FSA Analytical Notes

June 2023

Introduction

As financial institutions' business environments and profit structures change, it is important to understand economic and market trends based on data, and to accurately grasp the business conditions of individual financial institutions and also the resilience and vulnerability of the financial system as a whole.

From this perspective, as stated in the report "The JFSA Strategic Priorities July 2022-June 2023," the FSA decided to assess the situations of corporate borrowers from multifaceted aspects by utilizing data, especially to identify "details of companies' financial conditions and financial institutions' lending trends" and "the dynamics and quantitative impacts of economic and market trend changes on financial institutions" as well as to analyze new challenges, including "climate change."

This report summarizes and publishes the following three data analyses conducted by the FSA during the fiscal year 2022, in accordance with the above report.

While data analysis could provide quantitative and clear results, such results are subject to models and assumptions of the analysis. Therefore, it should be noted that it is necessary to understand the data and model limitations as well as the underlying assumptions and premises, when interpreting the results of these analyses.

The data analyses presented here utilize granular data, such as individual corporate level data, loan level data, and geographical data, which the FSA emphasized in recent years. The analysis using such granular data is still in a pilot phase. The FSA will continue to enhance its analysis by collecting and accumulating granular data.

Enhancing the use of data in financial supervision and policy-making is a medium- to long-term agenda. The FSA will continue to build its data analysis capabilities and data infrastructure.

* Unless otherwise noted, the figures and tables in this report were prepared by the FSA.

【Contact】
Macro-financial Stability and Data Strategy Office（datastrategyoffice@fsa.go.jp）

Current Trends in Financial Conditions of the Corporate Sector

(Summary)

This paper attempts to show the impact of post-COVID-19 changes on financial conditions, based on financial data provided by a third-party vender. In food and accommodation services industry, where the impact of the COVID-19 pandemic has been significant, earnings have recovered to pre-COVID-19 levels on average. On the other hand, while the debt burden of the same sector shows a sign of improvement towards FY2022, its level remains above pre-COVID-19 levels, warranting continued monitoring.

I. Purpose

The purpose of this paper is to understand the impact of post-COVID-19 changes on financial conditions and recent trends in the corporate sector, based on financial data provided by a third-party vender[1]. It should be noted that this analysis is based on the data up to December 2022, and therefore does not necessarily show the latest status, and that due to data limitations, there may be a sample bias.

II. Current trends in profitability

Figure 1 shows the median of profitability (return on total assets [ROA]) by industry since fiscal year (FY) 2016. Looking at the food and accommodation industries, the education and learning support industry, and the lifestyle-related services industry (hereinafter, lumped together and referred to as "food and accommodation services"), ROA declined in FY2020 but recovered toward FY2021, ending up in broadly the same as that before the COVID-19 pandemic in FY2022 (Fig. 1). When comparing the proportion of enterprises with net losses, it is found that the proportion in the food and

[1] Based on corporate financial data provided by Teikoku Databank, this paper analyzes data for 42,614 companies for which financial data is available for three consecutive years from FY2020 to 2022. For 2016 to 2019, the analytical sample is limited to companies with available data for each FY (number of samples: 2016: 30,733 companies, 2017: 32,584 companies, 2018: 33,887 companies, 2019: 35,689 companies).

accommodation services increased sharply in FY2020 compared with other industries but declined for two consecutive years in FY2021 and 2022, nearing the level of FY2019 (Fig. 2).

Figure 1 Return on total assets by industry (median)

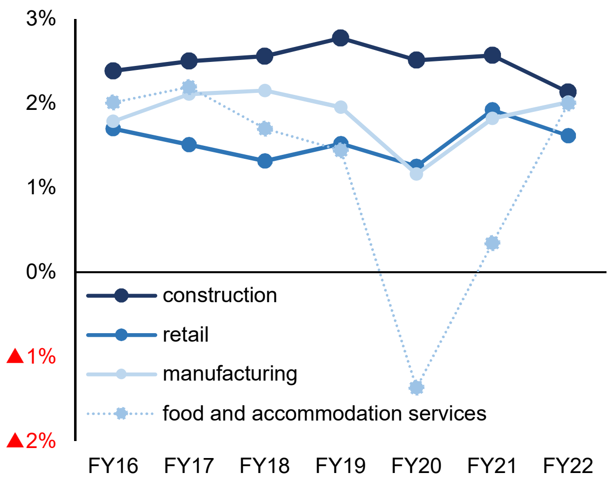
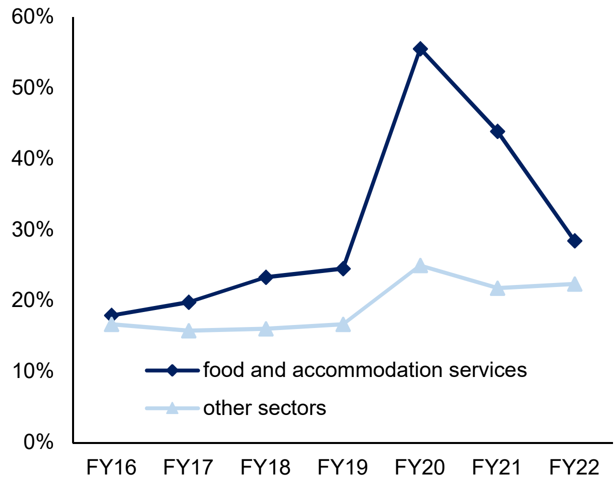
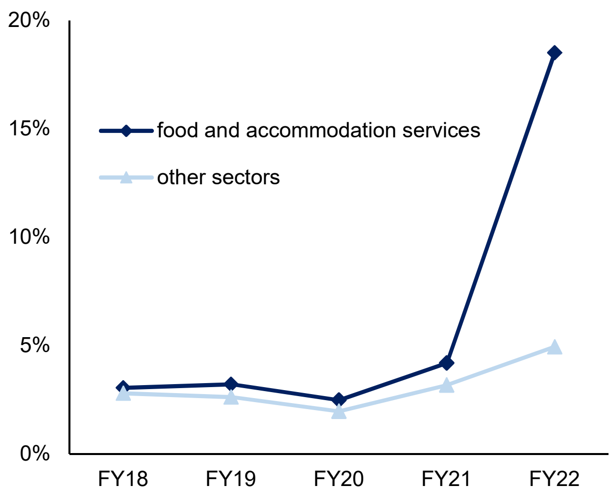


Figure 2 Proportion of enterprises with net losses (SMEs)



As seen above, while there are signs of recovery in profitability on average, some enterprises are still suffering from deterioration in earnings. Looking at the percentage of enterprises that have posted net losses for the past three consecutive years, it is observed that, while there has been a slight increase in other industries, there was a sharp rise in the food and accommodation services industry in FY2022, and it can be confirmed that around 20% of enterprises have posted net losses for three consecutive years since FY2020 (Fig. 3).

Figure 3 Percentage of enterprises that have posted net losses for the past three consecutive years (SMEs)



III. Current trends in debt

There has been improvement from the perspective of debt, but the recovery has been more moderate than that in income. Figure 4 shows the median of capital ratios by industry.

In contrast to other sectors, whose capital ratio have remained more or less unchanged amid the post COVID-19 phase, that for the food and accommodation services industry declined significantly in FY2020 and did not recover to the pre-COVID-19 level, despite some signs of recovery in FY2022. The same trends can be observed in Figure 5, which shows the proportion of insolvent enterprises. While the share has remained at almost the same level for other sectors, the food and accommodation service industry experienced a sharp increase in FY2020 and then only slight decline in FY2022, remaining at a high level. Figure 6 shows the net interest-bearing debt to sales ratio, where net interest-bearing debt is calculated by subtracting cash and deposits from interest-bearing debt. In the food and accommodation services industry, the ratio rose sharply in FY2020 and FY2021 and then declined in FY2022 but was still higher than pre-COVID-19 levels.

Figure 4 Capital ratios by industry (median)

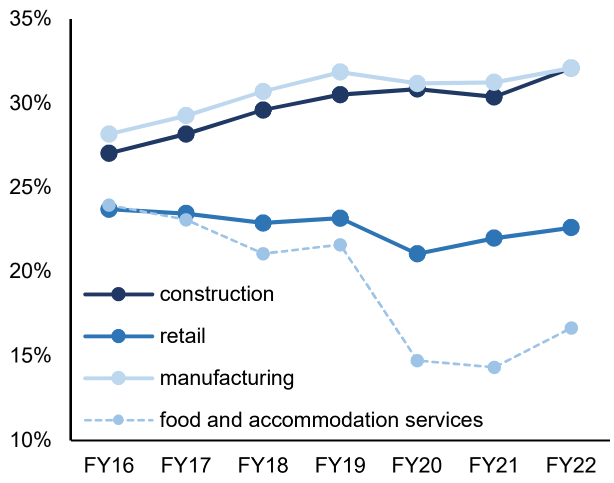


Figure 5 Proportion of insolvent enterprises (SMEs)

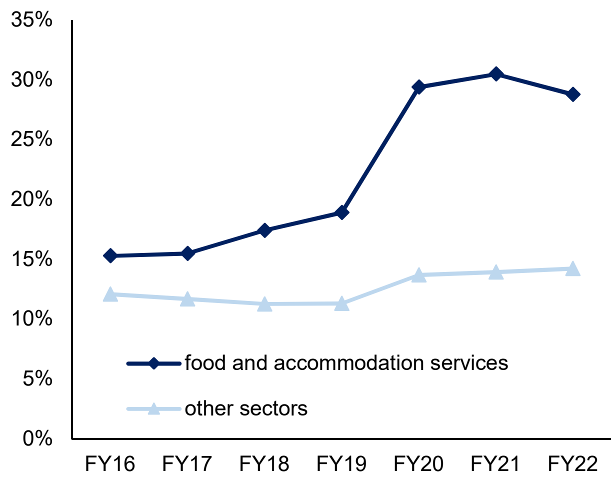
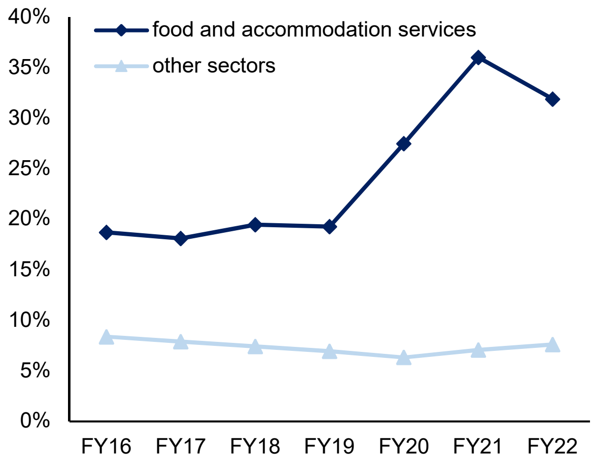


Figure 6 Real interest-bearing debt to sales ratio (median, SMEs)



IV. Current trends in profits and liabilities of low-profit enterprises

In order to understand the subsequent trends of enterprises with prolonged deterioration in profits, this section analyzes financial trends after deterioration in profits for enterprises who recorded net losses for three consecutive years between FY2001 and 2019 before COVID-19 (hereinafter referred to as “low-profit enterprises”).

First, with regard to profits, many enterprises that recorded continuous net losses turned profitable within a few years, while some enterprises remain in the red. Figure 7 shows the profitability of low-profit enterprises as of two data points, one year and three years after the time when they first incurred losses for three consecutive years, respectively. Around 50% of low-profit enterprises turned black one year after they posted losses for three consecutive years, however, around 20% remained in the red even after three years.

Next, looking at the debt of low-profit enterprises, it can be seen that the debt burden has generally improved in line with the recovery in profits. Figure 8 shows the changes in the capital ratio and the ratio of net interest-bearing debt to sales (both medians) for low-profit enterprises since they first incurred losses for three consecutive years. All indicators show a gradual recovery in the period.

Figure 7 Profitability of low-profit enterprises

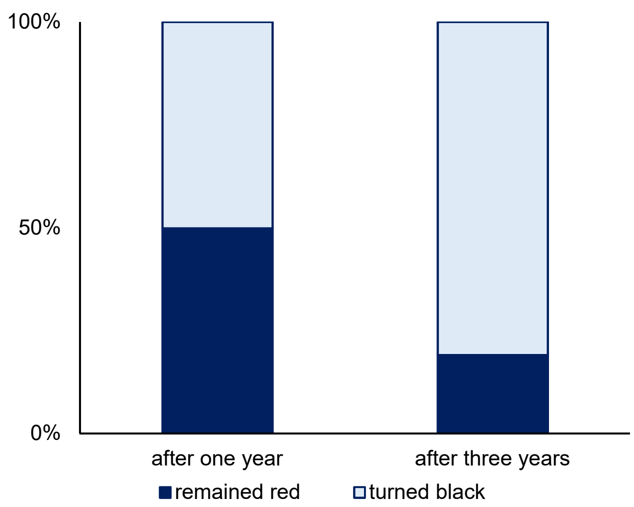
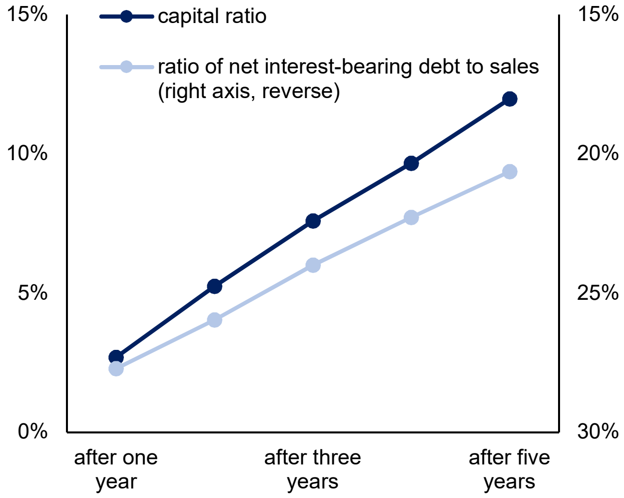
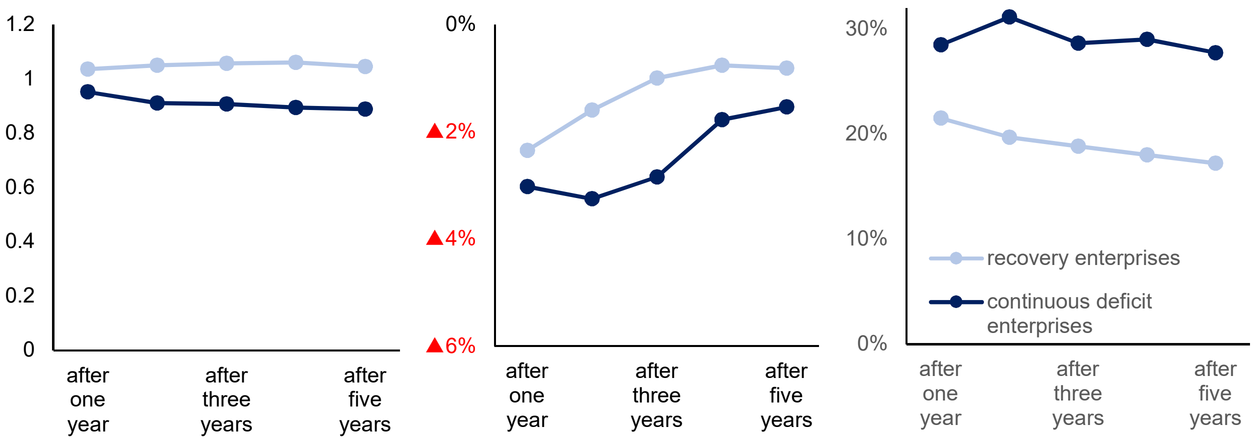


Figure 8 Capital ratio and the ratio of net interest-bearing debt to sales (median)



As can be seen from the above, low-profit enterprises are reducing their debt burden on average. On the other hand, enterprises that are lagging in improving their profits are continuing to have sluggish business. Figure 9 shows the trend in sales, growth rate of fixed assets, and ratio of net interest-bearing debt to sales for low-profit enterprises divided into two groups: those that turned black for two consecutive years (hereinafter referred to as "recovered enterprises") and those that remained in the red for two consecutive years (hereinafter referred to as "continuous deficit enterprises"), after posting losses for three consecutive years. In terms of sales, recovered enterprises made a steady recovery, while continuous deficit enterprises remained sluggish. As for investment in fixed assets, both groups reduced assets for several years after posting losses for three consecutive years, however, continuous deficit enterprises recorded a relatively larger decreasing rate compared to recovered enterprises whose decreasing rate gradually become moderate. Regarding the ratio of net interest-bearing debt to sales, recovered enterprises shows a decreasing trend, while the ratio remained high for continuous deficit enterprises.

Figure 9 Sales, investment, and debt for low-profit enterprises[2]
(divided into profit group, median within group)
(Left: sales / Middle: growth rate of fixed assets (YoY) / Right: ratio of real interest-bearing debt to sales)



V. Conclusion

As a summary, in food and accommodation services industry, where the impact of the COVID-19 pandemic has been significant, earnings have recovered to pre-COVID-19 levels on average, although some enterprises' earnings have continued to slump. On the other hand, while the debt burden of the same sector shows a sign of improvement towards FY2022, its level remains above pre-COVID-19 levels, warranting continued monitoring. Going forward, the FSA will continue to analyze the impact of COVID-19 on financial conditions in the corporate sector using various data and utilize the results in its dialogues with financial institutions and policy discussions.

[2] Sales are standardized to a value of 1 for the year in which the company has been in the red for three consecutive years.

Analysis of Credit Risks in Bank Loans

(Summary)

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

I. Purpose

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

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

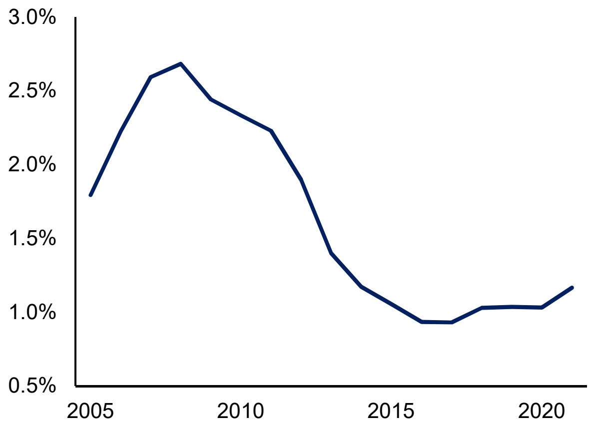
The estimation uses anonymized data of the financial statements and credit profiles of corporate borrowers from 62 member banks of the Regional Banks Association of Japan. The total number of samples for this data is approximately 50 million based on quarterly data from the end of March 2004 to the end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

II. Trends in borrowers' financial conditions and defaults

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

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

Figure 1 Default proportion (all industries[4])



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

[3] Other definitions may include a requirement that payments be in arrears for at least 90 days. For simplicity, this paper focuses only on borrower rating; however, conditions adding delinquency to the definition of default did not significantly change the overall results of our analysis.
[4] Financial, insurance and public service were excluded (hereinafter the same in this section).

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

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

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

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

---

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

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

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

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

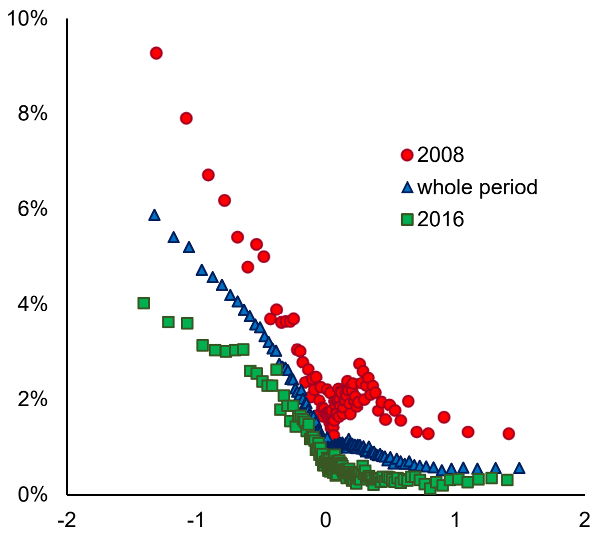
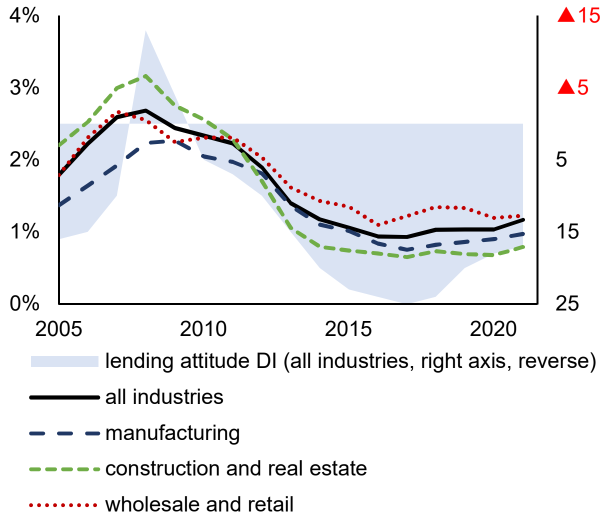


Figure 3 Default proportion by industry and lending attitude DI



III. Models and results

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

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

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

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

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

Table 4 Estimation results for each industry group[10]

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

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

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

Figure 5 Actual default proportion and estimated default probability

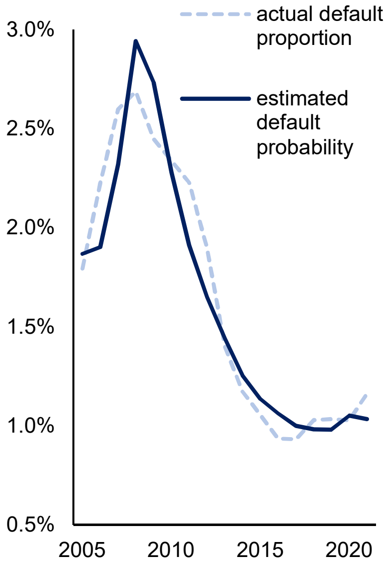
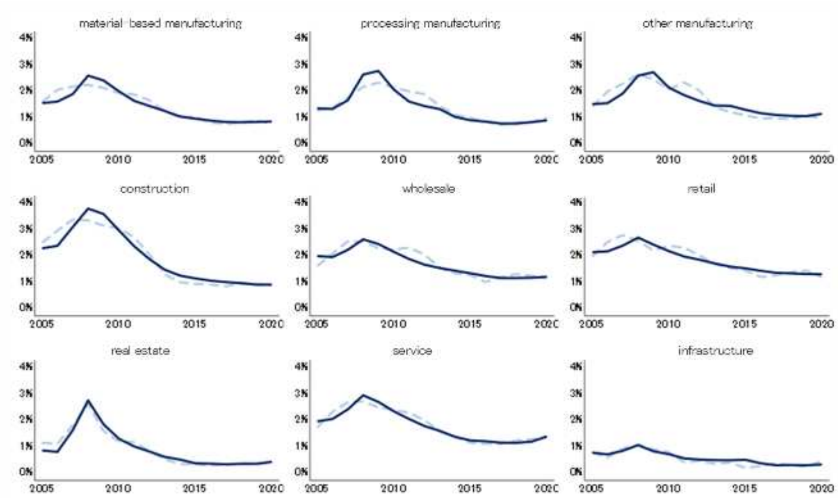
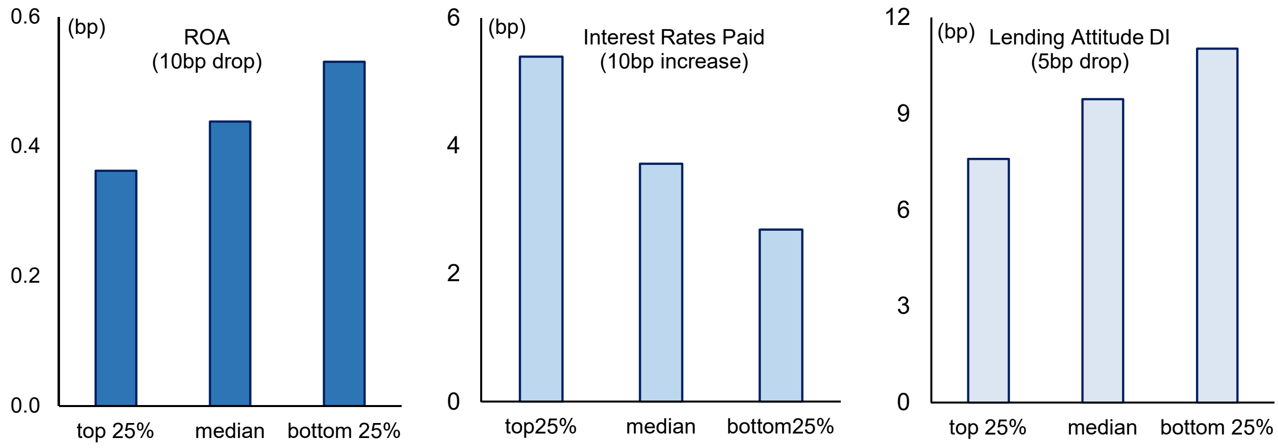


Figure 6 Actual default proportion and estimated default probability (by Industry group)



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

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



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

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

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

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

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

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

V. Conclusion

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

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

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

Analysis of climate-related financial risks

(Summary)

This paper uses granular data, such as details of transaction-level corporate loans, collected from 49 regional banks that participated in the experiment[11] for a common data platform. It then focuses on the industries, products, and geographic conditions of client companies and clarifies the characteristics of climate-related risks (transition risks and physical risks) faced by regional banks, as well as the regional differences in these characteristics. Data and methodologies related to climate change are still developing, and the FSA will continue to enhance its data infrastructure and analysis for use in dialogues with financial institutions.

I. Background

With growing global interest in climate change, many financial supervisors are making efforts to understand its impacts on the financial system (climate-related financial risks). In 2022, the Japan Financial Services Agency (FSA) published a discussion paper entitled "Supervisory Guidance on Climate-related Risk Management and Client Engagement."[12] In this paper, the FSA emphasizes how important it is for banks to assess climate-related financial risks and engage with their clients to support the clients' response to climate change. The FSA also expresses its intention to engage with banks to discuss banks' challenges in addressing climate-related financial risks.

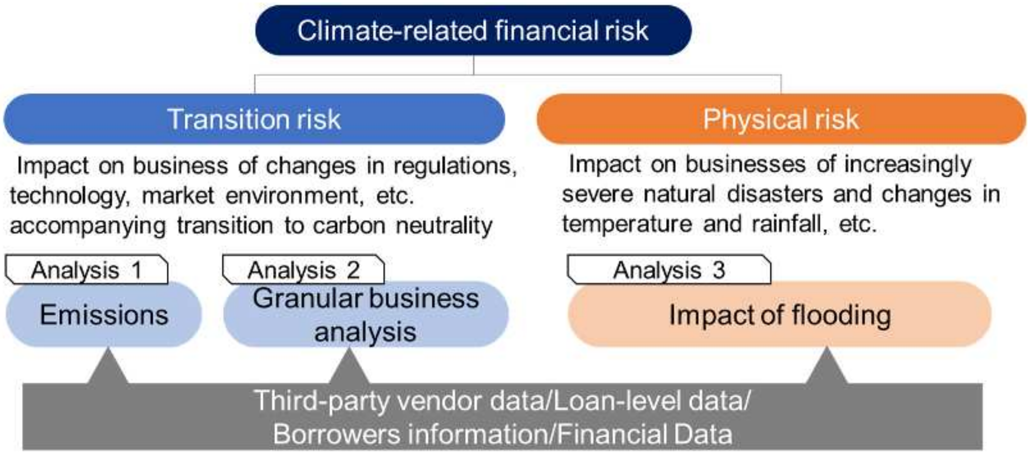
The impacts of climate change on banks may vary depending on their size and business model. For example, the sectoral composition of loan portfolios of regional banks may differ significantly from that of major banks. Therefore, in order for the FSA to engage effectively in dialogue with banks, it is important to deepen its understanding of banks' climate-related risk profiles.

From this perspective, the FSA conducted the following three trial analyses to better understand the characteristics of climate-related financial risks (both transition risks and physical risks) at regional banks for the use of future dialogues (Fig. 1).

[11] Progress in Data Integration and Next Steps
https://www.fsa.go.jp/en/news/2023/20230721/progressindataintegration.pdf

[12] https://www.fsa.go.jp/en/news/2022/20220715/03.pdf

Figure 1 Structure of the analysis



1. Analysis on financed emissions of regional banks using the CO2 gas inventory[13]
2. Analysis on exposure to engine-related companies that may be affected by the shift to Electric Vehicles (EVs)
3. Visualization of flood risks on banks using borrower address information and hazard map data

These analyses were conducted as part of the experiment to develop a common data platform. The analyses used loan-level granular data collected from 49 regional banks that participated in the study. As data and analytical methods for climate-related financial risks are still evolving, caution is warranted in interpreting the results. Moreover, the study also aims to deepen the understanding of the benefits and limitations related to granular data. The FSA intends to continue its efforts to address data issues identified in the analyses and to improve the overall analysis.

II. Analysis 1: Characteristics of financed emissions of regional banks

To assess climate-related financial risks on banks' business, it is considered useful, as a first step, for banks to monitor not only greenhouse gas (GHG) emissions from their own business operations, but also financed emissions (FEs) of companies they invest in or lend to. Many banks have already initiated steps to estimate their FEs. In this context, it will be also important for the FSA to estimate and understand the characteristics of banks' FEs to make dialogue with them more effective.

Therefore, this analysis attempted to clarify the characteristics of FEs of regional banks and their variations across regions.

[13] Data summarizing the amount of greenhouse gases emitted or absorbed by a country in one year. Compiled by the National Institute for Environmental Studies based on the IPCC guidelines. https://www.nies.go.jp/gio/en/aboutghg/

1. Calculation method

As indicated in the guidance[14] issued by the Ministry of the Environment, the FEs of banks are calculated by summing up the emission of each company multiplied by the corresponding attribution factor[15] across their clients in the loan portfolio (see below).

$$FEs = \sum_{i} Attribution\ \ factor_i \times Emissions_i$$

$$Attribution\ \ factor_i = \frac{Outstanding\ \ amount_i}{Total\ \ equity\ \ +\ \ debt_i}$$

$$(\text{with}\ \ i = borrower)$$

The calculation of FEs can be done either through a bottom-up analysis by adding up emissions of individual companies or through a top-down analysis by allocating Japan-wide total emissions to each company using an industry-specific emission factor (e.g., carbon intensity). This analysis adopted a top-down analysis to better capture the characteristics of FEs throughout regional banks' entire portfolios. The methodologies used to estimate FEs are described as follows.

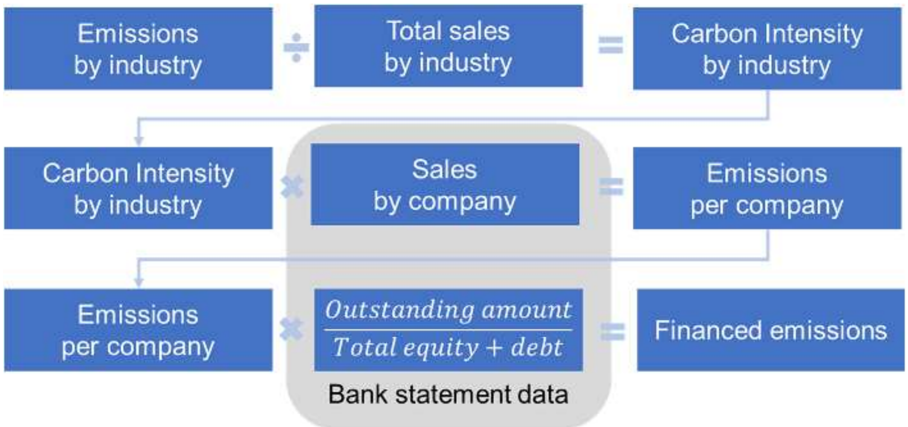
First, "carbon intensity by industry" was calculated by dividing "CO2 emission by industry" by total sales of companies in the industry. We then multiplied the "carbon intensity by industry" by the sales volume of each borrower company in the industry to estimate the CO2 emissions of each borrower company. The CO2 emissions of each borrower company thus estimated were further allocated to the bank in accordance with the attribution factor,[16] and the CO2 emissions allocated by the borrower companies for each bank were aggregated to estimate the FEs.[17] (Fig. 2)

"Carbon intensity by industry" is calculated using CO2 emissions after the distribution of electricity and heat by industry in the greenhouse gas inventory, from the perspective of understanding both scope 1 (direct emissions from the reporting company's factories, offices, vehicles, etc.[18]) and scope

[14] https://www.env.go.jp/content/000125696.pdf (available only in Japanese)
[15] Where financial information can be obtained from multiple regional banks through the aggregation of the names of borrowers, the financial information of the regional bank with the largest outstanding balance of loans to the borrower is used. Negative figures for equity are replaced with zero.
[16] Where the attribution factor was greater than 1, the attribution factor was set at 1.
[17] If the financial information of one firm is available at multiple banks, the information from the bank with the largest loan outstanding was used in the analysis. Zero floor is applied to capital and a ceiling of one is applied to an attribution factor. If there was no information on the sales volume or total funding amount of the borrower, FEs were estimated by multiplying the loan amount by the "FEs per loan by industry," which was calculated by dividing the total FEs in industry by the total loan amount in the respective industry.
[18] https://www.env.go.jp/earth/ondanka/supply_chain/gvc/en/supply_chain.html

2 (indirect energy-derived emissions from electric power and other energy consumed by the reporting company[18]) for each industry. As a result, the double counting of direct CO_2 emissions from the electricity and gas industry (Scope 1) and indirect CO_2 emissions from the use of electricity, gas, etc. by other industries (Scope 2) can be avoided because CO_2 emissions related to electricity, gas, etc. are allocated to each industry that uses them. On the other hand, it should be noted that the FEs of the electricity and gas industry will be smaller than the FEs calculated based on the actual CO_2 emissions because the allocated CO_2 emissions of the industry will be smaller than the actual CO_2 emissions of the industry.

Figure 2 FEs calculation process



2. Result of analysis

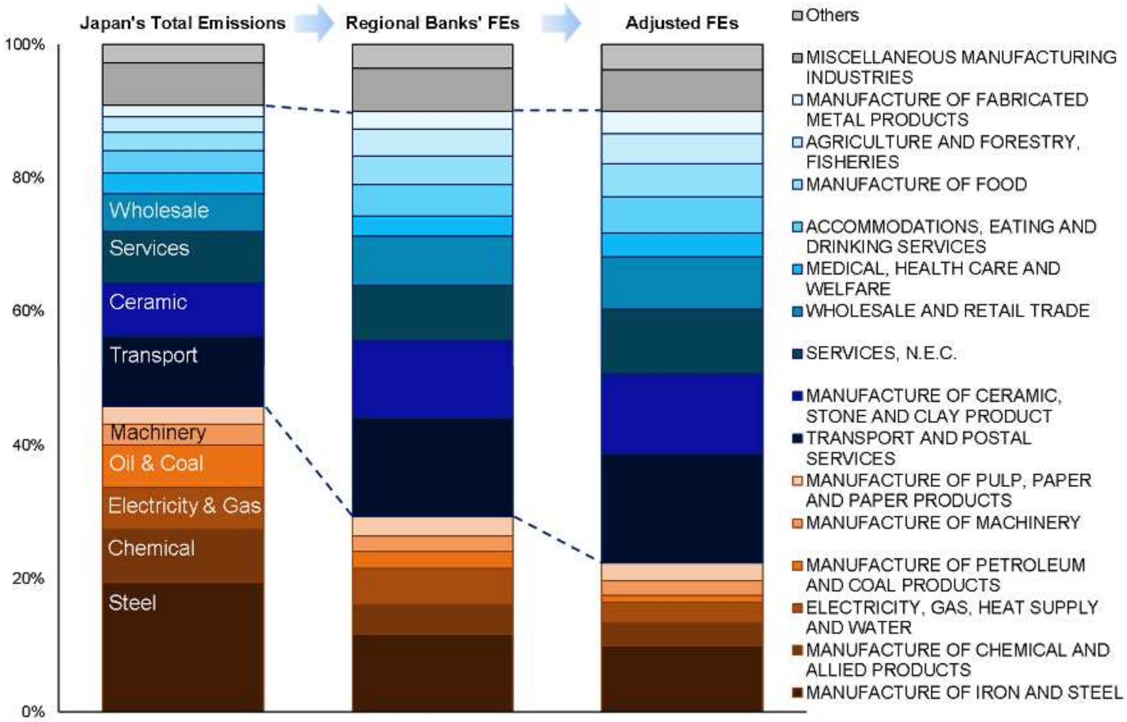
The left side of Figure 3 shows the composition of GHG inventory[19] by industry, and the center shows the composition of FEs by industry[20] for all regional banks that participated in the demonstration test (regional banks' FEs). In addition, whether or not a regional bank is the main bank of a corporate borrower is also an important factor in the form of support provided. Therefore, the FEs of a regional bank limited to a corporate borrower that is its main bank[21] (adjusted FEs) are estimated and shown on the right side of Figure 3.

In the GHG inventory, CO_2 emissions from industries generally referred to as high-emission industries, such as iron and steel, the chemical industry, electricity and gas, and oil and coal, account

[19] Based on final data for FY2021.
[20] Excluding financial/insurance business and public service.
[21] In this analysis, the bank with the largest loan outstanding as of the end of March 2022 to a firm is assumed to be the main bank of the firm.

for around 40% of Japan's total CO2 emissions. In the regional banks' FEs, however, the high-emission industries account for around 24% of Japan's total CO2 emissions. Furthermore, in the modified FEs, their share is around 17%.[22]

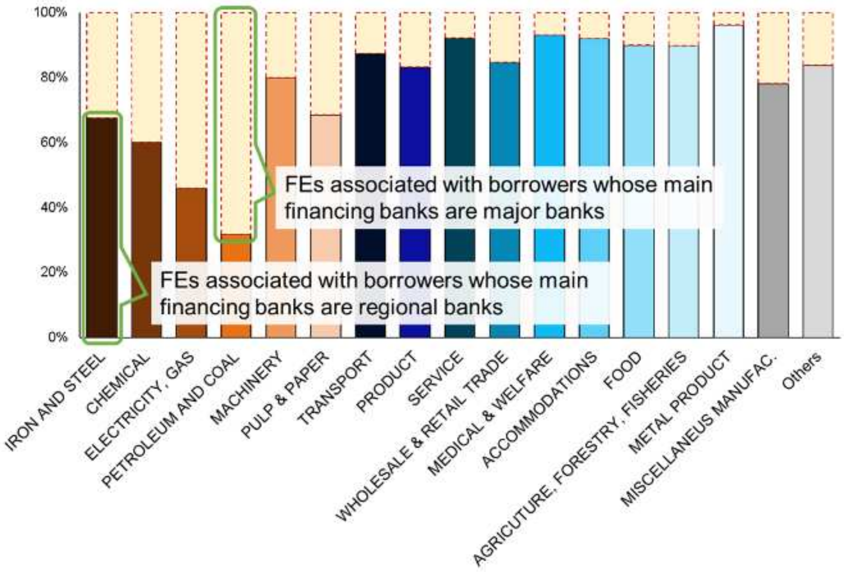
Figure 3 Comparison of Industry Composition of Regional Bank FEs



On the other hand, the share of the transportation, ceramic, stone and clay product manufacturing, and service industries turned out to be the highest for adjusted FEs, followed by regional banks' FEs, then Japan's total emissions. Although there were differences in the degree among banks, a similar trend was observed for individual banks. This may reflect the fact that there are relatively large enterprises in high emitting industries, such as iron & steel, chemical, electricity & gas, and oil & coal, and that in many cases, major banks such as mega-banks are the main banks for such enterprises. Looking at regional banks' FEs by who main banks are (major banks or regional banks), the proportion of the case where regional banks are main banks is low in high emitting industries, and it can be confirmed that a considerable portion of them belongs to major banks (Fig. 4).

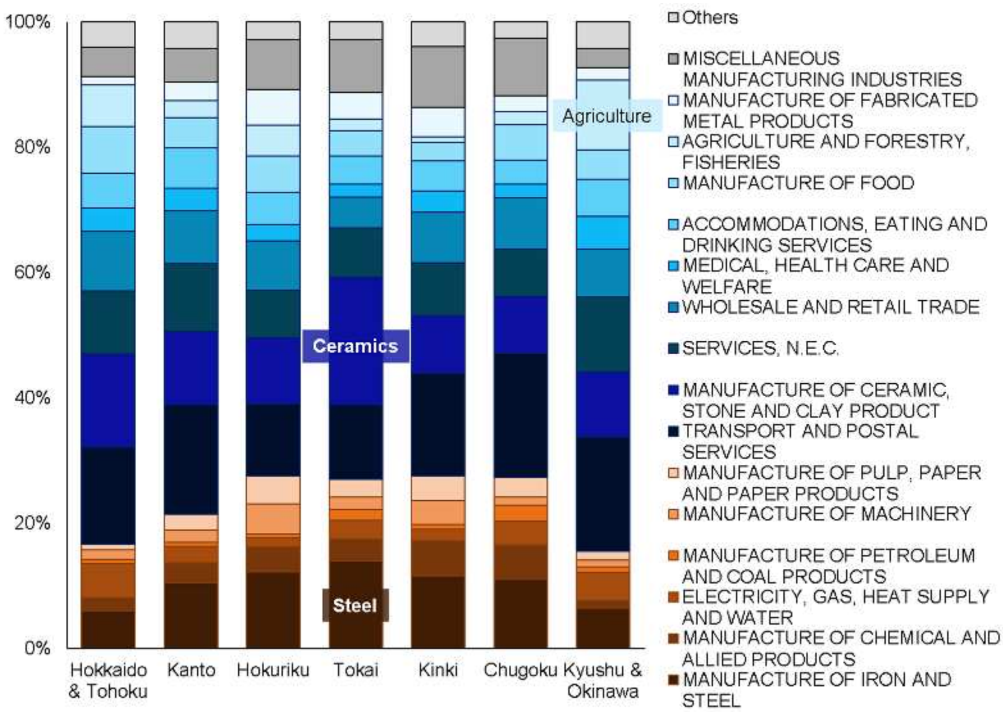
[22] When CO2 emissions from the GHG inventory before electricity and heat distribution are used for the electricity and gas industry, CO2 emissions from the high emission industries account for approximately 60% of the national total, 47% for the regional bank FEs, and 34% for the modified FEs.

Figure 4 Non-main bank portion of regional bank FEs (industry)



Next, the analysis on the characteristics of the adjusted FEs by region found that there is a considerable variation in the industry composition of the adjusted FEs by region. For example, the share of high emitting industries varies widely from 13% to 23% depending on regions. This variation is even more pronounced at the individual bank levels. The banks in the Tokai region have a relatively high share of the ceramic, stone and clay product manufacturing industries as well as the iron and steel industry in their adjusted FEs, while the banks in the Kyushu and Okinawa regions have a relatively large share of the agriculture, forestry and fisheries industries (Fig. 5).

Figure 5 Industry Distribution of Adjusted FEs by Region



These results suggest that it is important for regional banks to consider strategies for engaging in FEs reduction based on the characteristics of their regional and individual portfolios, instead of uniformly prioritizing high emitting industries. At the same time, it would also be important for the FSA to take into account the characteristics of the region and each bank's portfolio in its dialogue with banks.

3. Future Issues

These initiatives have identified the characteristics of the FEs of regional banks and the industry distribution of FEs by region. On the other hand, it should be noted that the present analysis is a mechanical estimation using the average carbon intensity of each industry. As the next step, in addition to improving the accuracy of the analysis by utilizing bottom-up information, such as CO2 emissions disclosed by borrowing companies, it may be advisable to consider a forward-looking analysis that takes into account the transition policies of each financial institution and borrowing companies.

III. Analysis 2: Risks of business changes due to climate change

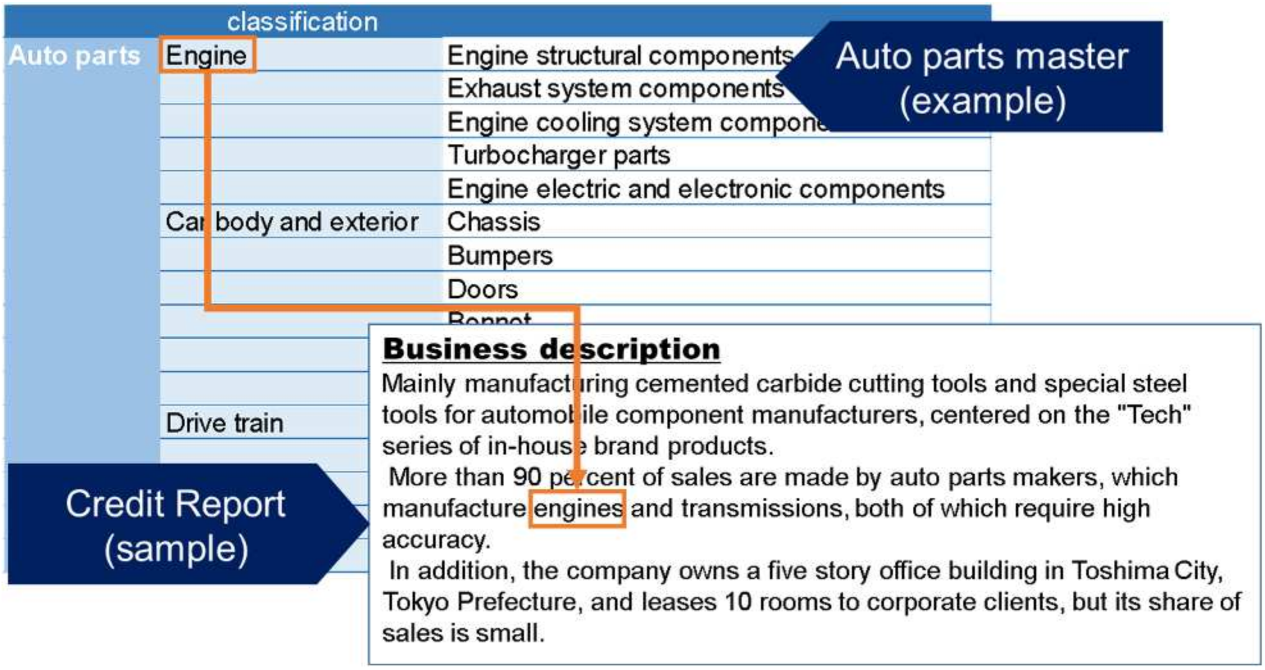
It has been pointed out that there is a possibility that the specifications of products manufactured by companies will change significantly due to companies' responses to climate change and changes in consumer preferences reflecting the increased awareness of climate change. Typical examples of such changes in product specifications include the next-generation of automobiles and the shift to EVs. In the future, as the shift to EVs progresses, companies that manufacture conventional engine parts may be exposed to significant changes in demand. Financial institutions are expected to support such companies' responses to changes accompanying climate change through engagement.

On the other hand, the CO2 emissions of the transportation machinery and equipment manufacturing industry, which is considered to include many of the companies that manufacture engine parts, account for only 1-2% of the total GHG inventory. Therefore, the risks of changes in demand for engine parts cannot be appropriately identified from the perspective of FEs analyzed in the previous section. In order to identify such risks, it is important to focus on manufactured parts and identify the companies that will be affected. Therefore, this section used business information of companies to identify and clarify the characteristics of engine part manufacturing companies that are potentially affected by the shift to EVs.

1. Analytical methods

According to the Japan Standard Industry Classification (JSIC), companies can be classified only into a broad category, such as "transportation machinery and equipment manufacturing" and cannot be classified by manufactured parts. Therefore, with the cooperation of TEIKOKU DATABANK, Ltd. (TDB), companies classified as transportation equipment manufacturers under the JSIC were selected, and companies that included the word "engine(s)" in the qualitative information of the TDB’s credit report of each company were flagged. Then, the characteristics of the extracted companies were analyzed (Fig. 6). It should be noted that this analysis mechanically flags whether or not the word "engine(s)" is included, and it is not possible to confirm whether or not the companies selected actually manufacture engine-related parts and to what extent engine-related parts account for the sales of those companies.

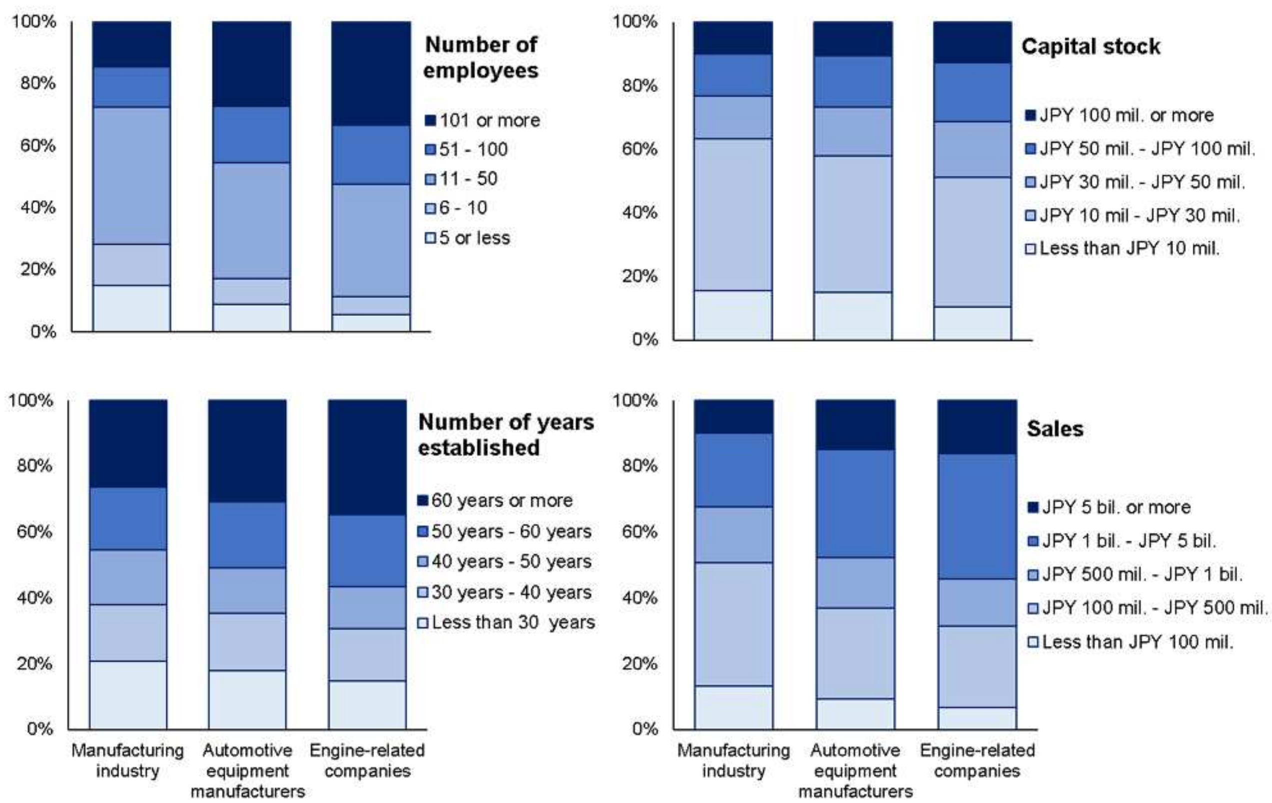
Figure 6 Method for identifying engine-related companies (example)



2. Result of analysis

Figure 7 shows the distribution of the number of employees, years established, the amount of capital stock and net sales of the manufacturing industry as a whole, the automotive-related transportation equipment manufacturing industry (automotive equipment manufacturers), and the companies flagged as engine-related companies (engine-related companies). In order to exclude, to the extent possible, enterprises engaged in diversified businesses including manufacturing of engine-related parts from the enterprises flagged as engine-related, the analysis focused only on SMEs.[23] From this analysis, it has become clear that the number of employees, number of years established, capital stock, and net sales of engine-related companies are larger than those of the manufacturing industry as a whole and the automotive equipment manufacturers, which may reflect the fact that engines have been a key component in the history of the auto industry.

Figure 7 Characteristics of automotive component manufacturers



[23] SMEs are defined as a company with capital of 300 million yen or less (100 million yen in wholesaling, 50 million yen in retail and food services), or regular employees of 300 or less (100 in wholesale service, 50 in retail and food services).

Next, when aggregating the share of loans to engine-related companies in corporate loans outstanding by region where the head offices of regional banks are located, it is found that the proportion of loans to such companies is relatively high in the Tokai and Chugoku regions (Fig. 8). This is considered to reflect the proximity of major production bases of automakers to some extent. Mapping the locations of the headquarters of engine-related companies revealed that they were concentrated in the Tokyo metropolitan area, the Tokai region, Osaka, Okayama, and Hiroshima prefectures, where automakers have major production bases. Furthermore, the share of loans outstanding[24] to automotive equipment manufacturers and that for engine-related companies by bank generally have a positive correlation, which indicates that regional banks with a high share of both tend to extend loans to major automakers[25] (Fig. 9).

Figure 8 Share of loans to engine-related companies in total corporate loans share of lending (by region)

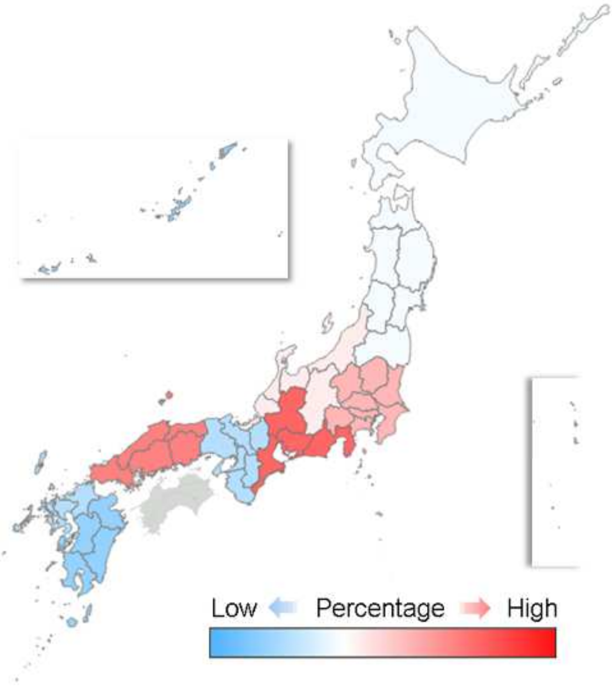
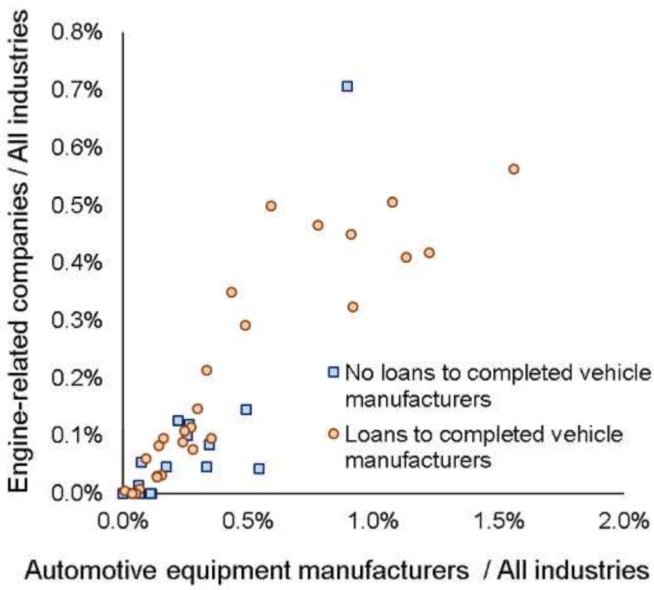


Figure 9 Convergence between engine-related companies and the manufacture of transportation equipment and the industry ratio of total assets by bank



[24] Aggregated figures for outstanding loans that can be linked to TDB data (as of the end of March 2022).
[25] Suzuki, Subaru, Daihatsu Motor, Toyota Motor Corporation, Nissan Motor Co., Ltd., Honda Motor Co., Ltd., Mazda Motor Corporation, Mitsubishi Motors Corporation

3. Future Issues

This analysis selected companies that included the keyword "engine(s)" in their business summaries and identified the characteristics of those companies. It is useful to examine the appropriateness of the sampling results through exchanges of opinions with financial institutions and to improve the sampling method. In addition, these engine-related companies often belong to the supply chain of a specific automaker. In this case, it will be important for multiple financial institutions that provide financing to companies in the supply chain to work together to promote climate change measures throughout the supply chain. An area for further exploration is to visualize the financing relationships between financial institutions and companies in the supply chain to promote collaboration among financial institutions related to the supply chain,.

IV. Analysis of physical risks using hazard maps

As global warming progresses, it has been pointed out that natural disasters are increasing in frequency and severity. If a borrower suffers damage due to a natural disaster, its sales and financial condition may deteriorate due to the suspension or stagnation of the business of the borrower, which may lead to the deterioration of credit risk for financial institutions (physical risk). This analysis used granular data, such as loan details of the regional banks that participated in the experiment, together with flood hazard maps, to understand the characteristics of the physical risks of flooding faced by regional banks, and attempted to visualize them on maps.

1. Analytical methods

First, banks' loan data was linked to the address of borrowers' head office to through Corporate Numbers (Japanese legal entity identifier) obtained from the National Tax Agency's Corporate Number publication site.[26] This was then mapped onto the flood hazard map[27] of the Ministry of Land, Infrastructure, Transport and Tourism (MLIT) to determine which inundation category (representing the risk of a flood) on the flood hazard map can be assigned to each borrower based on the location

---

[26] National Tax Agency Corporate Number Publication Site https://www.houjin-bangou.nta.go.jp/download/ (available only in Japanese)

[27] Ministry of Land, Infrastructure, Transport and Tourism https://nlftp.mlit.go.jp/ksj/gml/datalist/KsjTmplt-A31-v3_0.html (available only in Japanese)

of its head office. Next, the number of business suspension/business stagnation days[28] for each borrower (in the event of a flood) was estimated based on the borrower's inundation category using information from the Flood Control Economic Manual[29] of the MLIT. Then, the "flood risk level" of loans was defined as the number of business suspension/business stagnation days at each company times the amount of loans provided to the company. The flood risk levels were aggregated for each bank to analyze their characteristics (Fig. 10).

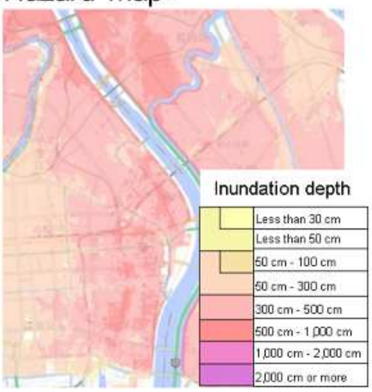
Figure 10 Methods for calculating degree of risk[30]

<Borrowers information>

Company name	Address	Loan balance
AA Company	…, Tokyo	¥ x,xxx,xxx,xxx

× Number of business suspension/ stagnation days = Flood risk level

<Hazard map>

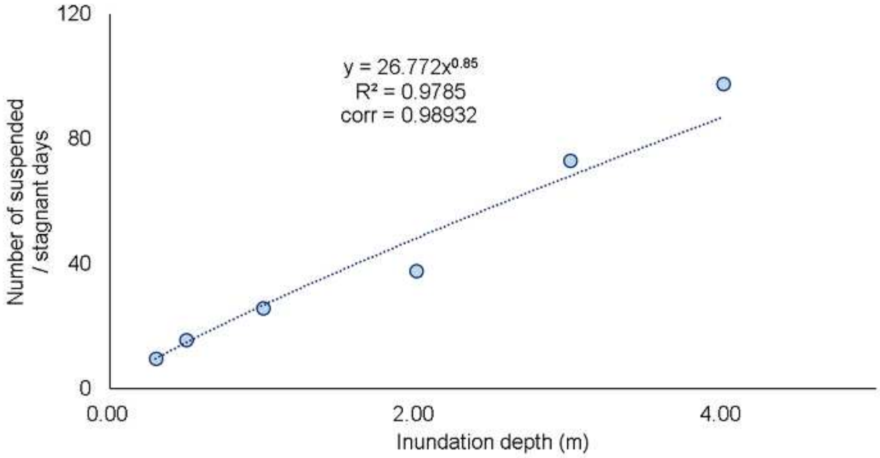


Inundation depth (cm)	Number of business suspension days	Number of business days	Number of suspended/ stagnant days
Less than 50	6.4	18.8	15.8
50 – 100	13.5	25.0	37.8
100 – 200	20.0	35.6	
200 – 300	41.2	64.0	
300 – 500	56.1	83.2	97.7
500 – 1,000	-		156.8
1,000 – 2,000			282.6
2,000 or more			356.1

Compiled based on the Economic Survey Manual for Flood Control issued by the Ministry of Land, Infrastructure

[28] The number of business suspension days is the period when no sales are recorded, and the number of business stagnation days is the period when a decline in sales is recorded. The decline of sales in the business stagnation days is assumed to be 50% and, based on the foregone sales, "the number of business suspension / business stagnation days" is defined as "number of suspended days" + "number of suspended days x 1/2". (Practical Guide to Scenario Analysis of Climate Change Risks and Opportunities in Line with the TCFD Recommendations (for the Banking Sector) (Ministry of the Environment), https://www.env.go.jp/content/900518880.pdf (available only in Japanese))
[29] Flood Control Economic Manual
https://www.mlit.go.jp/river/basic_info/seisaku_hyouka/gaiyou/hyouka/r204/chisui.pdf (available only in Japanese)
[30] Flood Hazard Mapping Handbook
https://www.mlit.go.jp/river/basic_info/jigyo_keikaku/saigai/tisiki/hazardmap/suigai_hazardmap_tebiki_202112.pdf (available only in Japanese)

Figure 11 Methods for calculating the number of suspended/stagnant days



Since the MLIT's Flood Control Economic Manual does not provide the number of business suspension / business stagnation days corresponding to an inundation depth beyond 300 cm, a power trendline was used for the extrapolation. Also, an adjustment was made to align the classification of Flood Control Economic Manual (e.g. "50 to 99 cm," "100 to 199 cm," "200 to 299 cm") and that of the hazard map (e.g. "50 cm to 300 cm").

2. Results of analysis

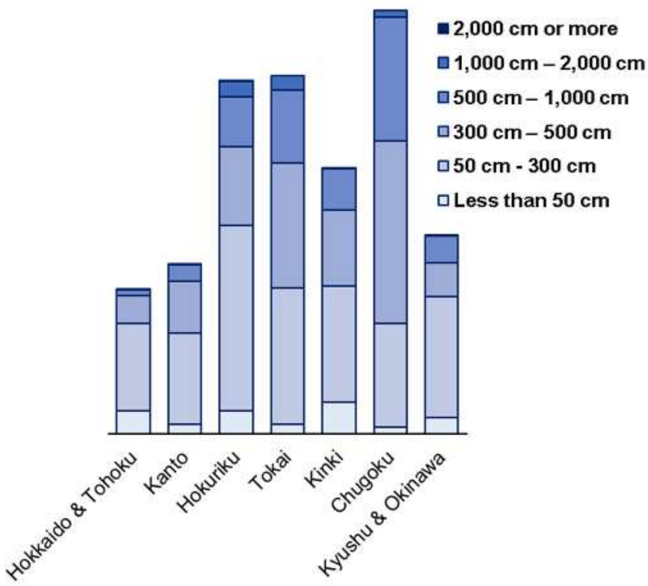
Figure 12 shows SMEs'[31] flood risk levels per loan outstanding, aggregated by region according to the location of the headquarters of lender banks.[32] This shows that the risk per loan balance is relatively high for regional banks whose head offices are located in the Chugoku, Tokai, and Hokuriku regions. It was found that the flood risk levels of these regional banks' borrowers differ greatly by municipality,[33] and that risks are concentrated in specific areas (Fig. 13). Such areas are often geographically located on the side of the mid-section or lower reaches of rivers that are prone to flooding in times of disaster. However, it should be noted that the corporate borrowers' address information included in the regional banks' granular data collected in the experiment is basically limited to the head office location, and does not take into account the locations of plants and other important business bases owned by the corporate borrowers. In addition, the data does not reflect the existence or effectiveness of flood control measures taken by the corporate borrowers.

[31] Excluding financial/insurance business and public service.

[32] Note that this graph is aggregated by the regions where the head offices of the regional banks that participated in the experiment are located, and loans may be extended to other regions (e.g., cases where a regional bank whose head office is in the Chugoku region extends loans to a company in the Kanto region), so it does not indicate the degree of risk by region.

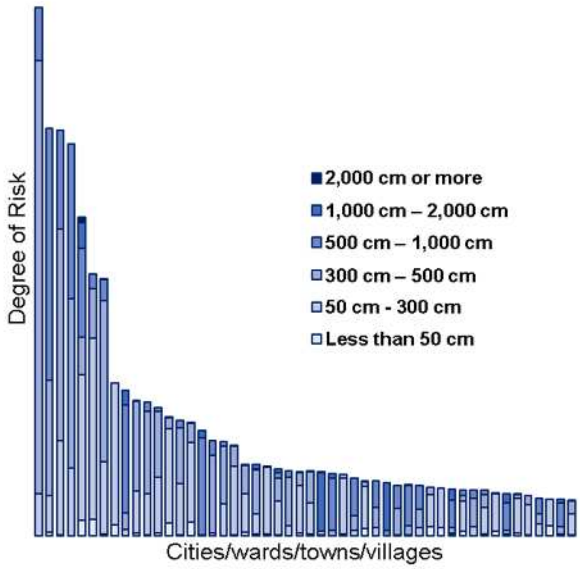
[33] Municipalities are aggregated separately for ordinance-designated cities, cities, special wards, wards, towns, and villages.(Reference: https://www.e-stat.go.jp/municipalities/number-of-municipalities (available only in Japanese))
The graph shows the top 50 most risky municipalities when the risks of regional banks with head offices in the Chugoku, Tokai, and Hokuriku regions are allocated to all 916 municipalities where the head offices of borrowing companies are located.

Figure 12 SMEs' flood risk levels per outstanding loan by region



(Flood risk levels per outstanding loan for each region where the head offices of regional banks are located (the legend in the graph indicates the inundation depth))

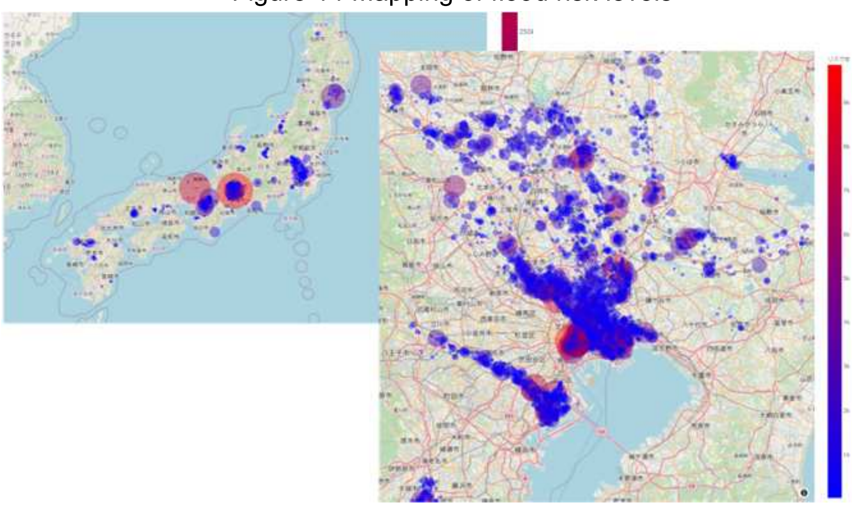
Figure 13 SMEs' Flood risk levels by municipality



(Flood risk levels by municipality for regional banks with head offices in the Chugoku, Tokai, and Hokuriku regions (the legend of the graph indicates flood depth))

A tool was created to show on a map of Japan both the location of a company and the degree of risk of each company by a color and the size of a circle, making it possible to visually identify which areas are affected most. For example, Figure 14 is a mapping of the flood risk levels of SMEs in the manufacturing sector in the Tokyo metropolitan area. This map shows that risks are concentrated along rivers such as the Arakawa River.

Figure 14 Mapping of flood risk levels



3. Future Issues

This analysis linked granular data collected from regional banks participating in the experiment with hazard maps to compare the degree of physical risk (water disaster risk) across regions. In addition, by mapping the flood risk levels of each corporate borrower on a map and turning it into a tool, it has become possible to visualize flood risk levels for specific regions and banks. These tools will be further improved and developed to understand the physical risks of financial institutions and the geographical characteristics of the areas in which they operate.

V. Conclusion

This paper conducted a pilot analysis on climate-related risks at regional banks from three aspects: FEs, business changes in product lines, and geographical conditions, using granular data, such as loan details, collected from the 49 regional banks that participated in the experiment. As a result, it became clear that the share of high-emission industries in the FEs of borrowers for which regional banks are the main banks is considerably lower than the share of high-emission industries among total CO2 emissions in Japan. The analysis also revealed the geographical characteristics of engine-related companies and flood risks. In addition, it was reaffirmed that the use of a wide range of data beyond the financial sector is effective in order to better understand climate-related risks. Going forward, the FSA will continue to enhance its data infrastructure and analysis related to climate change, in order to facilitate dialogues with financial institutions regarding their understanding of climate-related risks and support for clients in responding to climate change.