Attempt to Identify Early Warning Signals on Credit Risks using Regional Banks' Loan Data and Macroeconomic Indicators

(Summary)

This paper presents a machine learning model designed to predict trends in credit risk by leveraging regional banks' granular loan data combined with macroeconomic indicators, with the aim of detecting early warning signs potentially affecting the management of banks. The analysis targets downward transitions in borrower classifications and identifies indicators that appear useful for capturing such warning signs, as well as offering insights into the current economic environment compared to past crisis periods. With the full-scale launch of the Common Data Platform, we will keep on making efforts to expand the scope of analysis, refine indicator selection, enhance the model, and apply these findings in dialogues with financial institutions.

I. Introduction

Amid the domestic economy's gradual recovery from the shock caused by the spread of COVID-19[1], the environment for the corporate sector has been undergoing noteworthy changes: the repayment period for interest-free unsecured loans provided by private financial institutions is arriving; labor shortages and wage increases are raising personnel costs; and rising raw material prices are pushing up inflation. Given these circumstances, the downward trend in bankruptcy cases has reversed recently, with numbers now increasing (Figure 1). Moreover, uncertainty over economic policy—including trade policies in various countries—has heightened (Figure 2).

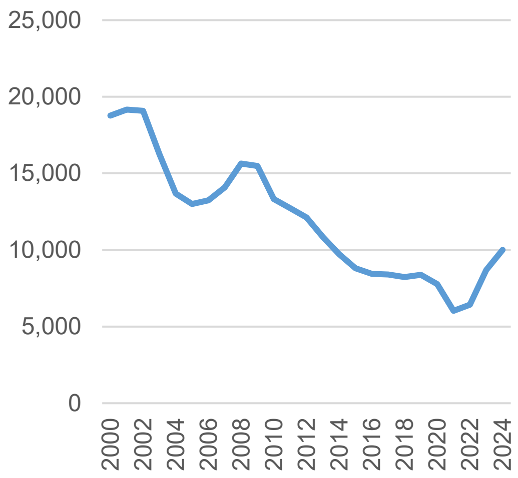
With a view to detecting environmental changes early—such as a future increase in credit risk—that could potentially affect the management of financial institutions, this paper constructs a machine learning model[2] to predict downward transitions in borrower classifications by using loan-detail data

[1] Cabinet Office, Monthly Economic Report (March and April 2025)

[2] The construction methodology of the machine learning model and the selection of macroeconomic indicators in this paper follow the studies titled "Research and Survey on Improving the Efficiency of Management Improvement Support Using AI and ICT Technologies" and "Research and Survey on Improving the Efficiency of Management Improvement Support Using AI Technologies," both commissioned by the FSA to KPMG AZSA LLC for the FY2022 and 2023. https://www.fsa.go.jp/common/about/research/20230330_1/20230330_1.html (Japanese only)

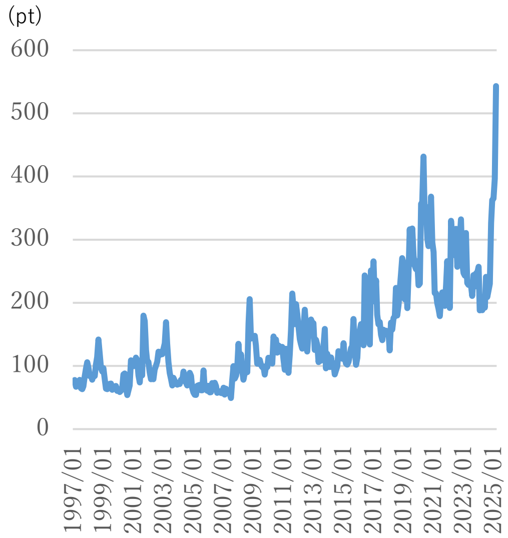
collected from regional banks[3] and both domestic and international macroeconomic indicators, and attempts to capture early signs of changes in domestic industries' conditions.

Figure 1: Number of Bankruptcies



(Source) Tokyo Shoko Research, Ltd.

Figure 2: Economic Policy Uncertainty Index



(Source) Economic Policy Uncertainty

II. Developing machine learning model

This section describes our machine learning model construction including dataset, industry selection and variable selection.

1. Dataset

The data used in this analysis comprise corporate loan details from regional banks and macroeconomic indicators. These two datasets are merged on a reference-date basis and treated as a single dataset. The loan-detail data include two types: (1) data extracted and processed from the Credit Risk Information Total Service (CRITS) database maintained by the Regional Banks Association of Japan, and (2) loan-detail data from the Common Data Platform. The former spans from FY2004 through FY2023, while the latter covers data from the platform's phased launch starting in FY2023

[3] 62 member banks of the Regional Banks Association of Japan (as of September 2024).

2. Industry selection

Since the impact of macroeconomic changes on firms varies by industry—and to secure the necessary sample size for machine learning—this analysis limits the target firms to those within industries where sufficient data is available, thereby facilitating variable selection and interpretation of results. In this paper, analysis is conducted focusing on the manufacturing sector, as it accounted for approximately 20%[4] of Japan's GDP in 2023, the largest proportion by industry. As of the end of March 2023, domestic bank lending to manufacturing sector totaled ¥64.7 trillion[5], and in the dataset used for model construction, approximately 30.4 % of that amount (¥19.7 trillion) could be captured.

3. Variable selection

The variables used in the model construction are shown in Figures 3 and 4. The macroeconomic indicator dataset comprises 64 domestic and international indicators. In addition to representative macro indicators related to finance and economics, indices believed to be particularly relevant to the manufacturing sector—such as electricity generation performance and order volumes from public institutions—were selected

[4] Cabinet Office, National Accounts.
[5] Bank of Japan statistics.

Figure 3: Variables in loan-detail dataset

NO	Indicator	Classification
001	Current Period Sales	Finance
002	Current Period Operating Income	
003	Current Income	
004	Depreciation and Amortization for Current Period	
005	Current Period Interest and Dividend Income	
006	Current Period Interest Expense – Discount	
007	Total Current Period Assets	
008	Current Period Cash – Deposits	
009	Current Period Current Assets	
010	Current Period Fixed Assets	
011	Current Period Current Liabilities	
012	Current Period Long-Term Liabilities	
013	Current Period Short-Term Loans Payable	
014	Current Period Long-Term Loans Payable	
015	Share Capital in the Current Period	
016	Current Period Net Worth	
017	Credit Balance – Gross	Lending
018	Credit Balance – Guarantee Association	
019	Conservation Amount – Total Amount	
020	Conservation – Guarantee Association	
021	Average Loan Interest Rate	
022	Average Remaining Maturity	
023	Maximum Number of Months in Arrears	
024	Number of Months in Arrears at the End of	
025	Borrower Classification	

Figure 4: Variables in macroeconomic indicators dataset

NO	Indicator	Classification	Source
001	TOPIX	Finance	Tokyo Stock Exchange
002	Dow Jones Total Stock Market Index		S&P
003	Unsecured Call O/N Rate		Bank of Japan
004	Government Bond Yields (Japan, 1 Year)		Ministry of Finance
005	Government Bond Yields (Japan, 3 Years)		Ministry of Finance
006	Government Bond Yields (Japan, 5 Years)		Ministry of Finance
007	Government Bond Yields (Us, 5 Years)		Federal Reserve System
008	10-Year U.S. Government Bond Yields		Federal Reserve System
009	Exchange (JPY / USD)		Bank of Japan
010	Exchange (JPY / EUR)		European Central Bank
011	Exchange (USD / EUR)		Federal Reserve System
012	Nominal Effective Exchange Rate		Bank of Japan
013	Average Total Loan Balance (Foreign Banks, Yen Loans)		Bank of Japan
014	Average Contracted Interest Rate On Loans (New / Short-Term)		Bank of Japan
015	Average Contracted Interest Rate On Loans (New Loans, Long-Term)		Bank of Japan
016	Average Contracted Interest Rate On Loans (Stock, Short-Term)		Bank of Japan
017	Average Contracted Interest Rate On Loans (Stock, Short-Term)		Bank of Japan
018	Nominal Gdp Growth Rate (Compared to the Previous Fiscal Year)	Business conditions	Economic and Social Research Institute Cabinet Office
019	Nominal Gdp Growth Rate (Compared to the Same Period)		Economic and Social Research Institute Cabinet Office
020	Real Gdp Growth Rate (Compared to the Previous Fiscal Year)		Economic and Social Research Institute Cabinet Office
021	Real Gdp Growth Rate (Compared to the Same Period)		Economic and Social Research Institute Cabinet Office
022	Real Gdp Growth Rate (U.S., Compared to the Previous Term)		Federal Reserve System
023	Real Gdp Growth Rate (Euro Area / Compared to the Previous Quarter)		Federal Reserve System
024	Real Gdp Growth Rate (Asia, Compared to the Previous Term)		Federal Reserve System
025	Business Conditions DI (SMEs, Manufacturers, Actual Results)		Bank of Japan
026	Business Conditions DI (Small And Medium-Sized Enterprises, Non-Manufacturers, Actual)		Bank of Japan
027	Business Conditions DI (Medium-Sized Enterprises / Manufacturers / Results)		Bank of Japan
028	Business Conditions DI (Medium-Sized Enterprises / Non-Manufacturers / Actual)		Bank of Japan
029	Business Conditions DI (Large Manufacturers, Actual Results)		Bank of Japan
030	Business Conditions DI (Large, Non-Manufacturing, Actual)		Bank of Japan
031	Coincident CI		Economic and Social Research Institute Cabinet Office
032	Leading Indicators CI		Economic and Social Research Institute Cabinet Office
033	Coincident CI Index		Economic and Social Research Institute Cabinet Office
034	Leading Indicators DI		Economic and Social Research Institute Cabinet Office
035	SME Sales Outlook DI		Japan Finance Corporation
036	Number of Bankruptcies (Nationwide)		Ministry of Internal Affairs and Communications
037	Bankruptcy Liabilities - Nationwide		Ministry of Internal Affairs and Communications
038	Power Generation Results - Nationwide	Production	Agency for Natural Resources and
039	Orders Received From Public Institutions		Ministry of Land, Infrastructure, Transport and Tourism
040	New Construction (Residential) Floor Space - National		Ministry of Land, Infrastructure, Transport and Tourism
041	Scheduled Construction Cost of New Buildings (Residential) - Nationwide		Ministry of Land, Infrastructure, Transport and Tourism
042	Cargo Transportation Volume		Ministry of Land, Infrastructure, Transport and Tourism
043	Industrial Shipment Index		Ministry of Economy, Trade and Industry
044	Index of Industrial Inventories		Ministry of Economy, Trade and Industry
045	Manufacturing Production Capacity Index		Ministry of Economy, Trade and Industry
046	Machinery Orders (Original Series, Manufacturing)		Economic and Social Research Institute Cabinet Office
047	Machinery Orders (Original Series, Non-Manufacturing)		Economic and Social Research Institute Cabinet Office
048	Tertiary Industry Activity Index (Tertiary Industry Overall)	Consumption	Ministry of Economy, Trade and Industry
049	Commercial Sales - Total Commercial		Ministry of Economy, Trade and Industry
050	Commercial Sales - Wholesale Total		Ministry of Economy, Trade and Industry
051	Total Retail Sales		Ministry of Economy, Trade and Industry
052	Number of Foreign Visitors to Japan - Total		Japan National Tourism Organization
053	Passenger Traffic Volume		Ministry of Land, Infrastructure, Transport and Tourism
054	Consumer Sentiment Index		Economic and Social Research Institute Cabinet Office
055	Domestic Corporate Goods Price Index (Gross Average)	Prices	Bank of Japan
056	Land Prices - Nationwide		Ministry of Land, Infrastructure, Transport and Tourism
057	WTI Crude Oil Price		U.S. Energy Information Administration
058	Unemployment Rate (Original Figure)	Employment	Ministry of Health, Labour and Welfare
059	Labour Force (Original Figures)		Ministry of Health, Labour and Welfare
060	Number of New Job Offers		Ministry of Health, Labour and Welfare
061	Ratio of Job Offers to Job Seekers (Original Figures)		Ministry of Health, Labour and Welfare
062	Population Projections (T + 1) - Nationwide		National Institute of Population and Social Security Research
063	Basic Resident Register Population - National		Ministry of Internal Affairs and Communications
064	Unemployment Rate(U.S.)		Federal Reserve System

4. Model construction

This analysis targets the borrower classification[6] assigned by each financial institution—reflecting borrower financial condition and credit risk—and tries to predict whether borrowers classified as "normal" at the reference date experience a downward transition in classification one year later (hereafter, "downward borrower-classification transition"). Typically, a downward transition from "normal" to "needs attention" or lower denotes a deterioration in a borrower's business conditions, including macroeconomic factors, and is expected to increase credit costs and affect a financial institution's performance. Therefore, predicting downward borrower-classification transitions aligns with this analysis' objective: capturing signs of industrial stress that may influence regional banks' soundnress.

The machine learning model in this analysis is built using XGBoost[7] (eXtreme Gradient Boosting), a method widely used in research across the machine-learning field and renowned for its high predictive power.

We split the dataset to suppress overfitting during training[8]. Due to data availability constraints, the data up to FY2022 were divided into three sets—(i) training, (ii) prediction-performance validation, and (iii) results confirmation—whereas FY2023 data were used for (ii) prediction-performance validation and (iii) results confirmation[9].

The explanatory variables fed into the machine learning model are the preprocessed versions of the variables listed in the previous sub-section. Specifically, for each variable shown in Figures 3 and 4, four patterns were input: (1) the raw value at the reference date, (2) the raw value one year earlier, (3) the difference from one year earlier (raw minus one-year-prior value), and (4) the ratio to one year earlier (raw divided by one-year-prior value), totaling 352 variables. Meanwhile, the dependent variable is the downward borrower-classification transition: assigned "0" if no downward transition occurred and "1" if otherwise.

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[6] The borrower classification categories in this paper are "Normal", "Needs attention", "Needs special attention", "In danger of default", "De facto bankrupt", and "Bankrupt".

[7] CHEN, Tianqi; GUESTRIN, Carlos. XGBoost: A scalable tree boosting system. In: *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining.* 2016. p. 785-794.

[8] To prevent skewed distributions of data across reference dates during dataset splitting, sample sizes are standardized across time points. Similarly, for downward borrower-classification transitions, sample counts are balanced to avoid class imbalance. As shown in Figure 5 in the next section, the actual rate of downward transitions is low—sometimes below 10 % by fiscal year. Training the model directly on such imbalanced data could bias learning, so non-transitioning borrowers are undersampled.

[9] The number of samples in each data subset is as follows (figures in parentheses indicate the count of downward borrower-classification transitions): (1) Training set (through FY 2022), 149,135 borrowers (72,820 downward transitions), (2) Validation set for predictive accuracy (through FY 2022), 37,284 borrowers (18,205 transitions) and 70,948 borrowers (6,125) in FY2023, and (3) Test set for result confirmation (through FY 2022), 143,194 borrowers (10,193 transitions) and 117,871 borrowers in FY2023.

Since this analysis aims at future forecasting, the explanatory and dependent variables are not aligned at the same timestamp: the explanatory variables consist of data from the reference date and the same date one year earlier, whereas the dependent variable indicates whether a downward borrower-classification transition occurred on the date one year after the reference date. In other words, the model makes future predictions using only data that would have been available at the reference date[10].

III. Results

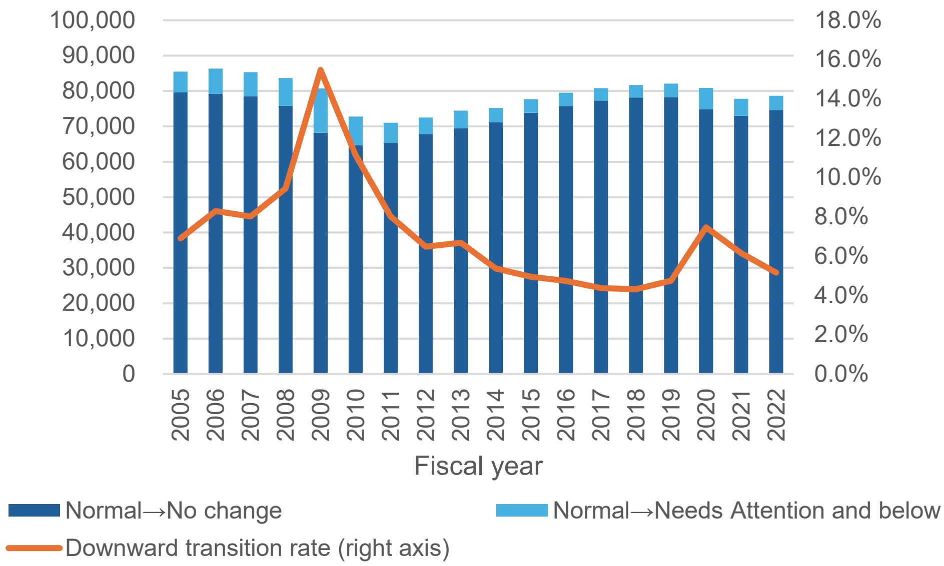
This section examines the predictive accuracy of the constructed machine learning model, reviews its outputs, and interprets the results.

1. Overview of downward borrower-classification transition

Figure 5 presents the actual rate of downward borrower-classification transitions for the analysis target (industry: manufacturing; borrower classification at the reference date: “normal”). After a sharp increase in the transition rate during the FY2009 amid the Great Financial Crisis (GFC), the rate gradually declined, rose again modestly during the COVID-19 pandemic in FY2020, and then gradually receded again.

[10] In practice, many indicators—such as official statistics and financial statement data—become available a few months after the reference date. However, since the prediction horizon is one year ahead, incorporating this few-month delay does not introduce any future information into the model.

Figure 5: Downward borrower-classification transition



2. Model performance and variable contribution

We use AUC[11] as a performance metric (see Figure 6). While other performance measures—such as accuracy[12] and recall[13]—are also used to evaluate machine learning models, they require a threshold to be set to distinguish correct from incorrect predictions. In contrast, AUC is threshold-independent, minimizing arbitrariness in evaluation.

Figure 6: Model performance (AUC)

Period		～FY2022
Data segmentation	(ii) prediction-performance validation	0.822
	(iii) results confirmation	0.773

Although the model's accuracy declines slightly on the (iii) results confirmation, its performance

[11] AUC is a metric that reflects the ordering of a machine learning model's outputs, taking a value between 0 and 1. An AUC of 0.5 indicates performance equivalent to random chance, and higher values signify better predictive accuracy.

[12] Accuracy: The proportion of a machine learning model's predictions that are correct, calculated as the number of correct predictions divided by the total number of predictions.

[13] Recall: Among the borrowers who experienced a downward transition, recall is the proportion that the model correctly predicted as such.

remains relatively high on both the (ii) and (iii) data subsets[14].

This sub-section also examines the contribution of explanatory variables to the model's predictions, using the SHapley Additive exPlanations (SHAP) method[15]. A SHAP value represents, for each individual sample, how much each variable contributes to the prediction: the magnitude of a SHAP value indicates the strength of its contribution, while the sign indicates the direction (positive or negative). Results are shown in Figures 7 and 8.

Figure 7: Variables with large contribution (Average of absolute SHAP value)

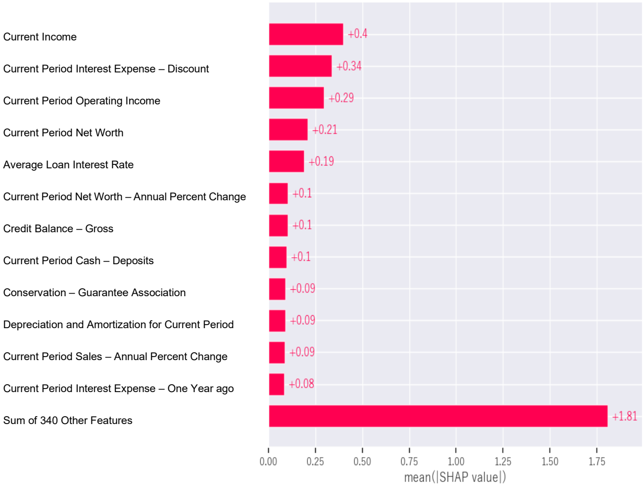
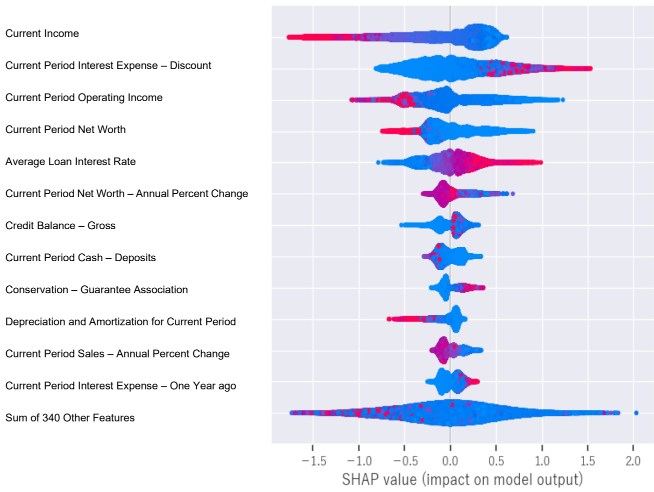


Figure 8: Distribution of SHAP values for each individual sample



From Figure 7, it is shown that "current income" contributes most to prediction, followed by "Current period interest expenses_Discount" and "Current period Operating income", indicating that lending- and borrower-financial-related indicators rank at the top. Note that Figure 7 shows the mean of absolute SHAP values for each individual borrower, so it does not indicate whether the contribution to prediction is positive or negative.

Figure 8 uses a beeswarm plot to display the SHAP value distribution across individual samples. In this plot, color reflects the variable's value (high values shown in red, low in blue), horizontal position

[14] When the constructed model was applied to the 2023 data—now available for accuracy confirmation on the Common Data Platform—the AUC dropped to 0.633, lower than the performance up to FY2022. This decline appears to stem from discontinuity between the two loan-detail datasets used. Specifically, several variables related to finance and lending lacked values from one year before the reference date in the 2023 data, which caused the corresponding difference- and ratio-based features to be missing. Such missing features are known to adversely affect classification accuracy.

[15] For more detail, see Lundberg, S. and Lee, S. A Unified Approach to Interpreting Model Predictions. "*Proceedings of the 31st International Conference on Neural Information Processing Systems*", 2017. p.4768-4777., and FSA Analytical Notes (2025.6): Understanding the utilization of Credit Guarantee System

indicates the SHAP value for each sample, and vertical spread shows the distribution density of SHAP values for that variable. For example, for "Current income", higher values (red) are associated with lower SHAP values, meaning they contribute to reducing the predicted probability of a downward borrower-classification transition. Conversely, for "Current period interest expenses_Discount", higher values (red) correspond to higher SHAP values, meaning they contribute to increasing the predicted risk.

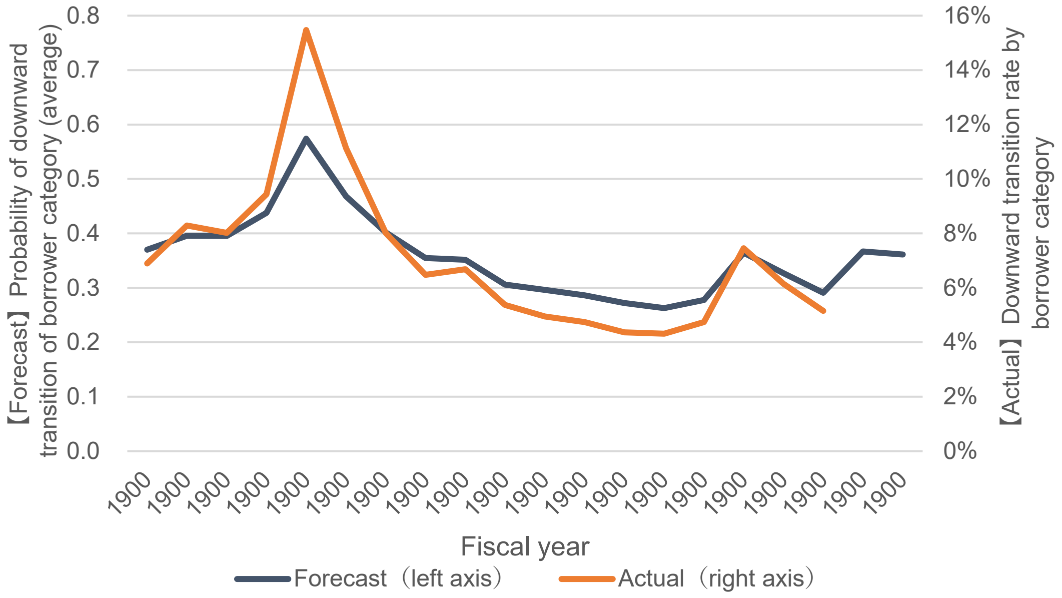
In the SHAP analysis applied to the constructed machine learning model, macroeconomic indicators were not among the top-ranked variables[16]; instead, lending- and financial-related variables contributed most to predictions[17]. However, when the model was built using only macroeconomic indicators, the AUC on the validation dataset (ii) was 0.601. Although this is lower than the model using all variables, it still exceeds the randomness threshold of AUC = 0.500, indicating that macroeconomic indicators do possess a meaningful degree of explanatory power.

3. Output

Figure 9 shows the plot in which the mean predicted probability of downward borrower-classification transition—calculated across individual borrowers—is overlaid against the actual observed transition rates.

[16] Although omitted from Figure 7, the macroeconomic indicator with the highest mean absolute SHAP value across individual samples is the Economic Trend Index CI (Leading Indicator), with a value of 0.03.
[17] When the model was constructed using only lending- and borrower-financial- related indicators, the AUC on (ii) the validation dataset was 0.816. While slightly lower than the AUC achieved with the full indicator set, this result still represents high predictive accuracy. This finding suggests that lending and borrower financial variables provide strong explanatory power for predicting downward borrower-classification transitions.

Figure 9: Comparison of downward borrower-classification transition rate (forecast vs. actual)

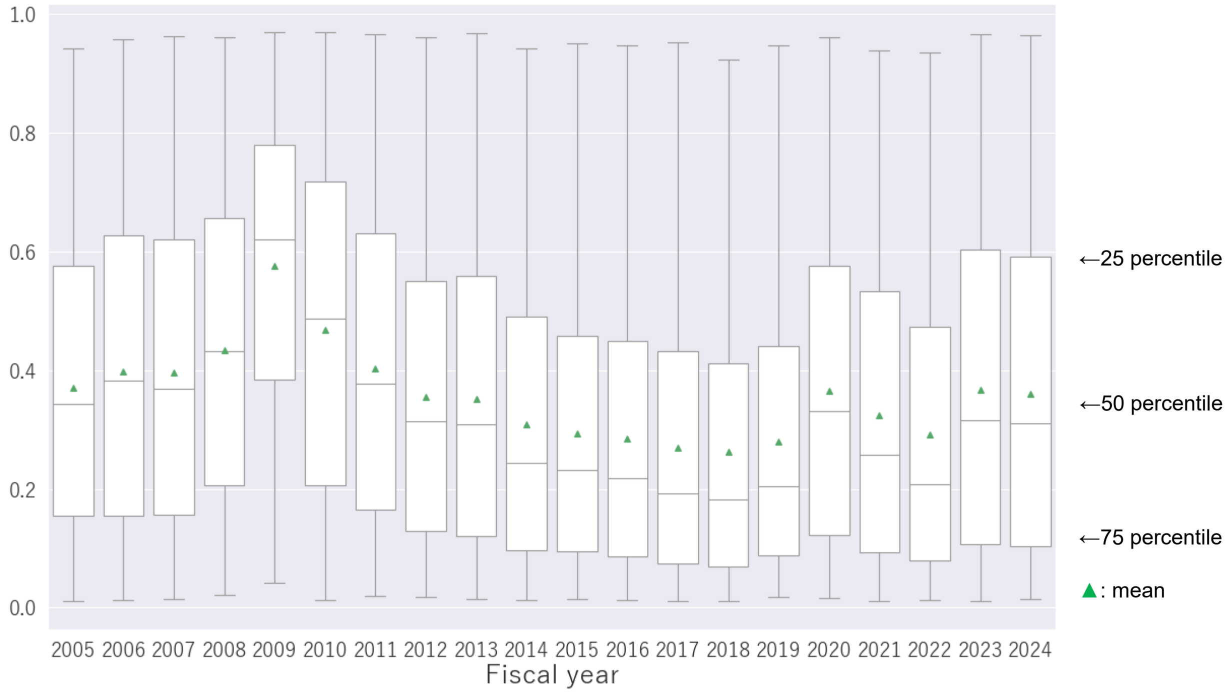


The trend in predicted versus actual outcomes exhibits similar behavior, indicating that the machine learning model captures the dynamics of downward borrower-classification transitions effectively. It is important to note, however, that the predictions represent the simple average of the model's output probabilities for borrowers, while the actuals represent the proportion of downward transitions within the annual population. As a result, some divergence in their absolute levels is expected[18].

Furthermore, Figure 10 illustrates the time-series evolution of the distribution of predicted transition probabilities for individual borrowers.

[18] As noted in footnote 8, undersampling was performed during training to improve predictive accuracy for the rare event of downward borrower-classification transition—by selectively reducing the number of majority-class (non-transitioning) samples. As a result, the model outputs extreme probabilities (often tens of percent or more) for certain borrowers, which raises the overall predicted probability level above that of the actual data. Since the aim of this analysis is to detect overall trends in credit-risk precursors using model output, no adjustment to predicted levels has been made. However, if this model were to be used for estimating individual borrower probabilities, applying a calibration adjustment—such as scaling according to empirical prevalence—could be conceivable.

Figure 10: Time-series evolution of the distribution of predicted transition probabilities



The mean and median (50th percentile) of predicted probabilities for downward borrower-classification transitions exhibit dynamics similar to the actual transition rates shown in Figure 5. Notably, they surged markedly during the FY2008–2009 amid the GFC, with a smaller rise observed during the COVID-19 pandemic in FY2020. As mentioned in the previous section, post-2023 data reflect a change in the dataset and should be considered as reference values.

Among these years, we select data for FY2009, FY2018, FY2020, and FY2024, and their probability distributions are shown in Figures 11 to 14. FY2018 represents a period of relatively stable economic conditions, while FY2009 and FY2020 correspond to the GFC and COVID-19 pandemic periods, respectively.

Figure 11: Probability distribution (FY2009)

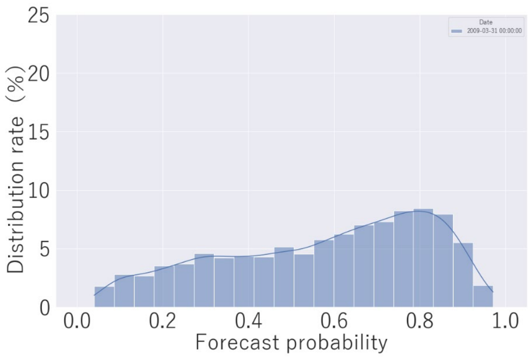


Figure 12: Probability distribution (FY2018)

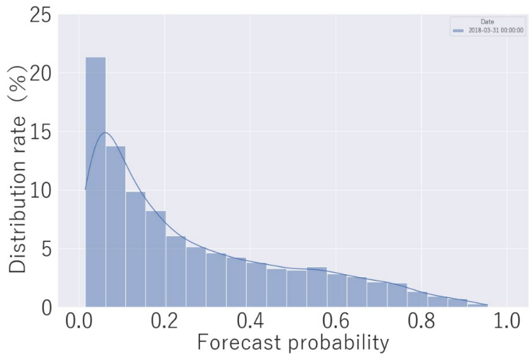


Figure 13: Probability distribution (FY2020)

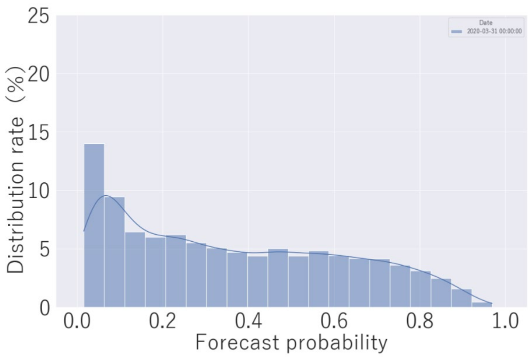
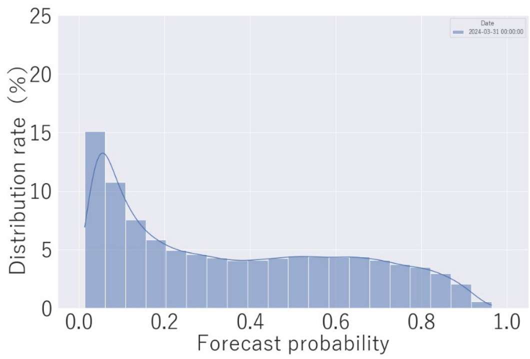


Figure 14: Probability distribution (FY2024)



In FY2009 (Figure 11), the distribution is concentrated toward higher values with a slowly tapering tail to the lower side—reflecting the many borrowers whose financial conditions worsened due to the GFC, which drove up overall downward transition probabilities. In FY2018 (Figure 12), the distribution shifts toward lower values, with a tail extending upward—signifying fewer borrowers in financial distress and a corresponding decline in downward transition probabilities during this stable period. In FY2020 (Figure 13), the concentration at lower values is reduced, and higher-value frequencies rise—indicating that the pandemic-induced economic shock impaired borrower finances and modestly lifted overall transition probabilities. Finally, the distribution for FY2024 (Figure 14) remains similar to that for FY2020. However, this pattern may reflect changes in borrower financial conditions and macroeconomic indicators, as well as the dataset switch noted previously; thus, ongoing monitoring is warranted.

This analysis examines three key distributional shape metrics—IQR [19], skewness [20], and kurtosis[21]—over time, as shown in Figures 15 to 17.

Figure 15: IQR

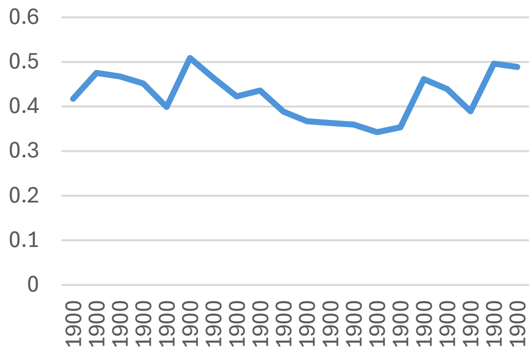


Figure 16: Skewness

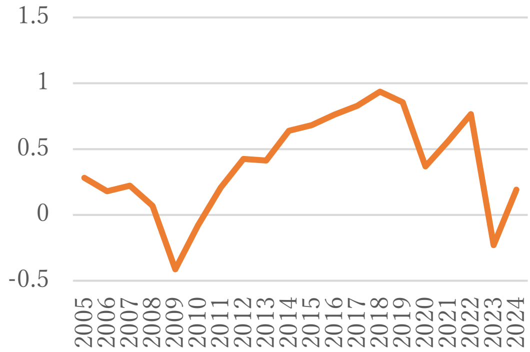
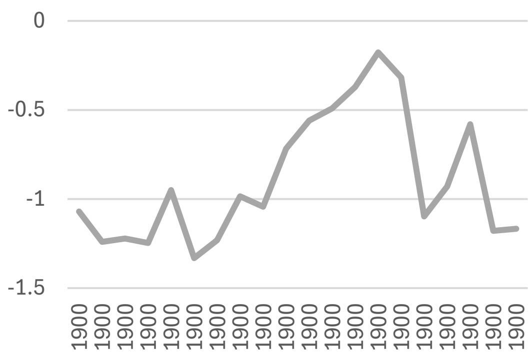


Figure 17: Kurtosis



In Figure 16, skewness shows a substantial decline during FY2009 (the GFC period) and again during FY2020 (the COVID-19 pandemic period). This indicates that, while most predicted probabilities are typically clustered at low values (resulting in high skewness), these crisis periods saw many borrowers with substantially elevated transition probabilities—consequently flattening the distribution and reducing skewness. In contrast, the trends in IQR (Figure 15) and kurtosis (Figure 17) did not show consistent patterns aligned with economic downturns; rather, they moved in opposite directions during the GFC and COVID-19 periods, suggesting no clear relationship with recession risk signals.

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[19] IQR (Interquartile Range): The value obtained by subtracting the first quartile (25th percentile) from the third quartile (75th percentile). It is a measure of data dispersion, indicating the spread of the middle 50% of observations.

[20] Skewness: A metric that indicates the asymmetry of a distribution. In frequency distributions like the example in this paper, a value of 0 means the data are symmetrically centered, a positive skew indicates the bulk of the data lies to the left of the center (long right tail), and a negative skew indicates concentration to the right of the center (long left tail).

[21] Kurtosis: A metric that represents the "peakedness" or tailedness of a distribution: a higher kurtosis value implies a sharper peak and heavier tails (more extreme values), while a lower kurtosis value indicates a flatter, more even distribution.

4. Future issues

The preceding sub-section suggests that, for detecting early signs in domestic industries that could affect financial institutions' management, monitoring the shape of the model's output distribution—particularly mean, median, and skewness—offers clear and interpretable insight into current changes. As benchmarks for these indicators, year-over-year comparisons may be made, assessing trend shifts or contrasting against specific periods such as the GFC or the COVID-19 pandemic.

However, some challenges remain. First, regarding the prediction timing, this analysis used data as of each March-end as the reference date for training the model. Therefore, if an economic shock occurs after the reference date, its effects cannot be reflected until learning from the following fiscal year's data. Second, a challenge exists in data continuity when updating the model. Since the data collection via Common Data Platform started in September 2023, a discontinuity exists compared to the dataset used for the current model. Consequently, careful attention must be paid to the model's behavior going forward. In particular, the potential impacts of this data transition—such as lowered predictive accuracy in FY2023 (see Figure 6, footnote 14)—warrant close observation.

IV. Conclusion

This analysis sought to detect early warning signals of domestic industrial changes that could affect financial institutions' management by using regional banks' loan-detail data and macroeconomic indicators. Despite remaining challenges related to data constraints, we successfully developed a machine learning model that could predict downward borrower-classification transitions for individual borrowers with reasonable performance. Furthermore, by comparing the model's predictions with historical crisis periods, it has been confirmed that the model has the potential to offers meaningful insights into current warning signals.

This analysis focused on the manufacturing sector as a pilot; however, manufacturing itself comprises diverse fields—such as food and machinery—suggesting that further segmentation by subsector, along with tailored macroeconomic variable selection, could yield different results. Moreover, the same methodology could readily be expanded to cover all industries or industry-specific segments beyond manufacturing.

Looking ahead, we will keep on making efforts to expand the scope of analysis, refine variable selection, and improve model accuracy, with the goal of supporting ongoing dialogues with financial institutions about current economic conditions and borrower credit risk. Additionally, with the full-scale launch of the Common Data Platform, we will explore the potential to harness loan-detail data for enhanced monitoring.