A Quantitative and Textual Analysis of Climate-Related Risks in the Banking Sector

(Summary)

This paper attempts a comprehensive assessment of banks' initiatives on climate change by conducting a quantitative analysis of greenhouse gas (GHG) emissions and a textual analysis of disclosure reports using large language models (LLMs). The quantitative analysis demonstrates that, although GHG emission levels differ depending on business types and other factors, overall GHG emissions from banks are on a declining trajectory. Furthermore, the textual analysis indicates that references to climate change in the disclosure reports have increased, in line with the declining trend identified in the quantitative analysis.

I. Introduction

As the frequency and severity of natural disasters such as windstorms and flood caused by global warming is reportedly increasing, efforts toward carbon neutrality and green transformation (GX) are expanding both domestically and internationally. Companies are gradually advancing initiatives aimed at decarbonization. Financial institutions are also promoting efforts to reduce their carbon emissions and support their clients in doing decarbonization. The Financial Services Agency (FSA), recognizing that the substantial economic, industrial, and social changes accompanying decarbonization bring both opportunities and risks to financial institutions, has engaged in dialogue with these institutions to monitor the status of their decarbonization initiatives.[1]

This paper explores methods for comprehensively assessing banks' responses to climate change by employing both quantitative and qualitative approaches. The quantitative analysis utilizes lending data from financial institutions and greenhouse gas (GHG) emissions data provided by external data vendors to examine, for each bank, the time-series changes in its own GHG emissions (Scope 1 + 2 emissions[2]) and to analyze differences across business types and regions regarding GHG emissions

[1] FSA published the report "Practices and Issues on Climate-related Risk Management ～ Building on "Supervisory Guidance on Climate-related Risk Management and Client Engagement" ～."

[2] Scope 1 emissions refer to direct greenhouse gas (GHG) releases produced by an organization's own operations—for example, on-site fuel combustion or emissions from company-owned vehicles. Scope 2 emissions denote indirect GHG emissions resulting from the organization's consumption of externally supplied electricity, heat, or steam.

associated with the loan portfolios of regional banks[3] (Scope 3 emissions for regional banks[4]).

Furthermore, the qualitative analysis examines climate-change–related disclosure trends in the disclosure publications[5] published by regional banks using methods such as large language models (hereafter, "LLMs[6]").

II. Quantitative analysis on GHG emissions

This section presents a quantitative analysis of banks' GHG emissions. First, it analyzes the trends in Scope 1 + Scope 2 emissions for major banks[7] and regional banks from fiscal year 2017 to fiscal year 2022.

Next, focusing on regional banks, this section assesses climate-related risks in corporate loan portfolios by calculating the weighted average carbon intensity (defined later) of those portfolios, and analyzing variations across regions and business types, as well as changes over time.[8]

1. Dataset

GHG emissions data were sourced from S&P Global Inc. (hereafter, "S&P"). The dataset includes both company-level estimated GHG emissions and industry-level[9] estimated carbon intensity values. For the analysis of each bank's own GHG emissions (Scope 1 + 2)—discussed in the next sub-section—estimates from S&P, based on values published by the banks themselves in their disclosure reports and similar publications, were used.

Meanwhile, the analysis of weighted average carbon intensity in corporate loan portfolios of regional banks—presented in sub-section 3 and beyond—employs the estimated carbon intensities

[3] "Regional banks" refer to those member institutions of the Regional Banks Association of Japan (hereafter, "regional banks I") and the Second Association of Regional Banks (hereafter, "regional banks II").

[4] Scope 3 emissions denote greenhouse gas (GHG) emissions that occur indirectly, excluding those accounted for under Scope 1 and Scope 2, but are nevertheless associated with an organization's activities via emissions produced by other entities.

[5] In this paper, "disclosure publications" refer to the sections of annual reports and integrated reports that describe business activities and related information, excluding detailed financial data (e.g., "Data Section") and accompanying technical notes. When both types of documents are published, the integrated report is used in principle.

[6] This paper utilizes an offline large language model (LLM)—constructed as described in FSA Analytical Notes (2025.5), "Verification of text-data analysis using AI technologies"—for the textual analysis.

[7] In this paper, "major banks" refer to Mizuho Bank, MUFG Bank (Mitsubishi UFJ Bank), Sumitomo Mitsui Bank, Resona Bank, Saitama Resona Bank, Sumitomo Mitsui Trust Bank, SBI Shinsei Bank, and Aozora Bank.

[8] Since detailed analyses of climate-related risks—such as alignment with TCFD recommendations—are generally available for major banks, this paper focuses on regional banks.

[9] S&P's estimated values classify industries according to the Global Industry Classification Standard (GICS), which does not fully align with the industrial classifications used in the Financial Services Agency's collected data. For the present analysis, the most closely matching GICS category was selected to correspond with each FSA category. As a result, it is important to note that the carbon intensity values used in this analysis may not accurately reflect the true carbon intensity of each industry. Furthermore, because estimated carbon intensity values are applied at the industry level, efforts by individual companies within the same industry to reduce GHG emissions may not be captured.

(GHG emissions in metric tons of CO_2 equivalent per USD 1 million of revenue[10]) by industry, specifically using Scope 1 and Scope 2 emission intensities.

Furthermore, for analyzing emissions associated with regional banks' loan portfolios, quarterly lending data categorized by industry (e.g., manufacturing, retail, services) were used. This study covers reported values from the fiscal period ending March 2020 (fiscal year 2019) through the fiscal period ending March 2025 (fiscal year 2024).

2. Analysis on own GHG emission

Figure 1 shows the estimated values of each bank's own GHG emissions (Scope 1 + 2) by business type. Note that in Table 1, only banks with estimated values available for the entire period from fiscal year 2017 to fiscal year 2022 are included, to ensure a consistent time-series comparison.

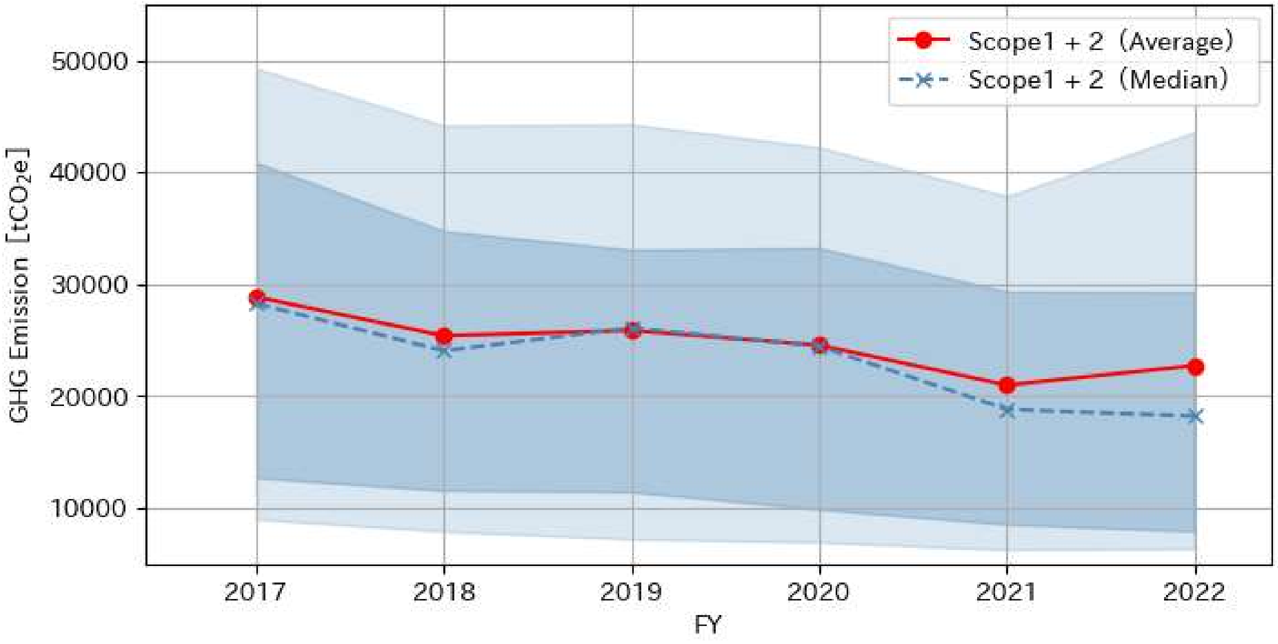
The figure reveals differing trends between major banks and regional banks. The average own GHG emissions of major banks have shown a continuous decline from fiscal year 2017 onward. This result suggests that major banks initiated efforts to reduce their own GHG emissions relatively earlier than others.

Meanwhile, the average own GHG emissions of regional banks appear to have plateaued since fiscal year 2021. This period coincided with significant societal changes, such as the global spread of COVID-19, making it difficult to pinpoint a single factor responsible for this trend. However, the timing aligns with the Japanese government's 2050 carbon neutrality declaration, suggesting that growing societal momentum toward decarbonization may have accelerated regional banks' efforts to reduce their own GHG emissions..

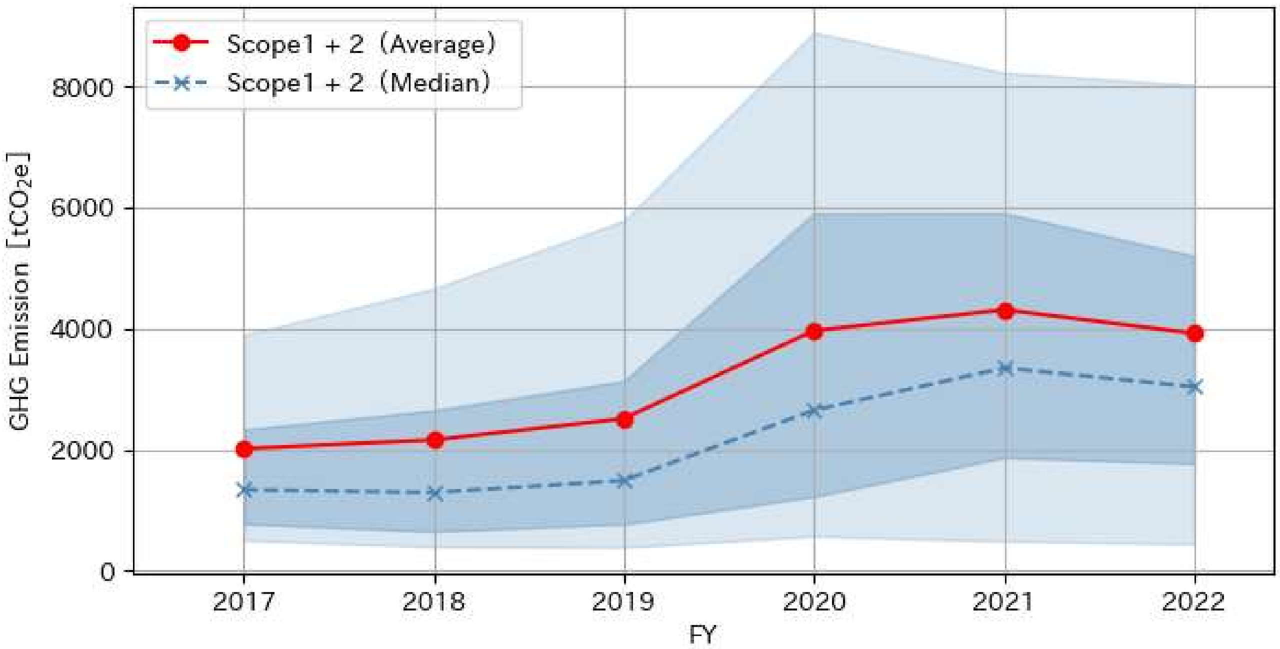
[10] The conversion from greenhouse gas (GHG) emissions per USD 1 million of revenue to per JPY 1 million was conducted using the Bank for International Settlements' (BIS) annual average bilateral exchange rates.

Figure 1: Each bank's own GHG emission（Scope 1+2）

Major banks



Regional banks



Note 1: The red line and the blue dotted line represent the average and median values, respectively, of each bank's own GHG emissions.

Note 2: The darker blue shaded area covers the range from the 25th percentile (lower bound) to the 75th percentile (upper bound), while the lighter blue shaded area spans from the 10th percentile to the 90th percentile.

Note 3: Values were calculated for banks whose emissions data were available for all years from fiscal year 2017 through fiscal year 2022. The analysis includes six major banks (including the three megabanks) and 49 regional banks.
(Source) S&P Global Inc.

3. Analysis on GHG emissions in loan portfolio

An indicator that is known for measuring the GHG emissions of financial institutions' portfolios is financed emissions (FE) [11], which calculates the absolute emissions of borrowers or investee companies. However, this paper attempts an analysis using the weighted average carbon intensity ("WACI") of regional banks' corporate loan portfolios. The weighted average carbon intensity (W_I) in this paper is defined as follows:

$$W_I = \sum_J CI_J \times r_{I,J} \qquad \text{(Eq. 1)}$$

where CI_J represents the carbon intensity (Scope 1 + 2) per unit of revenue for sector J, and $r_{I,J}$ denotes the share of loans to sector J within regional bank I's corporate loan portfolio (excluding loans to local public entities, such as local governments). The weighted average carbon intensity W_I was calculated for each regional bank to examine regional characteristics and time-series changes.

Because this definition of W_I normalizes GHG emissions by revenue, the influence of individual bank portfolio size is largely offset. Consequently, this metric is not suitable for assessing the absolute magnitude of GHG emissions in loan portfolios. However, it is useful for comparative analysis across banks of different sizes. Note that since the latest available carbon intensity data (CI_J) by sector are for 2022, a strong assumption is made that CI_J remains constant beyond the fiscal year ending March 2023.

Figure 2 presents the weighted average carbon intensity for each regional bank in the fiscal year ending March 2025. These results show that there is no clear correlation between corporate loan portfolio size and weighted average carbon intensity. Given that, as indicated by Eq. 1, weighted average carbon intensity depends on the sectoral composition of a regional bank's corporate loan portfolio, this result indicates that the differences in intensity are not necessarily driven by portfolio size. It's important to note that this analysis uses estimated carbon intensity values by industry, which do not reflect individual companies' efforts to reduce emissions. Given the limited number of

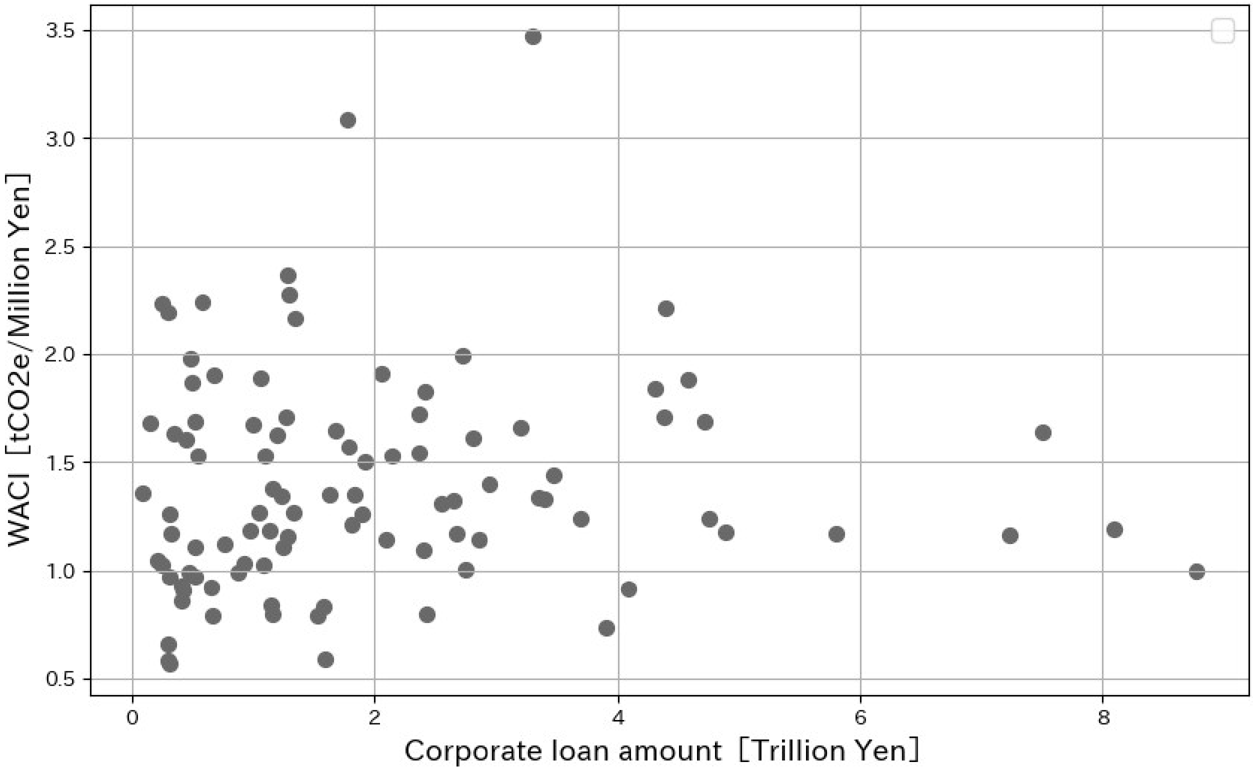
[11] In the Task Force on Climate-related Financial Disclosures (TCFD) recommendations, weighted average carbon intensity (WACI) is identified primarily as a metric to assess climate-related risks for investment portfolios held by asset owners/managers and for insurance underwriting portfolios. Conversely, for loans, the TCFD specifically refers to financed emissions (FE) as the measurement indicator.

companies disclosing detailed GHG reduction efforts, incorporating such data could significantly alter WACI results. Therefore, interpretation should consider these data limitations.

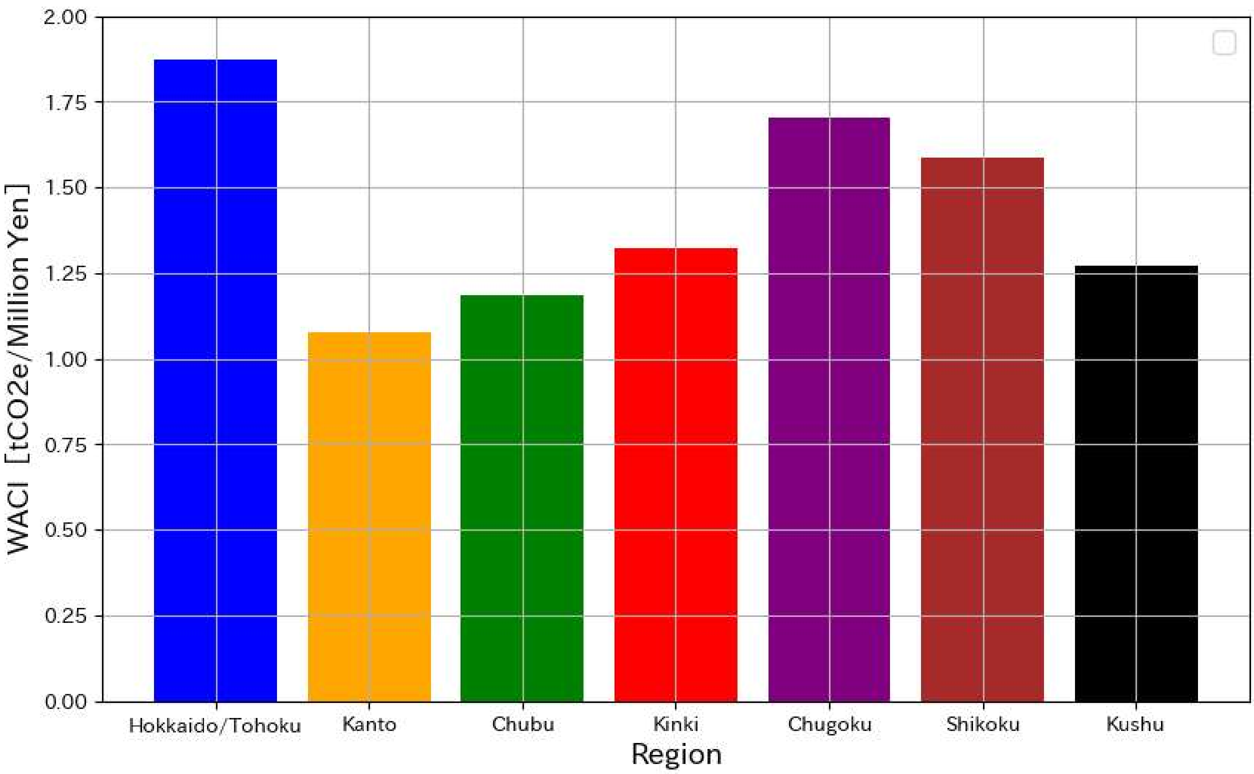
When comparing weighted average carbon intensities across banks, most regional banks fall within the range of 0.5–2.0. Banks at the upper bound (2.0) of this range have borrowers emitting four times more GHG per unit of revenue than those at the lower bound (0.5) for the same loan amount. This implies that in the event of future policy changes—such as the implementation of a carbon tax—banks with higher weighted average carbon intensity are likely to have loan portfolios that are more vulnerable to such changes. This suggests that transition risks may disproportionately affect those banks.

Figure2: WACI and corporate loan size (as of March 2025)

Each bank level



WACI in each region (average)



Note: "Corporate loan amount" refers to the value of loans extended to corporate borrowers, excluding loans provided to local public entities.
(Source) S&P Global Inc.

4. Evaluation via Regression Analysis

Figure 2 reveals that regional banks located in the Kanto region exhibit lower weighted average carbon intensity compared to those in other regions. Based on this observation, a regression analysis was conducted to quantitatively assess the regional dependency of weighted average carbon intensity, using the following equation:

$$W_I = \alpha + \beta_1 L_I + \sum_{regiona \neq kanto} \beta_{region} I_{region} + \beta_{banktype} I_{banktype} + \epsilon_I \qquad \text{(Eq. 2)}$$

Figure 3: Estimation results (March 2025)

	Coefficient	Std.Error	p-value
α	1.122	0.153	0.000
L	0.019	0.028	0.492
$I_{Hokkaido\text{-}Tohoku}$	0.825	0.157	0.000
I_{Chubu}	0.120	0.147	0.415
I_{Kinki}	0.179	0.173	0.305
$I_{Chugoku}$	0.657	0.176	0.000
$I_{Shikoku}$	0.561	0.184	0.003
I_{Kyushu}	0.227	0.148	0.129
$I_{Banktype}$	-0.261	0.100	0.011
$N_{obs.}$	97		
Adj. R^2	0.330		
Prob.(F-stats.)	0.000		

Note: The estimated coefficients for the regional dummy variables represent the incremental increase in weighted average carbon intensity for regional banks located in the regions other than Kanto region, relative to regional banks in the Kanto region. Likewise, the estimated coefficient for the business-type dummy variable indicates the incremental increase in weighted average carbon intensity for regional banks II compared to regional banks I.

In Equation 2, I_{region} and $I_{Banktype}$ are dummy variables for each bank's location and the distinction between regional banks I and regional banks II. The equation as a whole serves as a regression model to analyze the impact of both the bank's region and its business type (regional bank I vs. regional bank II) on weighted average carbon intensity[12]. Here, L_I denotes the corporate loan amount of bank I (measured in trillions of JPY).

Figure 3 presents the regression results. First, corporate loan amount (L) showed no statistically significant dependence[13] at the 5% level, consistent with the findings from Figure 2 that loan portfolio size did not impact weighted average carbon intensity in the analysis. On the other hand, this regression analysis did reveal statistically significant regional differences. Chugoku, Shikoku, and Hokkaido–Tohoku regions exhibit higher weighted average carbon intensity compared to those in the Kanto region. Additionally, the bank-type dummy coefficient indicates that regional banks II have a lower weighted average carbon intensity than regional banks I.

To explore the underlying cause of the observed regional and business-type differences, a second regression for the weighted average carbon intensity (W_I) was conducted using the sectoral[14] composition ratios of regional banks' corporate loan portfolios. This analysis employs the following regression equation (Eq. 3).

$$W_I = \alpha + \sum_{Sector \neq Fina} \beta_{Sector} r_{I,Sector} + \beta_{Banktype} I_{Banktype} + \epsilon_I \qquad \text{(Eq. 3)}$$

The regression results reveal that the contribution to weighted average carbon intensity differs markedly across industry classifications. Some of these distinctive findings are shown in Figure 4. For the electricity, gas, and water utilities sector, the estimated coefficient is significantly larger compared to other sectors, indicating that changes in the proportion of this sector within regional banks' corporate loan portfolios have a substantial impact on weighted average carbon intensity. Conversely, the difference between regional banks I and regional banks II is not statistically significant. This suggests that the bank-type differences observed in the regression based on Eq. 2 are attributable to variations in sectoral composition within corporate loan portfolios.

[12] The banks' regional classification is determined based in the prefecture where its head office is located.
[13] Unless otherwise noted, a 5% significance level is applied throughout.
[14] Note that the granularity of sector classifications used in this regression analysis is coarser than that employed in Eq. 1. Therefore, the estimated coefficients for each sector represent the average contribution to weighted average carbon intensity across roughly analogous sectors.

Figure 4: Regression results on sectoral dummy (March 2025, excerpt)

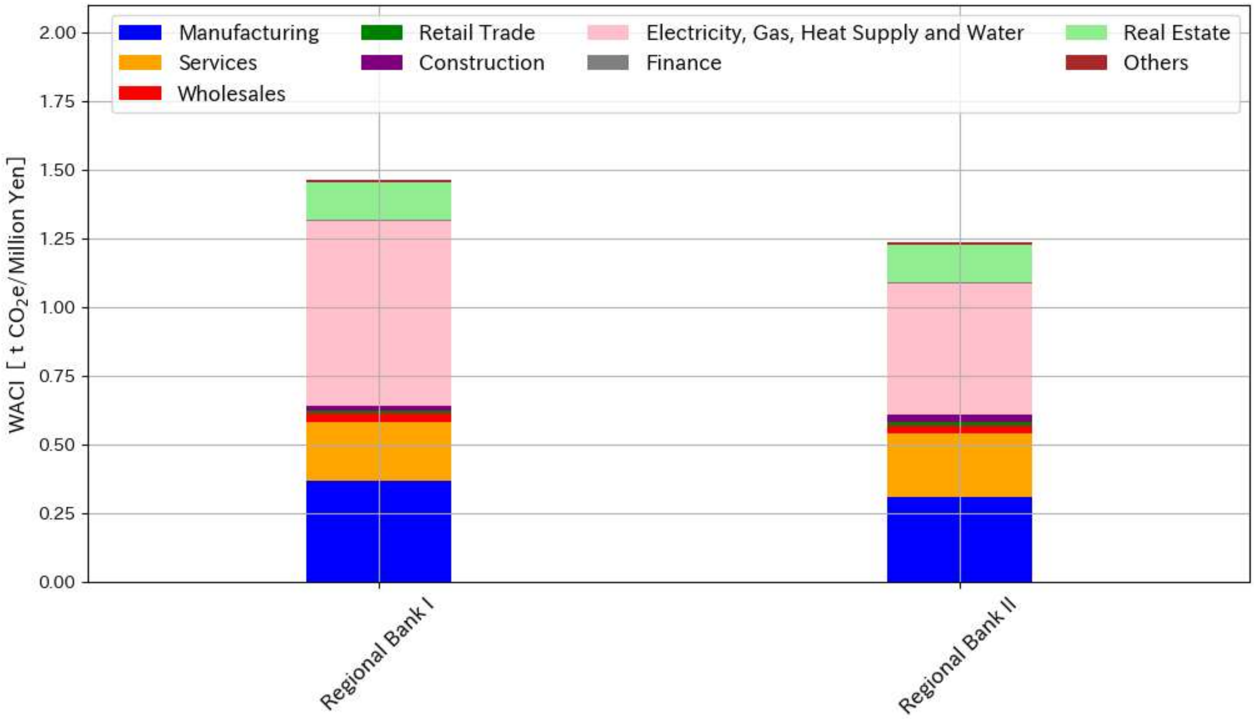
	Coefficient	Std.Error	p-value
α	0.231	0.140	0.102
$r_{\textit{Electricity-Gas-Water}}$ [%]	0.232	0.007	0.000
$I_{\textit{Banktype}}$	0.056	0.030	0.066
$N_{obs.}$	97		
Adj. R^2	0.950		
Prob.(F-stats.)	0.000		

Note: The estimated coefficients for the sectoral loan composition ratios (*r*) were derived using financial-sector exposures as the baseline. They represent the increase in weighted average carbon intensity when the proportion of each sector in a bank's corporate loan portfolio increases by 1%, while holding proportions of non-financial sectors constant.

When examining the average contribution of each sector to weighted average carbon intensity across bank types (Figure 5), it is evident that, for both types, the utilities (electricity, gas, water), manufacturing, and service sectors contribute significantly. In particular, regional banks I allocate a higher proportion of loans to the utilities and manufacturing sectors compared to regional banks II, suggesting that these composition differences underlie the statistically significant variation observed in Figure 3. Similarly, on a regional basis, regional banks in Hokkaido-Tohoku and Chugoku—regions that showed a statistically significant difference compared to Kanto—also allocate a larger share of loans to the utilities sector, indicating that such regional differences in loan composition influence the observed inter-regional variation.

However, it is important to note that this analysis employs industry-level estimates of carbon intensity. For example, when comparing company-level carbon intensity estimates from S&P as of 2023 within firms classified in the electricity sector, a five-fold difference between the maximum and minimum values was observed. If individual client conditions were examined in greater detail, it is possible that the results differ significantly.

Figure 5: Proportion of WACI by sector (March 2025)



Note: The values of weighted average carbon intensity for each bank type were calculated by averaging, across all regional banks within each region, their sector-specific weighted average carbon intensity values—using each bank's corporate loan amount as the weighting factor.

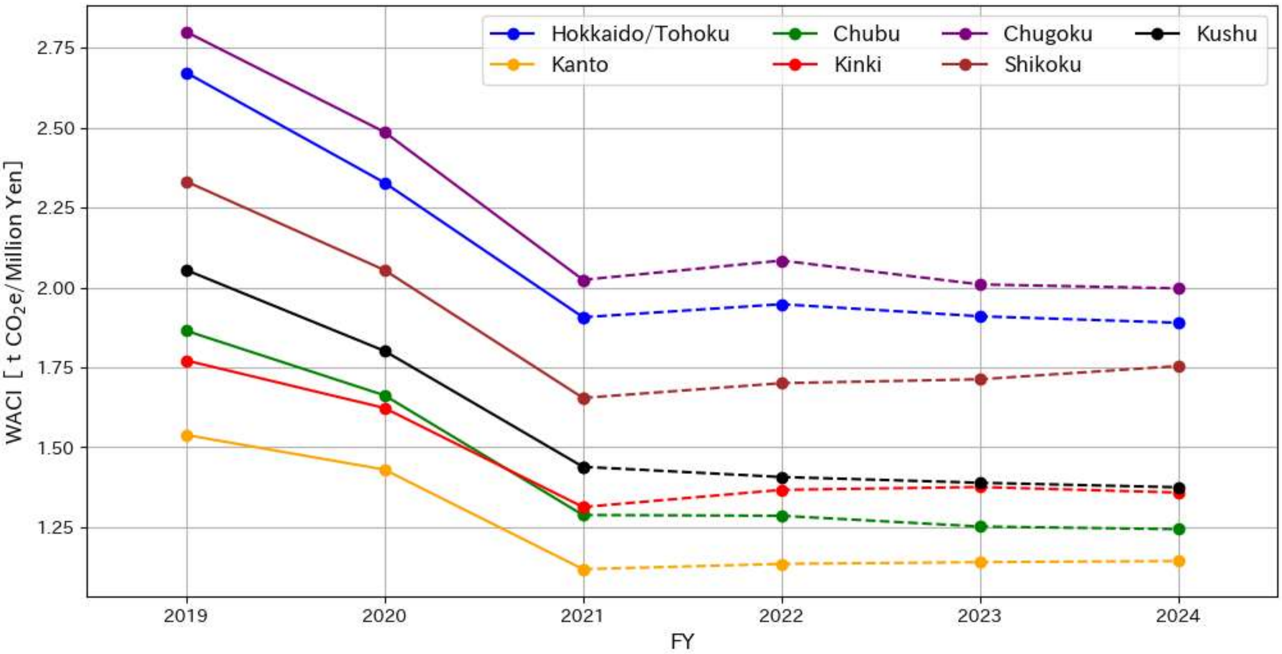
(Source) S&P Global Inc.

5. Time-series analysis

This sub-section examines temporal changes in the weighted average carbon intensity for each region. Both changes in carbon intensity across sectors and changes in each bank's corporate loan portfolio must be considered. However, since available carbon intensity estimates are limited to the period from 2019 to 2022, calculations for the period from the end of fiscal year 2022 (March 2023) onward use the 2022 carbon intensity estimates.

Figure 6 displays the calculated results. From the fiscal period ending March 2019 to March 2021, every region experienced a significant decrease in weighted average carbon intensity. This suggests that reductions in sectoral carbon intensity among borrowers made a substantial contribution. Conversely, the absence of major changes in each region's weighted average carbon intensity from fiscal year 2022 onwards likely reflects the long-term nature of corporate lending relationships, which result in limited short-term changes to each bank's loan portfolio.

Figure 6: Trends of regional banks’ WACI



Note 1: The solid-line portions represent periods whose weighted average carbon intensities are calculated using both S&P’s estimated carbon intensity values and changes in corporate loan portfolios. The dotted-line portions indicate intervals calculated using fixed 2022 carbon intensity values and considering only changes in corporate loan portfolios.

Note 2: The values of weighted average carbon intensity for each region and reference date are calculated as weighted averages of the regional banks within that region, using their corporate loan amounts as weights.

Note 3: Using fiscal year 2019 as the base, adjustments for price-level changes were made via Japan’s GDP deflator as published by the World Bank.

(Source) S&P Global Inc.

III. Textual analysis on disclosure publications

In the previous section, regression analysis confirmed that regional banks’ GHG emissions generally decreased, particularly from fiscal year 2021 onward, suggesting progress in their climate-related initiatives. This section focuses on disclosure reports—one of the materials in which banks report on their climate-related efforts—and conducts a qualitative validation of the previous section’s findings by examining trends in climate-related descriptions within those reports using TF-IDF[15] and LLM

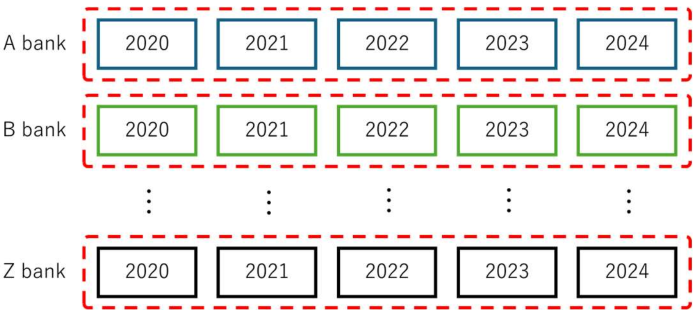
[15] An indicator used to assess the importance of words in a text is calculated by multiplying term frequency (TF) by inverse document frequency (IDF).

methods.

1. Analysis Method

This analysis targets disclosure reports from regional banks covering five years—from 2020 to 2024 (fiscal years 2019 to 2023).[16] The analytical method involves extracting text data from the disclosure reports and ranking the terms based on their frequency using TF-IDF (Figure 7). From the top 1,000 ranked words,[17] climate-related terms were extracted using LLM, and the reciprocal sums of these terms' ranks were then computed to construct a "trend score." This value is used as an indicator of the coverage on climate-related issues (Figure 8).

Figure 7: TF-IDF in this analysis



*Number indicates the year of publication.

TF × IDF = **Term frequency** × **Term rarity**

Term frequency: How many times term "X" appears in document A (Disclosure Report Published by ● Bank in ● Year)

$$\text{TF} = \frac{\textit{Number of times term "X" apprears in document A}}{\textit{Number of all words appreas in text A}}$$

Term rarity: How rare a word is across a set of documents, with higher values assigned to words that appear infrequently in other documents (The number of sentences containing the term "X" within all disclosure reports published by ● Bank.)

$$\text{IDF} = In\left(\frac{\textit{Number of all documents}}{\textit{Number of documents including term "X"}}\right) + 1$$

[16] The analysis targets disclosure reports available on financial institutions' websites as of January 2025.
[17] Terms deemed to be influenced by special factors were excluded from the top-ranked terms.

Figure 8: Calculation of trend score

Top 1,000 Terms by TF-IDF Calculated for Each Bank and Fiscal Year

Rank	Term	TF-IDF
1	AAA	0.07
2	BBB	0.06
3	CCC	0.05
4	DDD	0.04
5	EEE	0.03
⋮		
1000	GGG	0.0001

Climate-related Terms Identified by the LLM (Highlighted in Red)

Rank	Term	TF-IDF
1	AAA	0.07
2	BBB	0.06
3	CCC	0.05
4	DDD	0.04
5	EEE	0.03
⋮		
1000	GGG	0.0001

Sum of the Inverse Ranks of Climate-related Terms

$$0.7 = (1/2) + (1/5)$$

(The larger this value (trend score), the higher the estimated frequency and distinctiveness of climate-related terms.)

2. Results

Figure 9 shows some words identified by the LLM as climate-related from the top 1,000 terms ranked by TF-IDF, along with the rationale provided by the LLM for its selections. To mitigate AI-specific risks such as hallucinations, the analysis did not rely solely on the conclusions. Instead, both the selected terms and the reasoning behind their classification were included in the results, which were manually reviewed for verification and corrections.

Figure 9: Sample of words selected as relevant to climate change by LLM and its rationale

Climate-related Terms	Rationale Provided by the LLM
Offset (Carbon Offset)	Offsets are deeply related to climate change because they involve compensating for greenhouse gas emissions by subtracting an equivalent amount of emissions reduced elsewhere.
Green Purchasing	Green purchasing is an initiative that contributes to sustainability by selecting environmentally friendly products and services.
Emissions	Emissions are deeply related to climate change and natural disasters because they contribute to environmental impacts such as climate change and air pollution.
Global Warming	Global warming is a term closely related to climate change, referring to the phenomenon of rising average global temperatures.
Carbon Dioxide	Carbon dioxide is a greenhouse gas identified as a major cause of climate change and has a significant impact on global warming, making it deeply connected to climate change.

Based on the extracted climate-related terms, the trend score for each region was calculated (defined as the sum of the inverse ranks of the identified terms divided by the number of banks in the region). The results are shown in Figure 10.[18] Across all regions, the frequency and rarity of climate-related terms in these publications have notably increased. Furthermore, as noted in the previous sub-section, regions such as Chugoku, Shikoku, and Hokkaido–Tohoku, which exhibited higher

[18] In cases where disclosure reports are published on a group level, they were allocated and aggregated under the region of the regional bank with the largest loan volume among the affiliated banks.

weighted average carbon intensity compared to other regions, also show a growing trend in climate-related descriptions in their disclosures. These patterns may reflect a heightened awareness of climate change among regional banks. It should be noted, however, that available disclosure reports vary by banks and year. These patterns may reflect a heightened awareness of climate change among regional banks.

Figure 10: Trend score by region (2020=1.0, ( ) indicates the number of banks)

	2020	2021	2022	2023	2024
Hokkaido・Tohoku	1.0 (10)	0.8 (12)	2.6 (13)	4.1 (13)	4.7 (13)
Kanto	1.0 (13)	1.3 (13)	4.7 (13)	4.8 (13)	3.8 (13)
Chubu	1.0 (19)	1.4 (21)	5.5 (20)	5.3 (20)	5.0 (20)
Kinki	1.0 (7)	1.0 (7)	1.4 (8)	1.1 (8)	1.4 (8)
Chugoku	1.0 (8)	1.1 (8)	2.7 (8)	3.6 (8)	3.9 (8)
Shikoku	1.0 (5)	1.5 (5)	2.9 (6)	3.6 (6)	4.5 (6)
Kyushu	1.0 (12)	1.0 (14)	0.9 (14)	1.3 (14)	1.4 (14)

IV. Conclusion

This paper conducted a quantitative analysis of banks' climate change initiatives using data on GHG emissions and lending. While variations exist depending on business type and other relevant factors, overall GHG emissions have been trending downward, suggesting progress in banks' decarbonization efforts.

Additionally, textual analysis of regional banks' disclosure reports using LLMs confirmed a marked increase in the frequency and significance of climate-related terms in recent years, indicating rising awareness of the materiality of climate change among regional banks. Taken together, these analyses suggest that heightened consciousness and action toward decarbonization in regional banks are reflected both in actual reductions in GHG emissions and in more extensive communication via disclosure reports. These developments are likely to lead to a reduction of transition risk[19] faced by banks.

When interpreting the results of this paper, it is important to be mindful of several data limitations. For the quantitative analysis, climate-related risk measurement methodologies remain under

[19] Transition risk among climate-related risks refers to the risk that changes in regulations, technology, markets, and other aspects accompanying the shift to a decarbonized society will have an impact on business operations.

development, and the insufficient granularity of available data may make it difficult to accurately reflect the actions of individual borrowers. For the textual analysis, some regional banks disclose climate-related information outside of disclosure reports, which are not included in this study.

Moreover, it should be noted that GHG emissions data reflect past information and may not necessarily reflect recent actions taken by customer companies to reduce emissions, initiatives toward green transformation, or financial institutions' supports. The FSA will keep on improving analyses and monitoring from multiple perspectives to enhance the understanding of financial institutions' climate-change responses and customer support efforts.