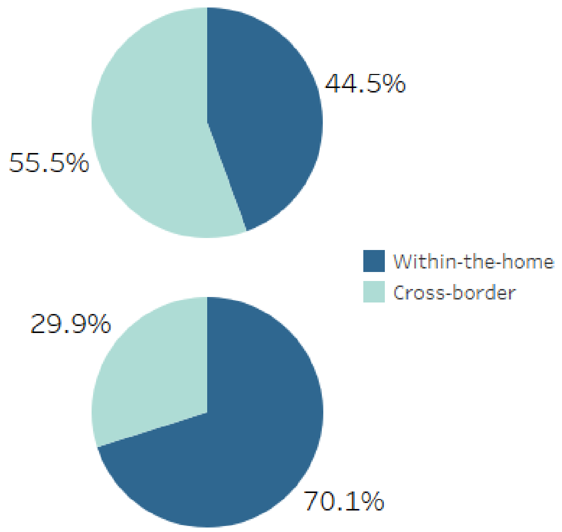
[6] In terms of average loan amount per borrower, cross-border shared borrowers have the highest figure at approximately 410 million yen. In comparison, within-the-home single-bank borrowers average around 180 million yen, cross-border single-bank borrowers about 60 million yen, and within-the-home shared borrowers around 80 million yen.

Figure 3: Share by single-bank/shared borrowers
Upper chart: loan amount basis, lower chart: borrower count basis



Single-bank borrowers	Loan (1 T yen)	20.7
	n	329,812
Shared borrowers	Loan (1 T yen)	76.5
	n	273,431

Figure 4: Share by cross-border characteristics
Upper chart: loan amount basis, lower chart: borrower count basis



Within-the-home	Loan (1 T yen)	43.2
	n	423,105
Cross-border	Loan (1 T yen)	54.0
	n	180,138

2. Coverage ratio

This sub-section examines loan coverage from various perspectives using the coverage ratio.[7] Figure 5 presents coverage ratios by borrower classification, single-bank versus shared borrowers, and cross-border classification. The results show that, while borrowers classified as “in danger of default or below” tend to have high coverage overall, for borrowers classified as “normal” and “needs attention,” the coverage ratio tends to decline in the following order: single-bank/within-the-home, single-bank/cross-border, shared/within-the-home, and shared/cross-border. Notably, among shared borrowers, the difference in coverage between within-the-home and cross-border loans is more pronounced than it is for single-bank borrowers. One possible explanation for these trends is that, from the borrower’s perspective, negotiating collateral arrangements tends to be more difficult in the case of shared borrowers than single-bank borrowers, due to the involvement of multiple lenders. Similarly, for cross-border loans, weaker business relationships or the nature of new client acquisition

[7] In this paper, the “coverage ratio” is calculated as: (Collateral amount + Guarantee amount + Specific loan loss provisions) / Outstanding loan balance × 100, due to data limitations. It should be noted that this calculation does not take into account general loan loss provisions, which are typically included in the numerator of conventional coverage ratios.

may make such negotiations more challenging compared to within-the-home lending. It is also worth noting that borrowers classified as “in danger of default or below” generally exhibit relatively high coverage across all categories. Therefore, the following analysis will primarily focus on loan coverage for borrowers classified as “normal” and “needs attention.”

Figure 5: Coverage ratio (weighted average)

As shown in Figure 6, the distribution of coverage ratios across banks reveals notable variation. A closer examination shows that some banks do not follow the general trends observed in Figure 5. These differences are likely attributable to variations in loan portfolios, regional characteristics, and individual banks’ approaches to collateral management.

Figure 6[8]: Distribution of each bank's coverage ratio

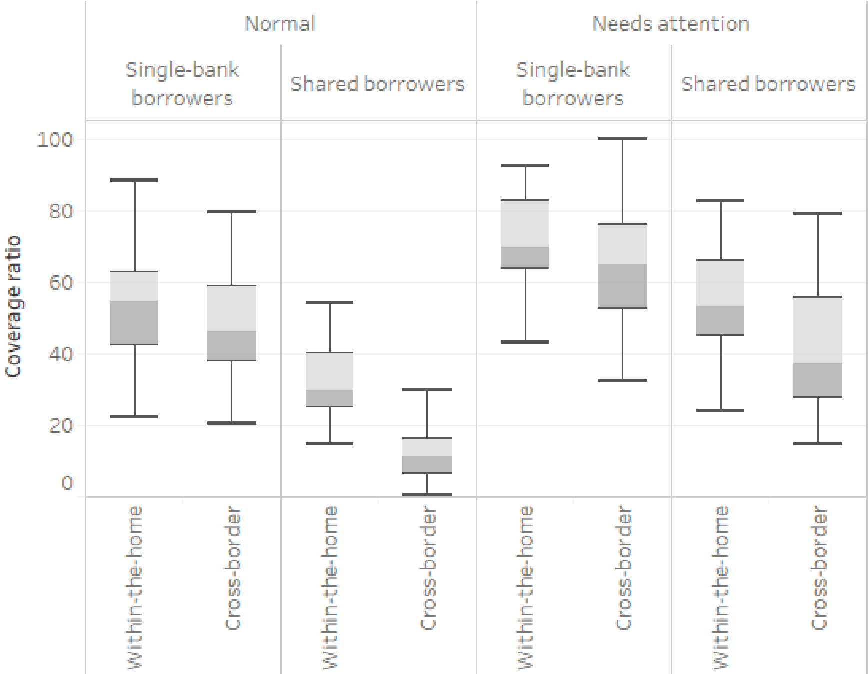


Figure 7 presents the loan balances and their proportions by industry, while Figure 8 shows the coverage ratios by industry. Together, these figures indicate that, among "normal" borrowers who are shared and cross-border, the financial industry accounts for a large share of loan balances but tends to have a relatively low coverage ratio. This is likely due to the concentration of large loan exposures to major financial institutions located in Tokyo. In contrast, the real estate industry shows a relatively high coverage ratio, which may reflect the fact that it is generally easier to secure collateral for loans to real estate businesses compared to other sectors.

[8] In the box plot, the top, middle, and bottom of the box represent the third quartile, median, and first quartile, respectively, while the upper and lower whiskers indicate the maximum and minimum values.

Figure 7: Loan profile by industry

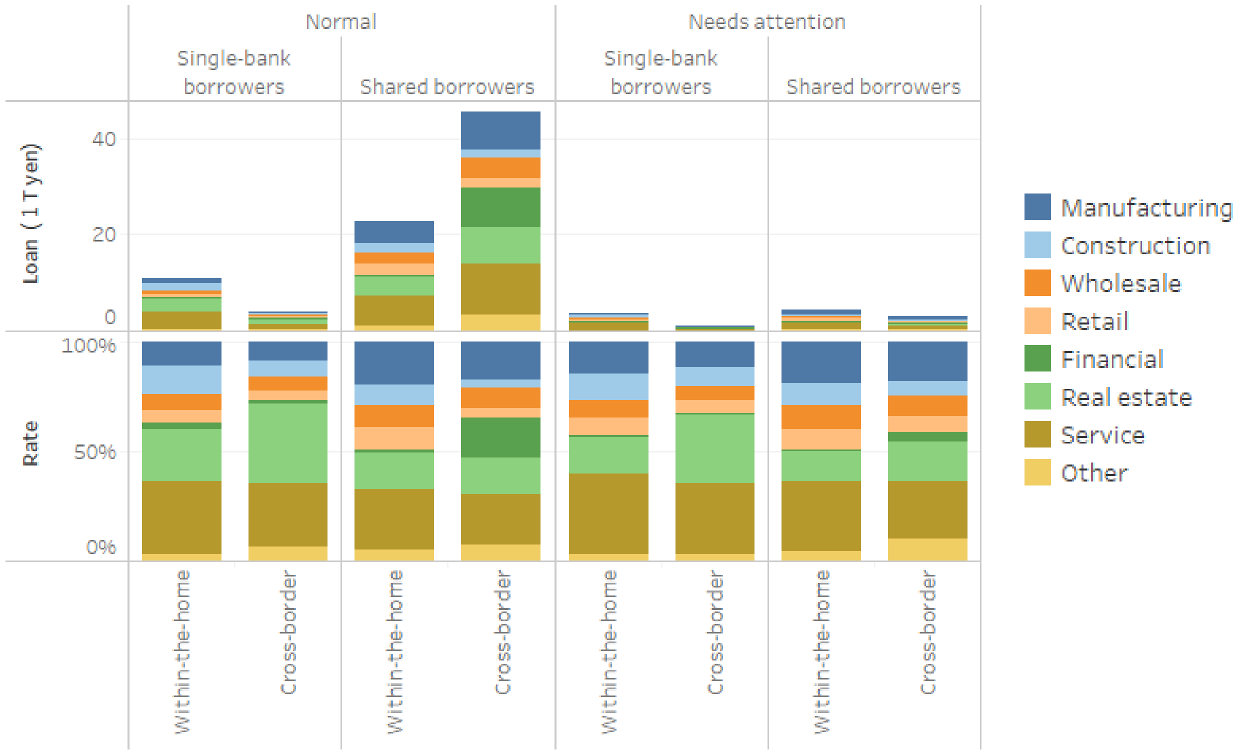


Figure 8: Coverage ratio by industry

	Normal				Needs attention			
	Single-bank borrowers		Shared borrowers		Single-bank borrowers		Shared borrowers	
	Within-the-home	Cross-border	Within-the-home	Cross-border	Within-the-home	Cross-border	Within-the-home	Cross-border
Manufacturing	44.8	41.6	22.4	6.5	68.9	64.2	43.7	30.7
Construction	58.3	50.7	38.4	17.5	81.4	73.6	65.5	48.6
Wholesale	52.4	40.8	30.1	8.5	76.0	71.1	54.8	38.3
Retail	55.8	48.6	25.5	10.9	81.3	73.0	53.8	32.7
Financial	8.1	8.5	9.5	2.0	17.5	58.8	28.9	26.1
Real estate	69.4	62.3	54.8	22.3	73.2	67.7	66.3	57.0
Service	48.3	43.3	31.9	14.0	65.8	58.9	54.2	40.5

Figure 9 shows coverage ratios for each borrower classification, broken down by whether the borrower's classification is consistent[9] across banks and whether the lender is a main bank[10] or not, specifically for shared borrowers. Across all borrower classifications, non-main banks exhibit lower coverage ratios compared to main banks, even when the borrower classification is consistent among lenders.

[9] In this paper, borrower classifications are grouped into three categories: "normal," "need attention," and "in danger of default or below." A borrower is considered to have "consistent borrower classification" when all creditor banks assign the same classification within these categories.

[10] Due to data limitations, the bank located within the borrower's home region and with the largest share of loans is defined as the "main bank," while all others are categorized as "non-main banks." Accordingly, in cases where all creditor banks are located outside the borrower's home region, or where the bank with the largest loan share is a cross-border lender, all banks are classified as "non-main banks." It should also be noted that some "non-main banks" may in practice function similarly to main banks—serving as "quasi-main banks."

Figure 9: Coverage ratio by borrower classification consistency and by main/non-main

			Main	Non-main	
			Within-the-home	Within-the-home	Cross-border
Consistent borrower classification	Normal	Coverage ratio	33.7	28.5	17.7
		Loan (1 T yen)	12.5	6.1	20.9
	Needs attention	Coverage ratio	61.6	57.0	50.7
		Loan (1 T yen)	1.0	0.3	0.6
	In danger of bankruptcy or below	Coverage ratio	88.1	85.6	76.5
		Loan (1 T yen)	0.3	0.1	0.1

Figure 10 examines coverage ratios by borrower classification, focusing on cases of borrowers with inconsistent borrower classification[11] for shared borrowers. Specifically, it compares the loan coverage of main banks with that of non-main[12], cross-border lenders. The results suggest that non-main, cross-border lenders tend to have particularly low coverage—except in cases where the non-main[13] bank has assigned a borrower classification of "in danger of default or below." It should be noted, however, that borrower classification combinations vary widely, so caution is warranted in interpreting these results.

Figure 10: Coverage ratio of borrowers with inconsistent borrower classification

			Normal		Needs attention		In danger of bankruptcy or below	
			Within-the-home	Cross-border	Within-the-home	Cross-border	Within-the-home	Cross-border
Main(Normal)	Main	Coverage ratio	42.0					
		Loan(1 B yen)	2,091.7					
	Non-main	Coverage ratio	31.6	2.4	50.7	26.2	88.5	66.8
		Loan(1 B yen)	334.7	12,468.2	249.8	451.7	3.0	3.1
Main(Needs attention)	Main	Coverage ratio			54.6			
		Loan(1 B yen)			1,909.3			
	Non-main	Coverage ratio	43.6	24.0	40.7	23.5	81.0	70.3
		Loan(1 B yen)	213.8	337.8	137.7	254.8	41.3	44.5
Main (In danger of bankruptcy or below)	Main	Coverage ratio					87.3	
		Loan(1 B yen)					421.5	
	Non-main	Coverage ratio	66.9	23.8	49.0	30.2	89.7	78.3
		Loan(1 B yen)	5.6	6.3	33.5	45.7	31.1	51.0

[11] In this paper, borrower classifications are grouped into three categories: "normal," "need attention," and "in danger of default or below." A borrower is considered to have "inconsistent borrower classification" when at least one creditor bank assigns a different classification from the others within these categories.

[12] Since the analysis focuses on coverage ratios by borrower classification for main banks, borrowers without a main bank as defined in this paper are excluded from the aggregation.

[13] Even when comparing the coverage ratios of the bank with the largest loan share and those of other banks—regardless of whether the loans are cross-border—the same trend is observed: excluding borrowers classified as "in danger of default or below," the coverage ratio tends to be lower for the other banks.

Finally, an analysis was conducted from the perspective of loan origination timing. As shown in Figure 11, if there is only one loan claim (Pattern A), the start date of that loan is used as the loan origination date. In cases where there are multiple loan claims (Pattern B), the earliest transaction start date among them is used. In both patterns illustrated in Figure 11, the loan origination timing is identified as "March 2019" (shown as "19/3").

Figure 11: Loan origination timing

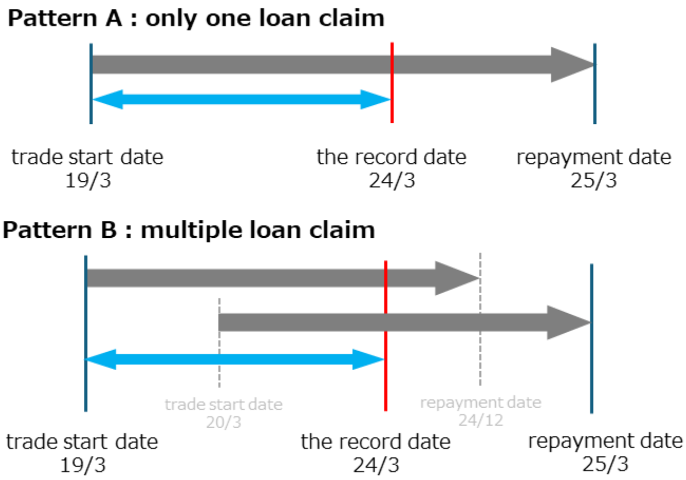


Figure 12 presents coverage ratios by loan origination year. The results show that coverage varies depending on the timing of loan origination. In particular, for borrowers classified as "normal," coverage ratios tend to be lower for loans originated in more recent years. On the other hand, this trend is less evident for borrowers classified as "needs attention," suggesting that lending without reliance on collateral or guarantees may have been increasingly promoted for more creditworthy borrowers. It is also worth noting that the relatively high coverage observed for loans originated in fiscal year 2020 (shown as "2020" on the horizontal axis) is likely due to the widespread use of credit-guaranteed loans during that period under application of effectively interest-free and unsecured loans by private financial institutions.

Figure 12: Coverage ratios by loan origination year[14]

[14] "~2008" indicates "2008 or earlier."

3. Statistical analysis

The preceding figures have shown that coverage ratios exhibit distinct patterns not only by borrower classification, but also by lending relationship type (single-bank vs. shared), cross-border status, loan origination timing, and across different banks. In this sub-section, a multiple regression analysis is conducted to examine the relationship between coverage and lending relationship type as well as cross-border status, while controlling for potential confounding factors such as corporate financial indicators and firm size.

The regression model used in this sub-section is as follows. The dependent variable (y_i) is the coverage ratio of corporate borrowers i, classified as "needs attention or above"[15], who have loans from regional banks. The explanatory variables include a dummy for shared borrowers ($Shared\ borrowers\ Dummy_i$), a dummy for cross-border loans ($Cross\ border\ Dummy_i$), and an interaction term between the two ($Shared\ borrowers\ Dummy_i * Cross\ border\ Dummy_i$). In addition, financial indicators[16], firm size, industry, borrower location, and loan origination timing—which are considered potential determinants of coverage—are included as control variables ($Controls_i$). For detailed definitions of the variables, see Figure 13.

$$y_i = \beta_0 + \beta_1 Shared\ borrowers\ Dummy_i + \beta_2 Cross\ border\ Dummy_i + \beta_3 Shared\ borrowers\ Dummy_i * Cross\ border\ Dummy_i + Controls_i + \varepsilon_i, \quad \varepsilon_i \sim N(0, \sigma^2)$$

Figure 13: List of variables

Object variable	y_i	coverage ratio（%）
Explanatory variables	1.Shared borrowers Dummy	"1"：shared borrower,"0"：otherwise
	2.Cross border Dummy	"1"：cross-border borrower,"0"：otherwise
	3.Shared borrowers Dummy*Cross border Dummy	interaction term of 1 and 2
Controls	Lending start year Dummy	lending start year dummy
	Order of loan Dummy	"1"：the first bank to lend,"0"：otherwise
	ROA	operating income/total assets
	Interest payable	interest expense/(short-term debt + long-term debt)
	Debt ratio	(short-term debt + long-term debt)/total assets
	Cash and deposit ratio	cash deposits/total assets
	Size	company size（ordinary logarithm of capital）
	Industry Dummy	manufacturing,construction,wholesale,retail,financial,real estate,service
	Prefectures Dummy	borrower location dummy

[15] In addition, the regression analysis focuses on borrowers of regional banks for whom financial information is available, excluding those whose loans are classified as syndicated loans.
[16] While the previous section indicated that borrower classifications also affect loan coverage, borrower classification is a measure that may reflect each financial institution's approach to credit risk management. Therefore, in this section, more objective indicators—such as corporate financial information—are used as control variables.

The estimation results are shown in Figure 14. All explanatory variables used in the analysis are statistically significant, with their coefficients indicating a negative correlation with the coverage ratio. In other words, even when controlling for financial indicators and other relevant factors[17], shared borrowers and cross-border loans are associated with lower coverage compared to single-bank borrowers and within-the-home loans, respectively. Moreover, the combination of being both a shared borrower and cross-border is associated with an additional reduction in coverage.

Figure 14: Estimation results

	Coefficient	Std.Error	
Shared borrowers Dummy	-12.066	0.185	***
Cross border Dummy	-7.457	0.248	***
*Shared borrowers Dummy*Cross border Dummy*	-7.778	0.302	***
n	318,828		
Adjusted-R^2	0.249		

***,** and * indicate significance at the 0.1%,1%,5% levels

4. Implication

This section examined loan coverage from various perspectives, with a particular focus on the differences in coverage ratios between single-bank and shared borrowers, as well as between within-the-home and cross-border loans. The results indicate that shared borrowers and cross-border loans tend to have lower coverage compared to their counterparts. Furthermore, statistical analysis confirmed that, even after controlling for financial conditions and other factors, these differences remain significant among borrowers classified as "needs attention" or higher.

However, with regard to prefecture-wise cross-border lending, it should be noted that banks differ in how they define their core business areas, and in some cases, lending outside the head office's prefecture may not necessarily be considered cross-border. Similarly, in the case of main banks, differences in loan purposes—such as the provision of loans primarily for capital investment—may also influence loan coverage. In addition, loan coverage is likely adjusted based on factors such as the borrower's financial condition, the strength of the bank-borrower relationship, local economic

[17] It is also confirmed that similar results are obtained when using borrower classifications (dummy variables for "normal" and "needs attention") as control variables, instead of corporate financial indicators and firm size.

conditions, and each bank’s credit risk management policies. Therefore, it should be emphasized once again that this analysis does not intend to assess the appropriateness of current loan coverage practices.

III. Rating transition prediction model

In previous issues of the FSA Analytical Notes[18], various approaches have been explored to estimate credit risk by focusing on borrower classifications (credit rating), with the aim of quantitatively assessing trends in credit risk. However, borrower classifications are determined not only based on financial information but also by incorporating qualitative factors. As a result, the accuracy of prediction models that rely solely on financial data may vary depending on the specific borrower classification. Against this backdrop, this section examines the predictive accuracy of models constructed using financial data for each borrower classification transition pattern, with a view to informing the development of future forecasting models[19].

1. Methodology

In this section, prediction models using financial information only for each transition pattern shown in Figure 15 are constructed, and their accuracy based on ROC curves[20] and AUC[21] are examined. The higher the prediction accuracy, the more likely it is that financial information alone is sufficient to make a prediction. Conversely, the lower the prediction accuracy, the more likely it is that qualitative information other than financial information has an impact on the assignment of borrower classifications.

[18] FSA Analytical Notes (2023.6): Analysis of credit risks in bank loans, FSA Analytical Notes (2024.7) vol.1: Analysis of trends of real estate loans by regional banks and study on credit ratings using machine learning.
[19] The data used in this section consist of borrowers from regional banks for whom financial information is available. The analysis covers the period from the end of September 2023 to the end of June 2024.
[20] This figure plots the true positive rate (True Positives / [True Positives + False Negatives]) on the vertical axis and the false positive rate (False Positives / [False Positives + True Negatives]) on the horizontal axis. It illustrates how the true positive rate and false positive rate change as the classification threshold of the model is varied.
[21] This represents the area under the ROC curve (AUC), where a larger value indicates higher predictive accuracy. A perfect prediction yields a value of 1, while a completely random prediction results in a value of 0.5.

Figure 15: Borrower classification transition patterns

Model name	Definition	No. of samples
[Model 1] Downgrade to needs attention	Borrower classified as normal in period t-1 but transit to needs attention in period t	Ranked-down: 5,740, Else: 474,959
[Model 2] Downgrade to in danger of default or below	Borrower classified as needs attention or higher in period t-1 but transit to in danger of default or lower in period t	Ranked-down: 659, Else: 563,896
[Model 3] Upgrade to normal	Borrower classified as needs attention in period t-1 then transit to normal in period t	Ranked-up: 5,159, Else: 78,181
[Model 4] Upgrade to needs attention or higher	Borrower classified as in danger of default or below in period t-1 then transit to needs attention or higher in period t	Ranked-up: 184, Else: 7,140

To objectively assess predictive accuracy, multiple machine learning models were used for comparison[22], including Random Forest, XGBoost, Logistic Regression, Support Vector Machine (hereinafter "SVM"), and Multi-Layer Perceptron (hereinafter "MLP"). To mitigate overfitting[23] arising from class imbalance—reflected in the number of observations shown in Figure 15—undersampling[24] was applied to address the imbalance in the dataset.

Figure 16 lists the features (i.e., the input variables used in the prediction models) employed in this section. Multiple financial indicators were initially constructed, and feature selection was performed using methods such as correlation coefficient analysis and the Boruta[25] algorithm.

[22] See Box below for the description of each model.
[23] A situation in which the prediction model becomes biased toward the majority class, resulting in reduced generalizability to the minority class.
[24] A method for addressing class imbalance by reducing the number of majority class samples to match that of the minority class.
[25] A method for selecting relevant features by adding variables that are unrelated to the prediction target and then running a random forest model to compare the importance of the original features against those unrelated variables.
Kursa,M.B. and Rudinicki,W.R:"Feature Selection with the Boruta Package", Journal of Statistical Software, Vol.36,Issue11(2010)

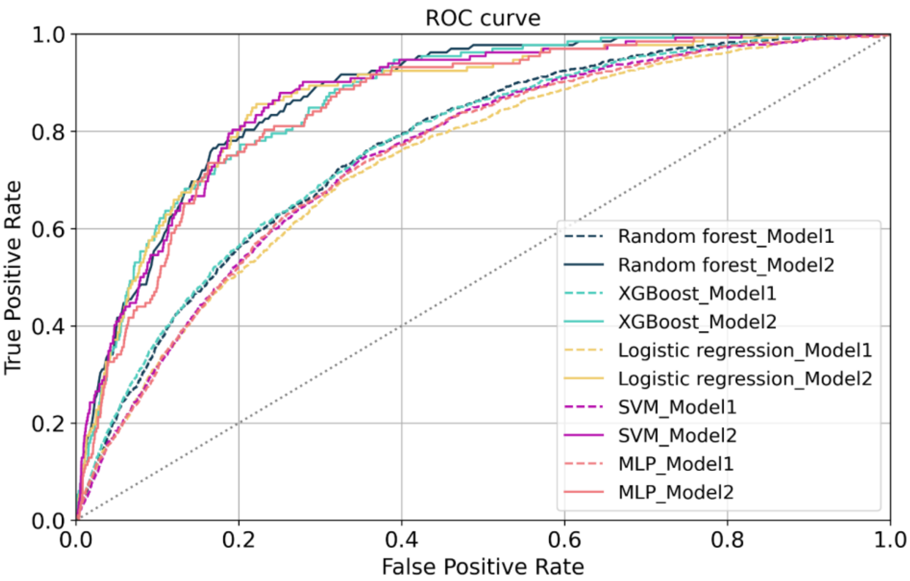
Figure 16: List of variables

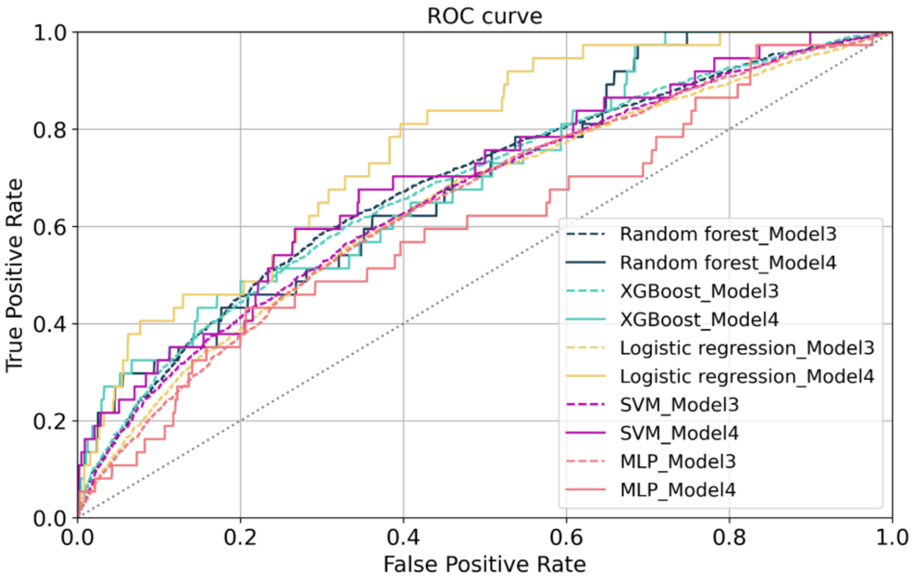
Feature	Definition
size	capital stock(common logarithm)
ROE	current benefit/self-capitalization
ROIC	(operating income＋appropritation for income taxes) / (total shareholders' equith＋short-term debt＋long-term debt＋corporate bond)
net DE ratio	((short-term debt＋long-term debt＋corporate bond) —cash and deposits) /net assets
net cash ratio	((cash and deposits＋marketable securities) — (short-term debt＋long-term debt＋corporate bond)) /total assets
capital adequacy ratio	self-capitalization/total assets
labors share	labor cost/value added (value added=operating income＋depreciation and amortization＋labor cost)
DCR	(short-term debt＋long-term debt＋corporate bond) / (cash and deposits＋marketable securities＋Property, plant and equipment)
sales interest expense ratio	Interest expenses/net sales
corporate profit margin	ordinary income＋non-operating expenses—appropritation for income taxes/net assets
common stock ordinary profit ratio	ordinary income/capital stock
operating cash flow per employee	(current benefit＋depreciation and amortization) / number of directors and employees at end of term

2. Results

Figure 17 presents the ROC curves and AUC values for each prediction model. The results show that Model 2 (downgrade to in danger of default or below) exhibits higher predictive accuracy compared to Models 1, 3, and 4 (downgrade to needs attention and upgrades). This suggests that for high credit risk cases involving downgrades to “in danger of default or below,” it is possible to construct highly accurate prediction models using only financial information. On the other hand, for prediction models related to borrower classification upgrades—regardless of the original classification—the use of financial information alone did not yield sufficient predictive accuracy, suggesting that other qualitative factors may be influencing such upgrades.

Figure 17: ROC curves and AUC
Upper chart: Model 1 and 2, lower chart: Model 3 and 4





	AUC			
	Model1	Model2	Model3	Model4
Random forest	0.77	0.87	0.68	0.69
XGBoost	0.77	0.87	0.68	0.70
Logistic regression	0.74	0.87	0.65	0.77
SVM	0.75	0.87	0.66	0.69
MLP	0.75	0.85	0.65	0.60

3. Implication

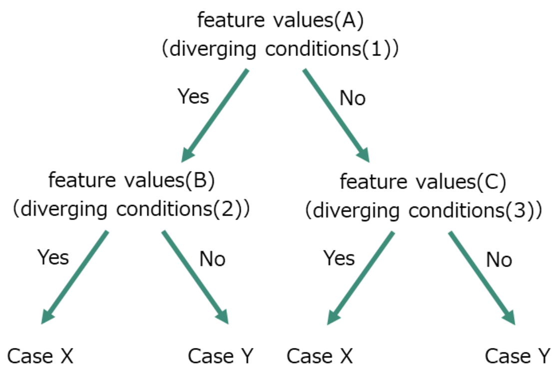
In this section, ROC curves and AUC values were used to compare the predictive accuracy of models constructed with financial information, based on different borrower classification transition patterns. The analysis confirmed that the accuracy of prediction models relying solely on financial data varies depending on the type of transition. In particular, when predicting upgrades in borrower classification, the findings suggest that it is necessary to consider non-financial (qualitative) information in model development. It should be noted, however, that each prediction is made by using only a single machine learning model. There remains the possibility that predictive accuracy could be improved by combining multiple models—for example, using XGBoost based on insights gained from Random Forest. In addition, potential sampling bias arising from the limited time span of the training data should also be taken into consideration.

BOX: Overview of machine learning models

This box provides a brief overview of the machine learning models used in this paper. It should be noted that the descriptions here are simplified summaries, and readers are encouraged to refer to the cited sources for precise technical details.

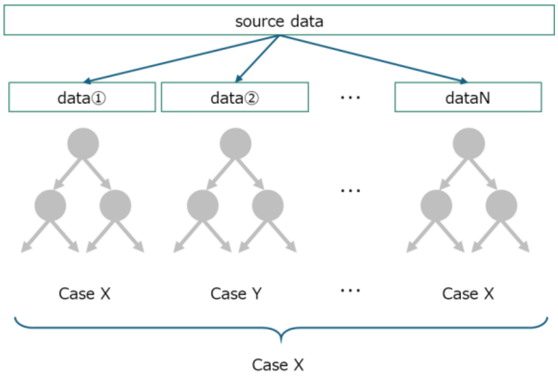
First, the Box introduces Random Forest and XGBoost. Both are machine learning models based on an algorithm known as decision trees. A decision tree is a method that performs prediction or classification by constructing a tree-like structure, as illustrated in Figure 18.

Figure 18: Decision tree



As shown in Figure 19, random forest[26] is an ensemble learning method[27] based on bagging[28], which combines multiple decision trees. Specifically, it involves performing bootstrap sampling on the original dataset to generate a number of random data subsets. A decision tree is then built for each subset, and predictions are made individually. Finally, the model aggregates these predictions by majority voting to produce the final output.

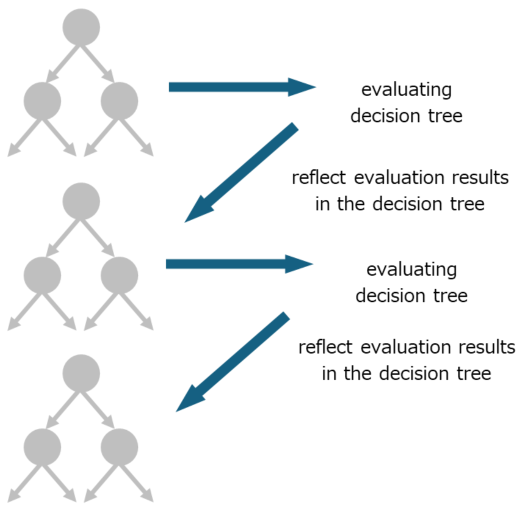
Figure 19: Random forest



As shown in Figure 20, XGBoost[29] implements gradient boosting for decision trees. Specifically, it begins by constructing an initial decision tree and evaluating its predictive performance. Based on this evaluation, a new, improved decision tree is created, and the model is re-evaluated—this process follows a gradient-based optimization approach. By repeating these steps and connecting the trees sequentially, the method aims to build a highly accurate predictive model. This iterative approach is known as "boosting."

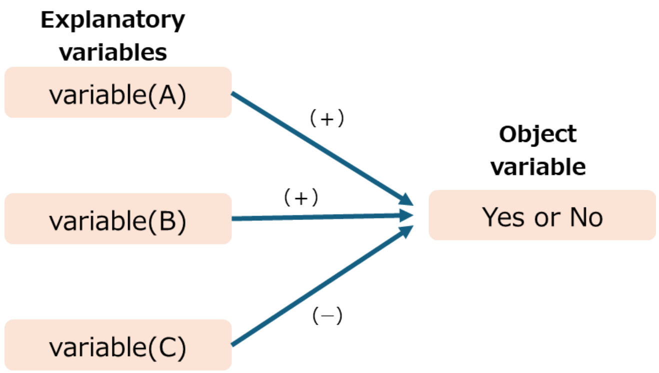
[26] L.Breiman:"Random Forests", Machine Learning, 45, 1, p.5-32(2001)
[27] A method in which multiple machine learning models—each with relatively low predictive accuracy on their own—are combined to build a highly accurate predictive model. Techniques such as "bagging," used in random forest, and "boosting," used in XGBoost (discussed later), are both types of ensemble learning.
[28] A method in which multiple predictive models are created using data obtained through bootstrap sampling—random sampling with replacement from the population for each decision tree—and the final prediction is determined by majority voting.
[29] T.CHEN and C.GUESTRIN:"XGboost: A scalable tree boosting system";Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining, p. 785-794(2016)

図表 20　XGBoost



Next, as shown in Figure 21, logistic regression is a method used to predict a binary outcome (objective variable), such as success or failure, based on multiple factors (explanatory variables).

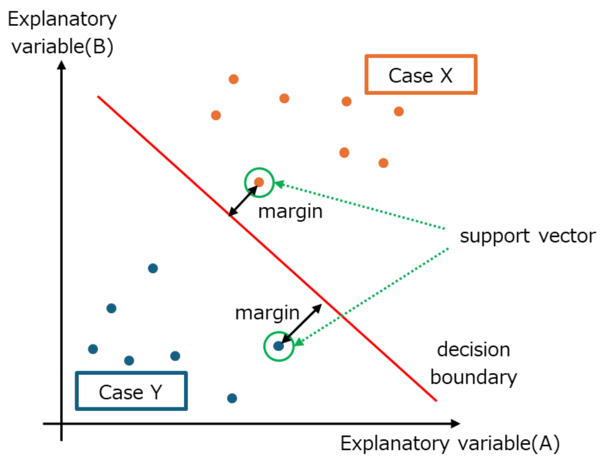
Figure 21: Logistic regression



Next, as shown in Figure 21, Support Vector Machine (SVM) [30] is an algorithm that learns by maximizing the margin—the distance to the decision boundary. The decision boundary refers to the line or curve that separates different classes. The data points closest to this boundary are called support vectors, and the model is constructed to maximize the margin between these support vectors and the decision boundary.

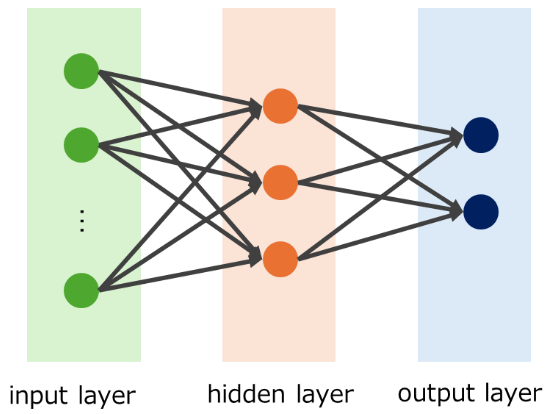
[30] Vapnik,V.N:"Statistical Learning Theory",Wiley(1998)

Figure 21: SVM



Finally, as shown in Figure 22, a Multilayer Perceptron (MLP) [31] is a type of mathematical model that mimics a neural network structure—specifically, a network of neurons. An MLP consists of at least three layers: an input layer, one or more hidden (intermediate) layers, and an output layer. Each node in a given layer is connected to all nodes in the preceding layer. The model is trained using an algorithm called backpropagation[32]. Specifically, the input layer receives external input data and passes it to the hidden layer(s), where the information is transformed to extract features. The output layer then generates the final prediction based on the processed information from the hidden layer(s).

Figure 22: MLP



[31] Single layer perceptron: F.Rosenblatt:"The perceptron:A preobabilistic model for information storage and organization in brain";Psychological Review,Vol.65,No.6,p.386(1958). Backpropagation: D.E.Rumelhart,G.E.Hinton and R.J.Wikkiams:"Learning representations by back-propagating errors";Nature, Vol.323,No.6088,p.533(1986)

[32] A method in which the model outputs a predicted value by multiplying the input data by parameters (weights), and then calculates the error against the true label. The error is propagated backward from the output layer to the input layer, and the weights in each layer are updated accordingly.

5. Conclusion

This paper aimed to deepen the understanding of financial institutions' credit risk management frameworks through quantitative data analysis, focusing on two main areas: an examination of coverage and a validation of transition prediction models for borrower classifications. In the first area, the analysis confirmed that, even when borrowers have similar financial conditions, those classified as shared borrowers or cross-border borrowers tend to exhibit lower coverage ratios compared to single-bank or within-the-home borrowers. In the second area, the validation of transition prediction models revealed that downgrades to the "in danger of bankruptcy or below" can be predicted with relatively high accuracy using financial information alone. However, in cases of upgrades, the findings suggest that incorporating qualitative information beyond financial data is necessary to improve predictive accuracy.

The FSA will continue to build its track record in diverse data analyses, including the use of granular data such as loan-level information, in order to enhance dialogue with financial institutions and advance more sophisticated monitoring efforts.

Understanding the Utilization of Credit Guarantee System

(Summary)

This paper conducted an analysis of the utilization of the Credit Guarantee System using loan-level data collected through the Common Data Platform. A machine learning approach was employed to identify the key factors influencing whether a loan is guaranteed. Among borrower-related factors, sales and capital ratio were found to have relatively large effects—borrowers with higher values for these indicators were less likely to utilize credit guarantees. While this analysis does not aim to assess the appropriateness of credit guarantee usage—given that such usage varies depending on borrower characteristics and other various factors—it did reveal that the tendency to use guarantees differs significantly based on whether a borrower is in excess liabilities, and difference across industries are also observed.

I. Introduction

This paper conducted an analysis using granular data from the Common Data Platform to better understand the actual usage of credit guarantees provided by Credit Guarantee System[1]—an important scheme that supports smooth financing for small and medium-sized enterprises (SMEs). As shown in Figures 1 and 2, the utilization of guarantees varies depending on the borrower's industry and financial condition. However, it should be noted that these figures also include large enterprises and overseas entities, which are outside the scope of the Credit Guarantee System.

[1] While other forms of guarantees exist—such as personal guarantees by business owners or guarantees by parent companies—this paper does not address those. Unless otherwise specified, the term "(credit) guarantee" refers solely to credit guarantees provided by Credit Guarantee Corporations.

Figure 1: Guaranteed ratio by type of industry

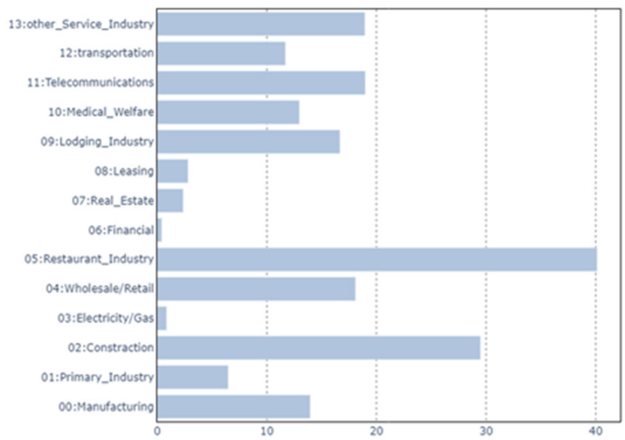
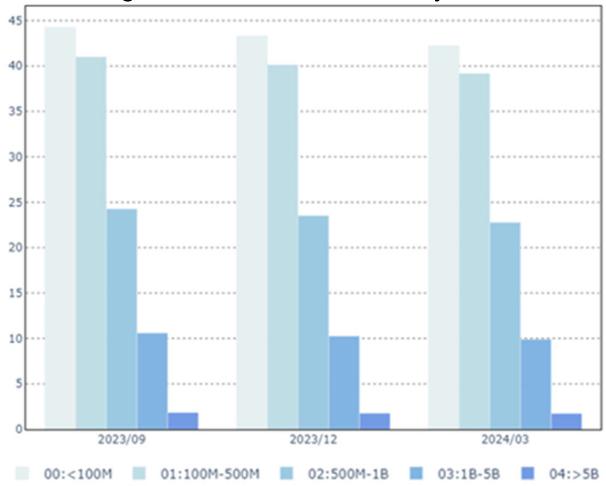


Figure 2: Guaranteed ratio by sales



(Note) Some industry categories such as finance and real estate are excluded. Borrowers with 0 sales are also excluded.
(Source) FSA Analytical Notes (2025.1) vol.2: Analysis of Borrower Classifications Assigned to Shared Borrowers, “Box: Utilization of Credit Guarantee System”

This paper conducts a quantitative analysis to identify the factors influencing the use of credit guarantees and associated trends, based on a more precisely defined set of conditions. It should be noted that the analysis presented here does not intend to assess the appropriateness of such usage —given that credit guarantees are utilized based on a comprehensive assessment of borrower characteristics and banks’ credit policies.

This analysis utilizes loan-level data from 62 member banks of the Regional Banks Association of Japan (the number of banks is as of the end-December 2024), specifically for the reference dates at the end of September 2023, December 2023, March 2024, June 2024, and September 2024. Given that the Credit Guarantee System is intended for designated types of small and medium-sized domestic enterprises in specific industries, the scope of analysis is limited to firms that meet the criteria outlined in Figure 3, thereby approximating the eligible population for credit guarantees[2].

[2] In addition to capital size and industry category, eligibility for the Credit Guarantee System is also subject to conditions such as the number of employees and detailed industry subcategories. However, due to data limitations, these criteria were not incorporated into the analysis. Furthermore, records with missing values in key fields related to credit guarantee usage were excluded from the dataset.

Figure 3: Scope of analysis

	Description
Region	Domestic firms
Firm size	Small and medium-sized enterprises, including sole proprietors; however, entities such as other types of corporations and firms with capital of 300 million yen or more are excluded.
Industry	Manufacturing, Construction, Wholesale & Retail, Food services, Accommodations, Healthcare & Welfare, Information & Communication, Transportation, Other services

II. Key feature analysis by machine learning

This section constructs a classification model using machine learning to predict the presence or absence of credit guarantees[3] based on various features, including bank characteristics and borrower attributes. The contribution of each feature was then examined to identify factors that influence the use of credit guarantees. The analysis employs CatBoost, a type of gradient boosting method based on decision trees. The loan data used as input for the machine learning model is limited to discounted bills or deed loans with an outstanding balance of at least 1 million yen.

1. Dataset

The features used in the machine learning model are listed in Figure 4. For model development, 75% of all records were randomly selected as training data, while the remaining 25% were used as test data to evaluate model performance. Since the Credit Guarantee System has a limit on the guaranteed amount, whether a newly originated loan receives a guarantee may be influenced by the amount already guaranteed to the borrower. To eliminate this effect, when multiple loan records existed for the same reference date, the loan with the earliest transaction start date was selected. Furthermore, to capture recent trends, only loans whose transaction start date was within three months of the reference date were included (sample size: N = 64,845). It should be noted that even when the model was trained on all newly originated loans as of the reference date without such

[3] This analysis is based on a binary classification of whether a credit guarantee is present or absence, and does not take into account variations in the guarantee coverage ratio—such as whether the guarantee covers 80% or 100% of the loan.

restrictions, the overall accuracy declined, but the top-ranking features in terms of importance remained broadly consistent.

Figure 4: List of features[4]

Category	Feature	Description
Bank attributes	Bank name	Name of the lender bank
	FI-HHI	HHI of the loan by financial institutions (including credit associations and credit cooperatives) in each prefecture
Loan attributes	Loan amount	Outstanding loan amount
	Loan maturity	Number of days from the transaction start date to the final repayment date
	Loan type	Discounted bills / deed loans
Borrower attributes	Core company flag	Set to "1" if the borrower has a separate parent company or main operating entity, "0" if otherwise
	Newly founded flag	3 categories: Whether the date of incorporation is less than three 3 years/3 years or more but less than five 5 years/5 years or more from the record date
	Cross-border flag	Set to "1" if the borrower prefecture and lender prefecture is different, "0" if otherwise.
	Industry	Manufaturing / Construction / Wholesale & Retail / Foods services / Accomodations / Healthcare & Welfare / Information & Communication / Transportation / Other services
	Prefecture dummy	47 prefectures
Borrower financial information	Sales	Sales revenue
	Capital ratio	= 100 * capital / total assets
	Operating profit ratio	= 100 * operating profit / sales
	Current profit	Current net profit
	ICR	= (operationg profit + interest income + divident) / interest and discounts expenses
	ROA	= 100 * oridinary profit / total assets
	Cash and deposits over debt ratio	= 100 * cash and deposits / debt
	Cash and deposits ratio	= 100 * cash and deposits / current liabilities
	Cash and cash equivalent ratio	= 100 * cash and cash equivalents / current liabilities
	Current ratio	= 100 * current assets / current liabilities
	Fixed ratio	= 100 * fixed assets / capital

(Ref) Number of samples in Train Data and Test Data

	Gurantee	23/09	23/12	24/03	24/06	24/09
Train	Absence	6,106	5,215	5,525	4,047	5,959
	Presence	4,634	4,343	4,582	3,669	4,553
Test	Absence	2,093	1,726	1,834	1,387	1,911
	Presence	1,492	1,504	1,544	1,245	1,476

[4] The Herfindahl-Hirschman Index (HHI), an indicator used to assess the level of market competition, is calculated here as the sum of the squared loan amount shares held by all financial institutions within the prefecture where the head offices of the financial institutions located. The "newly founded flag" is based on the basic information of entities granted corporate numbers, as published by the National Tax Agency. The variable "prefecture dummy" accounts for potential differences in credit guarantee policies—such as the criteria for issuing guarantees and the extent of coverage—across prefectural Credit Guarantee Corporations, as well as varying degrees of utilization of such guarantees depending on the region.

2. Result and implications

The performance[5] of the model was first evaluated, and as shown in Figure 5, all evaluation metrics indicate a sufficiently high level of performance. This suggests that the features used in the model provide a reasonable explanation for the presence or absence of credit guarantees.

Next, both the SHAP values[6] and feature importance[7] shown in Figures 6 and 7, respectively, indicate that loan maturity and loan amount have a relatively significant impact on the presence or absence of credit guarantees. According to the SHAP values in Figure 6, longer loan maturities tend to have positive SHAP values—contributing to the likelihood of a guarantee—whereas shorter maturities tend to yield negative SHAP values, indicating a stronger association with loans without guarantees. This is consistent with the general understanding that longer-term loans carry greater risk.

In contrast, loan amount exhibits the opposite pattern: smaller balances are associated with positive SHAP values (i.e., more likely to be guaranteed), while larger balances show negative SHAP values (i.e., more likely not to be guaranteed). This suggests that the loan amount may act as a proxy for firm size, implying that borrowers with smaller balances tend to be smaller in scale and generally possess lower creditworthiness. Additionally, as shown in the feature importance in Figure 7, the bank name ranked second in terms of contribution. This indicates that beyond loan attributes and borrower attributes, lender-specific factors—such as credit assessment policies—also have a material impact on whether or not a loan is guaranteed.

In addition, it was confirmed that borrower financial information such as sales and capital ratio also exert a certain level of influence. The next section provides a more detailed examination of the

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[5] The ROC curve is a graph that plots the true positive rate (TPR = true positives / [true positives + false negatives]) on the vertical axis against the false positive rate (FPR = false positives / [false positives + true negatives]) on the horizontal axis. It illustrates how the TPR and FPR vary as the classification threshold of the model is adjusted. The AUC represents the area under the ROC curve, where a higher value indicates better predictive performance. An AUC of 1 signifies perfect prediction accuracy, while a value of 0.5 corresponds to a completely random model.

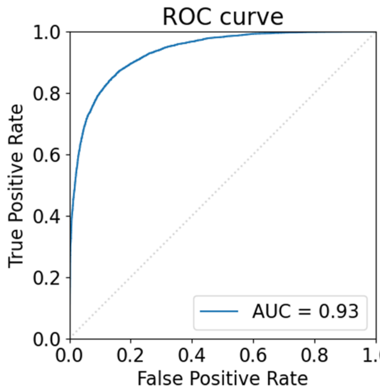
[6] The concept of SHAP (SHapley Additive exPlanations) values is based on calculating how each feature contributes to a prediction by sequentially adding features to the model. Specifically, it begins by computing the prediction when only feature *x* is included, then recalculates after adding feature *y*, and so on—assessing how the prediction changes as each feature is added. SHAP values apply the Shapley value concept from cooperative game theory to machine learning. Because the contribution of each feature can vary depending on the order in which features are added, SHAP values are calculated as the average contribution across all possible feature orderings. For more details, refer to sources such as the Bank of Japan's Working Paper Series *"Application of Machine Learning to a Credit Rating Classification Model: Techniques for Improving the Explainability of Machine Learning" (March 2023)*. Figure 6 visualizes the degree of contribution each feature makes to the actual prediction. In the figure, features represented in color use a scale where red indicates a high value of that feature, and the farther to the right the point lies, the more it contributes to a "presence" of guarantee classification; the farther to the left, the more it contributes to a "absence" of guarantee classification. Features shown in gray are categorical variables for which numeric ordering is not applicable.

[7] Feature importance refers to a numerical score that indicates the relative significance of each feature in building a machine learning model. In general, the more frequently a feature is used for decision splits (e.g., in decision trees), the higher its importance score tends to be. These scores are normalized so that the total across all features sums to 100.

relationship between financial condition and the presence or absence of credit guarantees.

Figure 5: Model performance

Indicator	Description	Score
Accuracy	The proportion of correct predictions made by the model across all data	0.856
Precision	The proportion of actually guaranteed data among data predicted as "presence" of the guarantee by the model	0.842
Recall	The proportion of data predicted as "presence" of the guarantee by the model among actually guaranteed data	0.833
F1-score	Harmonic mean of Precision and Recall = 2 × (precision×recall) / (precision＋recall)	0.838



∗Scores are calculated from Test Data

Figure 6: SHAP values

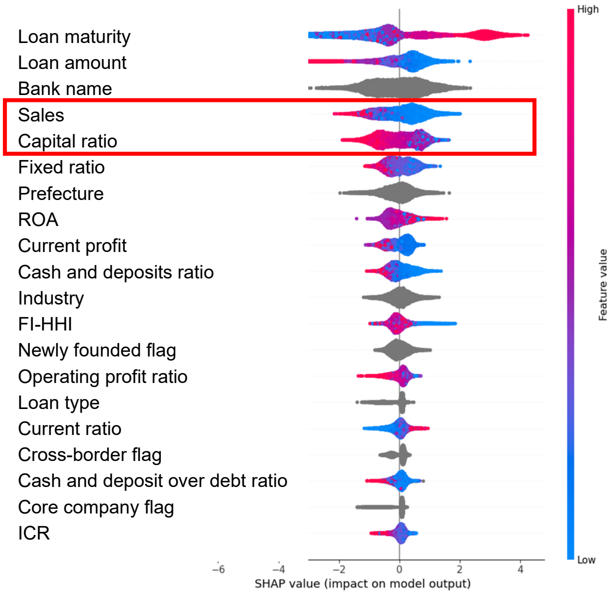
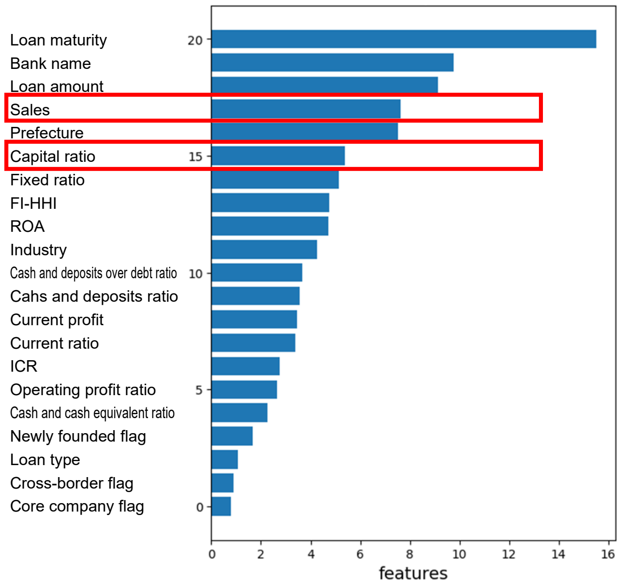


Figure 7: Feature Importance



III. Relationship between borrower financial condition and utilization of Credit Guarantee System

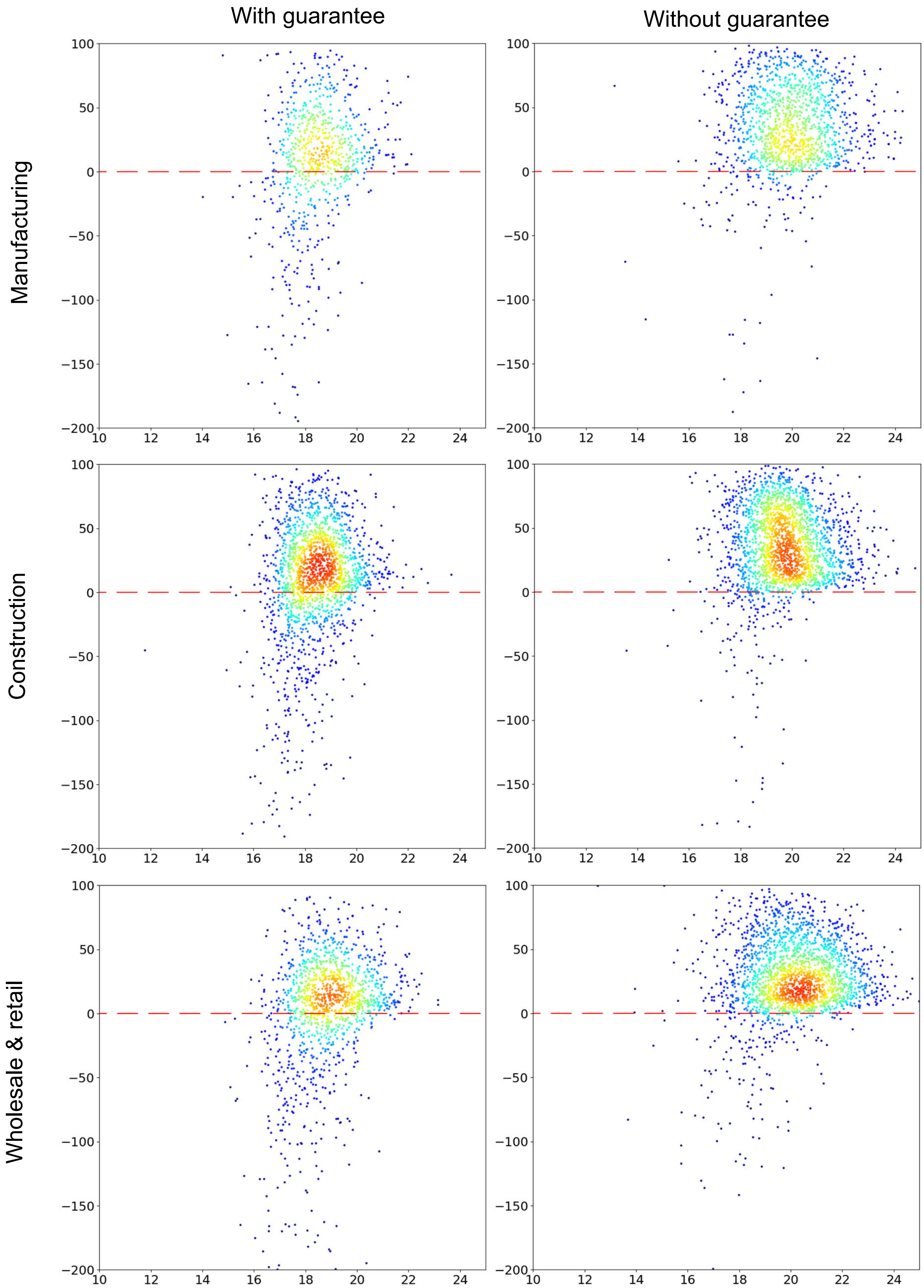
Among the financial information of borrowers, the previous section confirmed that “sales” and “capital ratio” have a certain degree of influence on the presence or absence of credit guarantees. This section examines the relationship between these indicators and the use of guarantees in more detail by borrower industry. The analysis is limited to data as of the end-September 2024, and graphs are presented only for industries with sufficient data: manufacturing, construction, wholesale & retail, food services, and transportation.[8]

1. Distribution of sales and capital ratio

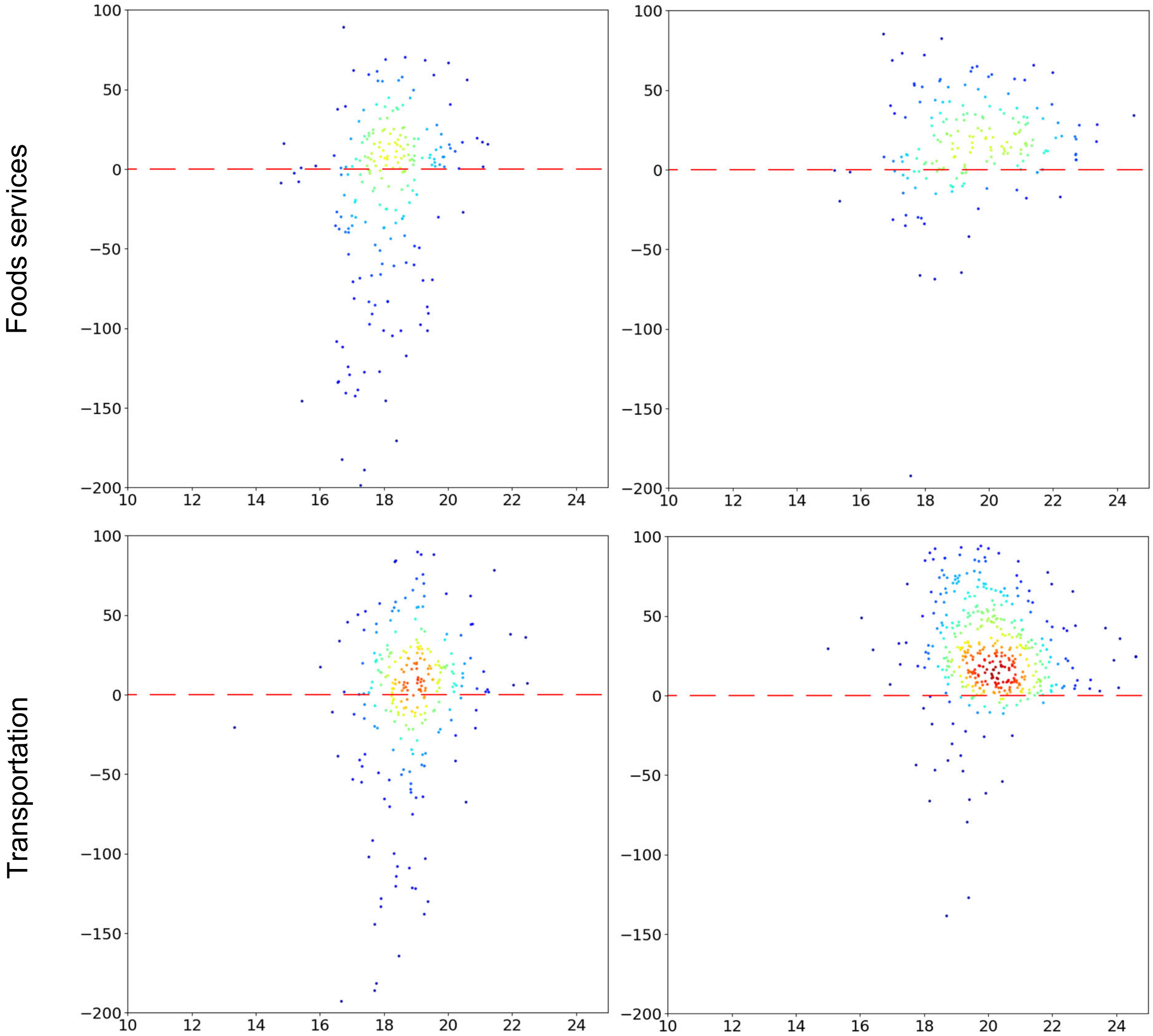
Figure 8 shows the relationship between “sales” and “capital ratio” of each borrower in a scatter plot. The red dashed line indicates a capital ratio of 0%, with points below this line representing debt-overhang firms. Across all industries, the distribution of loans without guarantees drops sharply below the red dashed line, indicating that loans without guarantees are rarely extended to firms with negative equity. Regarding sales, the distribution for loans without guarantees generally appears further to the right, suggesting that borrowers without guarantees tend to have higher sales than those with guarantees.

[8] The accommodation, healthcare & welfare, and information & communications sectors are excluded from this analysis due to an insufficient number of data points. In addition, the "other services" category is not illustrated, as it encompasses a wide variety of industry types.

Figure 8[9] Sales and capital ratio



[9] The X-axis represents the logarithmic value of sales (excluding cases where sales are zero), while the Y-axis represents the capital ratio of the borrower. The degree of concentration is visualized using a color scale based on kernel density estimation (approximated using a Gaussian distribution in this case), with areas of higher density shown in red. The color mapping, based on the output values of the estimated function, is applied using a consistent scale across all panels.



2. Relationship between sales and guarantee

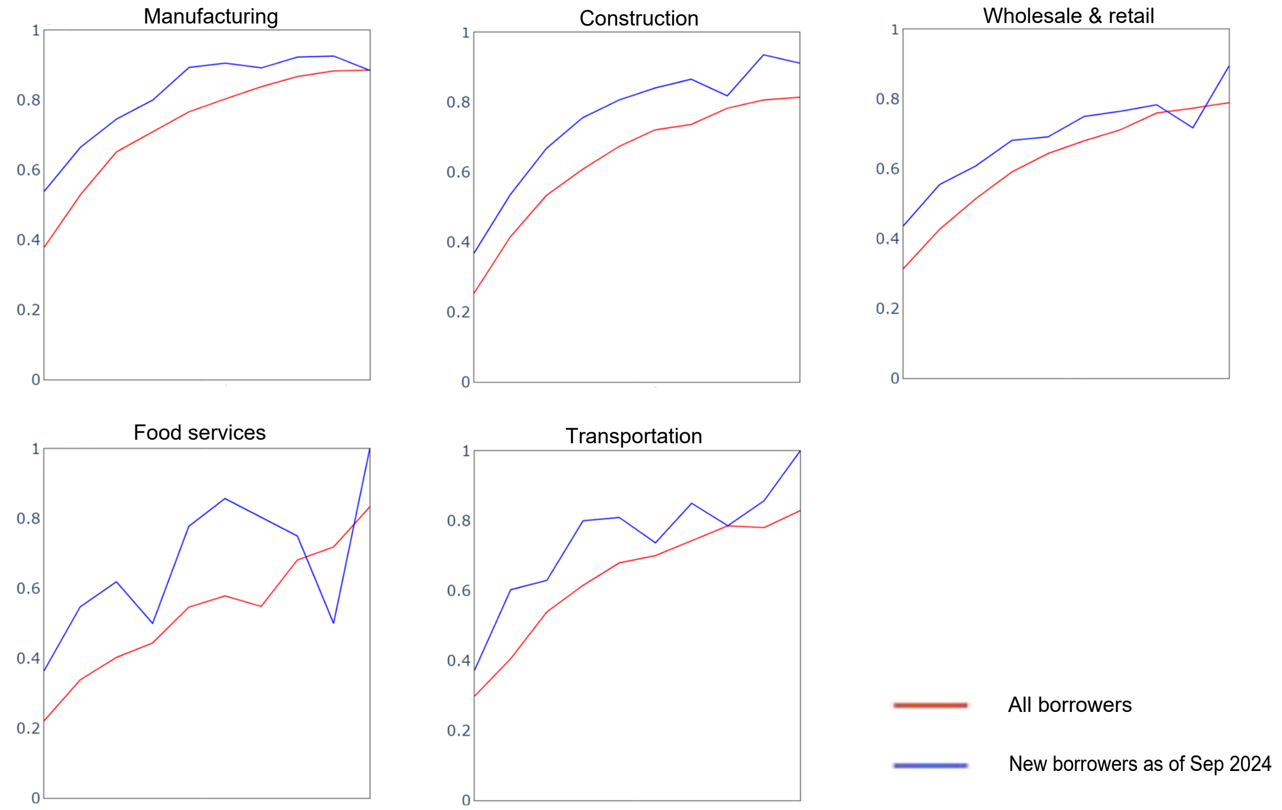
This section provides a more detailed examination of the utilization of guarantees by borrowers, categorized by sales volume[10]. In the following analysis, borrowers for whom the outstanding balance of guaranteed loans accounts for less than 50% of their total loan balance are defined as "non-guarantee-primary borrowers[11]." In Figure 9, the horizontal axis shows the sales categories[12] of borrowers, while the vertical axis indicates the proportion of non-guarantee-primary borrowers.

[10] It should be noted that the numerical data for sales and capital ratios are based on records as of the end of September 2024, and may differ slightly from the financial information available at the time of lending. In addition, to exclude the effects of effectively interest-free and unsecured loans offered by private financial institutions, the analysis is limited to loans executed from 2022 onward and is aggregated at the debtor level.

[11] In this analysis, whether credit guarantees are considered the primary source is determined based on a 50% threshold. However, in practice, approximately 80% of debtors fall into either of the two extremes—entirely without guarantees (0%) or fully guaranteed (100%).

[12] Divided into segments of 100 million yen each, ranging from 0 to less than 1 billion yen.

Figure 9: Sales (X-axis) and proportion of non-guarantee-primary borrowers (Y-axis)



The red line represents the full dataset used (all borrowers in the scope) in this analysis. Across all industries, the proportion of non-guarantee-primary borrowers tends to be lower for borrowers with smaller sales volumes. However, there was no notable trend indicating a sharp increase at a specific sales threshold. This suggests that the presence or absence of credit guarantees is not uniformly determined based on a fixed level of sales.

To examine the impact of whether a borrower is a new client on the usage of guarantee, the figure also plots in blue the data for borrowers who were new as of end-September 2024[13]. While their behavior generally mirrors that of all borrowers shown in red, the proportion of new borrowers tends to be higher across all industries[14] and sales levels. This may suggest that, prior to decisions on whether to apply guarantees, new borrowers are more likely to be selectively granted loans only if they are financially sound, or that when loans are newly extended to borrowers already served by a main bank, such loans are more likely to be unguaranteed. By industry, the proportion of non-guarantee-primary borrowers is particularly higher in manufacturing for borrowers with smaller sales volumes, and this trend is especially pronounced among new borrowers.

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[13] New borrowers as of end-September 2024 refers to borrowers who did not appear in the datasets as of the reference dates of September 2023, December 2023, March 2024, or June 2024, but are present in the dataset as of September 2024.

[14] For the food service and transportation sectors, it should be noted that the number of observations for new borrowers as of end-September 2024 in the sales range of 500 million to 1 billion yen is limited.

3. Relationship between capital ratio and guarantee

Next, Figure 10 plots the proportion of non-guarantee-primary borrowers by borrowers' capital ratio bracket[15]. The green dashed line represents a capital ratio of 0%, with the left side indicating negative equity (excess liabilities) and the right side indicating positive equity (excess assets).

Figure 10: Capital ratio (X-axis) and proportion of non-guarantee-primary borrowers (Y-axis)

Focusing on the red line representing the all borrowers, a consistent trend can be observed across all industries: the proportion of non-guarantee-primary borrowers increases significantly around the 0% capital ratio threshold. On the other hand, when the capital ratio is negative, the proportion of non-guarantee-primary borrowers remains relatively unchanged, even as the absolute value of the negative capital increases. Industry-specific patterns also emerge—construction and food service sectors generally show a lower proportion of non-guarantee-primary borrowers, likely because they tend to consist of smaller firms that make greater use of credit guarantees. In contrast, the

[15] Divided into 5% increments within the range of -50% to 50%.

manufacturing sector shows a relatively high proportion of non-guarantee-primary borrowers, even among borrowers with negative capital.

Additionally, the blue line represents borrowers whose sales are 100 million yen or less. Compared to the red line (which reflects all borrowers), the blue line shows no significant shift around the 0% capital ratio threshold. Across all industries, the proportion of non-guarantee-primary borrowers increases gradually and linearly. This suggests that for smaller-scale borrowers, credit guarantees tend to be utilized even if the firm is not in a state of excess debt as of the reference date.

IV. Conclusion

This paper utilized loan-level data obtained through the Common Data Platform to identify the key factors influencing the presence of credit guarantees using machine learning. In addition, a detailed analysis was conducted on the usage of credit guarantee by various attributes such as borrowers' size and industry. Among borrower-specific factors, sales and capital ratios were found to have relatively significant effects on guarantee usage. While no clear threshold in sales levels was observed that would significantly alter the share of non-guarantee-primary borrowers, a notable shift was seen around the zero percent threshold for the capital ratio, indicating a substantial difference depending on whether the borrower was in a state of excess debt. Differences were also observed across industries, with sectors such as construction and food services showing relatively low shares of non-guarantee-primary borrowers. This may reflect the prevalence of smaller firms in these sectors, which are more likely to utilize credit guarantees.

However, it should be noted that due to data limitations, the scope of this analysis was restricted to a short-term dataset from regional banks, beginning in the September 2023 period. Going forward, as more data becomes available, efforts will be made to enhance the sophistication of the analysis while continuing to monitor guarantee trends and deepen the understanding of the actual conditions.