BIS Working Papers

No 1078

Greenhouse gas emissions and bank lending

by Koji Takahashi and Junnosuke Shino

Monetary and Economic Department

March 2023

JEL classification: E51, G21, Q54.

Keywords: greenhouse gas, bank lending, leverage, loan-level data.

This publication is available on the BIS website (www.bis.org).

ISSN 1020-0959 (print)
ISSN 1682-7678 (online)

Greenhouse Gas Emissions and Bank Lending *

Koji Takahashi † Junnosuke Shino ‡

Abstract

This paper investigates the effect of the greenhouse gas (GHG) emissions of firms on bank loans using bank–firm matched data of Japanese listed firms from 2006 to 2018. Previous findings suggest that climate risks priced in corporate bonds or syndicated loans are statistically significant but economically minor. This paper investigates bank lending behavior in terms of the loan amount, which we consider to have a more direct effect on firm investment decisions. This paper finds that banks significantly decrease loans to firms with higher GHG emissions. Moreover, this GHG emissions effect appears to have prevailed even before the signing of the Paris Agreement, which the existing literature considers as the starting point where GHG emissions are incorporated in the pricing of debt instruments as credit risk. Finally, banks with greater leverage and a lower return on assets are more likely to decrease loans to firms with high GHG emissions.

Keywords: greenhouse gas, bank lending, leverage, loan-level data

JEL Classification codes: E51, G21, Q54

*The views expressed in this paper are those of the authors and do not necessarily reflect the official views of the Bank for International Settlements. This research was funded by the Center for Asian and Pacific Studies, Seikei University. The authors would like to thank Sumiko Takaoka, Ivan Etzo, Deniz Igan and colleagues in the Bank for International Settlements.

†Monetary and Economic Department, Bank for International Settlements; koji.takahashi@bis.org

‡School of International Liberal Studies, Waseda University, 1-6-1 Nishiwaseda, Shinjuku–ku, Tokyo, Japan 169-8050; junnosuke.shino@waseda.jp

1 Introduction

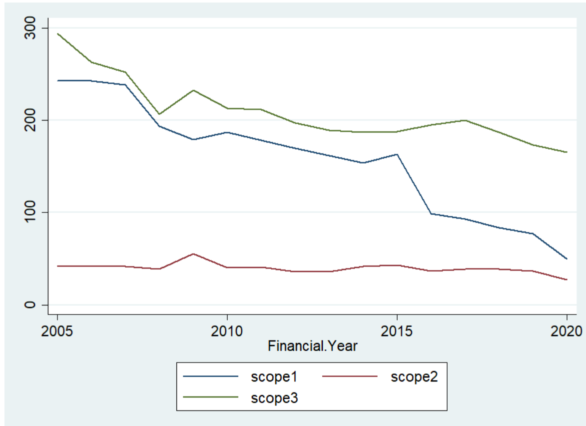
In recent years, and facing an urgent challenge with environmental problems, policymakers, including the European Central Bank and Bank of Japan (BOJ) have embarked on "green" monetary policies.[1] However, incorporating the impact of investment in the environment is not new to the field of finance. In the 2000s, some banks began to consider the effect of their investments on the environment. For example, in 2007, the European Investment Bank issued the world's first green bonds. In tandem with these changes in financial markets, firms have continued to improve their energy efficiency over time. For example, the intensity of greenhouse gas (GHG) emissions for Japanese firms has substantially decreased since the second half of the 2000s, as depicted in Figure 1.

To understand better the effects of these green operations, policymakers need to recognize the relationship between the behavior of financial intermediaries and climate risk. In general, banks could influence borrowing firms' stance toward the environment through their credit allocation. Therefore, a large and growing literature investigates the nexus of climate change and bank lending. Overall, the literature finds that a high environmental ESG score or low GHG emissions in a firm is associated with low credit costs. However, the current debate on climate is not limited to whether firm costs reflect environmental risks. Rather, financial institutions are under strong pressure to decrease investment in projects that undermine the environment. In other words, the quantity of credit in green and so-called "brown" firms lies at the center of policy discussion.

To address this gap in the literature, we investigate whether bank lending behavior is affected by the GHG emissions of borrowing firms. We also examine whether the relationship between bank loans and GHG emissions varies depending on the financial soundness of lending banks. Specifically, we use loan-level data for Japanese listed firms and quantify the effect of GHG emissions on bank lending. Using this bank–firm data, we obtain two main findings. First, Japanese banks allocate loans to firms with low GHG emissions and low intensity, a tendency we observe even before the signing of the Paris Agreement. This suggests that Japanese banks are concerned about the stance of borrowers

[1] As for the BOJ's strategy on climate change, see the following page: `https://www.boj.or.jp/en/announcements/release_2021/rel210716b.htm/`

Figure 1: Average intensity



Note: The line plots the simple average intensity of GHG emissions of Japanese firms. Scope 1 is emissions from directly emitting sources that are controlled by a company. Scope 2 emissions are those from the consumption of purchased electricity or other sources of energy generated upstream from a company's direct operations. Scope 3 emissions are all other emissions associated with a company's operations that are not directly owned or controlled by the company (Trucost (2018)).

toward the environment. Second, banks that are highly leveraged and less profitable are more likely to decrease loans to high GHG emitting firms. This indicates that the credit channel plays an important role in explaining the relationship between loans and GHG emissions.

A growing literature investigates the relationship among credit instruments, climate risk, and ESG scores. Among others, Ehlers et al. (2022) identify a "carbon premium" in syndicated loans after the Paris Agreement, although the impact is small.[2] Moreover, in terms of ESG scores and financial investment, existing studies report evidence that firms with high ESG scores carry lower credit risk (Sharfman and Fernando (2008), Goss and Roberts (2011), Chava (2014), Hasan et al. (2017), Hauptmann (2017)). In addition, Scatigna et al. (2021) investigate the risk premium in corporate bonds for firms with higher GHG emissions and find that these firms also have greater default risk, although the size of any premium is marginal.

Our paper is closely related to the study of firm ESG scores and bank lending in

[2]Ongena et al. (2018) demonstrate that a higher interest rate is charged on loans to firms with higher fossil reserves, whereas Kleimeier and Viehs (2018) finds that higher carbon emissions have a positive and significant effect on loan spreads.

Houston and Shan (2022). They find that banks tend to increase lending to firms with higher ESG scores. In addition, they point out that firms that borrowed from banks with higher ESG scores are more likely to have a high ESG score themselves than those firms that borrowed from banks with lower ESG scores. Reghezza et al. (2022) also investigates the effect of GHG emissions on bank loans focusing on the Paris Agreement and argues that afterward higher polluting firms were allocated less credit. Kacperczyk and Peydró (2021) exploit banks' commitments to carbon neutrality and syndicated loan data to global firms. They find that a bank's commitment decreases loans to firms with higher GHG emissions. Our paper is a complement to those studies as they focus on global firms and syndicated loans that do not necessarily coincide with the actual loan holdings of banks. Regarding Japanese credit instruments, Okimoto and Takaoka (2021) discover that high ESG scores decrease corporate bond spreads.

Voluminous literature also examines the relationship between stock prices and climate risk. Among others, Bolton and Kacperczyk (2021) reveal that the stocks of firms with higher carbon dioxide emissions earn higher returns, indicating that investors demand compensation for their exposure to GHG emissions risk. Finally, our study proceeds along the same line as the Japanese literature on firm performance and GHG emissions. For example, Aruga et al. (2022) conclude that firms with low GHG emissions are associated with better performance and lower costs of capital. More importantly, Nishitani and Kokubu (2012) and Fujii et al. (2013) showed that the low GHG emissions of firms exert a positive effect on firm performance using Japanese firm data from 2006 to 2008.

The contribution of our paper is twofold. First, we assess the relationship between bank loans and GHG emissions using comprehensive loan-level data. This contrasts with previous studies that included only small samples in syndicated loan markets or limited sample periods. In addition, those studies examined mainly the effect of GHG emissions on credit spreads whereas we investigate the relationship between GHG emissions and the amount of loans.[3] Second, we provide evidence concerning the mechanism through which GHG emissions affect loan allocation. Our findings imply that the credit risk

[3] A few papers including Kacperczyk and Peydró (2021) studied the effects of GHG emissions on credit allocation.

channel is the most prominent hypothesis to explain the effect of GHG emissions on bank loans. This has an important policy implication because it suggests a more efficient way to increase lending to greener firms through policymaking. For example, by showing a stricter attitude toward legal restrictions on products with a large negative environmental impact, policymakers can enlarge a firm's risk exposure to the transitional climate risk generated by a unit emission of GHG, and such an enhanced risk exposure may induce banks to lend more to greener firms.

2 Econometric Model and Data

To investigate how GHG emissions affect bank loans, we use loan-level data including firm and bank fixed effects (FEs). In this section, we explain the dataset and the baseline model for the following empirical analysis.

2.1 Data

To study the effect of GHG emissions on bank loans controlling for other factors, we combine two datasets. For the GHG emissions, we use the firm-level data from Trucost. We combine these data with loan data from Nikkei Financial Quest for Japanese listed firms. We also use bank and firm financial variables from Nikkei NEEDS. We specify yearly data from 2006 to 2018.

As for the GHG emission variables, we employ the following three categories of Scope 1, Scope 2, and Scope 3.[4] Scope 1 emissions are those from directly emitting sources that are controlled by a company. For example, the emissions produced by the internal combustion engines of lorry fleet owned by a trucking company are included in this category. Scope 2 emissions are those from the consumption of purchased electricity or other sources of energy generated upstream from a company's direct operations. Scope 3 emissions are all other emissions associated with a company's operations that are not directly owned or controlled by the company. In the following empirical analysis, we examine the effects of GHG emissions on bank loans by those categories. More particularly, following Bolton and

[4]Following descriptions are based on Trucost (2018).

Kacperczyk (2021) and Garvey et al. (2018), for each category we consider the simple GHG emission level as well as the ratio of the emission level to sales, i.e., emission intensity. We take the logarithms of both measures and denote them *GEL* and *GEI*, respectively.

The summary statistics of the variables are shown in Table 1. The average loan growth rates in this period are positive but the median is zero percentage points. The sample size of the loan growth rates is over 20,000 observations. The GHG emissions data available are more than 2,500 firm–year samples. The level for scope 1 GHG emissions exhibits greater variation than scopes 2 and 3. The ROA for firms in our sample has a positive value of 2.7% on average. As for the bank variables, the number of bank–year samples is about 1,200, which suggests that the number of banks in our sample is about 100 every year.

Table 2 details the number of firms in each sector in our sample, suggesting a wide range of industries. The capital goods industry accounts for the largest share of firms, with the materials industry second.

Table 1: Summary statistics

Variable	**Mean**	**Std. Dev.**	**25 percentile**	**Median**	**75 percentile**	**N**
Loan growth	8.4	60.1	–13.0	0.0	4.5	20246
GHG variables						
GEL1	11.5	2.3	10.0	11.6	12.8	2742
GEL2	11.3	1.8	10.1	11.3	12.5	2742
GEL3	13.1	1.8	11.9	13.2	14.5	2742
GEI1	3.6	1.5	2.7	3.3	4.4	2742
GEI2	3.4	0.9	2.8	3.4	3.9	2742
GEI3	5.2	0.8	4.6	5.4	5.8	2742
Firm variables						
Sales growth	8.1	169.3	–4.2	1.7	9.2	2699
Book leverage ratio	54.6	18.2	41.7	54.9	68.9	2742
Return on assets	2.7	4.6	1.0	2.4	4.4	2742
Size	12.3	1.5	11.4	12.4	13.4	2742
Distance-to-default	5.5	3.2	3.5	4.7	6.4	2734
Bank variables						
Book leverage ratio	95.0	1.6	94.0	95.0	95.9	1232
Return on assets	0.2	0.4	0.1	0.2	0.3	1232
Size	15.1	1.2	14.4	14.9	15.6	1232

Table 2: Number of firms by industry

Industry	Number of firms
Automobiles & Components	49
Capital Goods	178
Commercial & Professional Services	34
Consumer Durables & Apparel	49
Consumer Services	34
Diversified Financials	16
Energy	8
Food & Staples Retailing	23
Food, Beverage & Tobacco	37
Health Care Equipment & Services	20
Household & Personal Products	10
Materials	95
Media & Entertainment	8
Pharmaceuticals, Biotechnology & Life.	13
Real Estate	69
Retailing	49
Semiconductors & Semiconductor Equipm..	13
Software & Services	22
Technology Hardware & Equipment	48
Telecommunication Services	2
Transportation	35
Utilities	8
Total	820

2.2 Baseline Model

To investigate the effect of GHG emissions, we use an empirical model comprising the growth rate of bank loans from bank j to firm i from year $t-1$ to t ($\Delta LOAN_{ijt}$) as follows:

$$\Delta LOAN_{ijt} = \beta^m GE^m_{it-1} + FirmFE_i + BankFE_j + Control_{ijt} + Time_t + \varepsilon_{ijt}, \tag{1}$$

where GE^m_{it-1} is the GHG emissions of firm i of scope m. As noted, we consider two different measures for the variable GE. The first measure is the logarithm of the GHG emissions level (GEL). Although the GHG emissions level varies across industries, by using the level without any adjustment we can respond to the question of whether bank loans are sensitive to the level of GHG emissions, which has first-order importance in assessing climate risk. The second measure is GHG intensity (GEI) calculated as the logarithm of the ratio of GHG emissions to sales. As argued in Garvey et al. (2018), this measure can be regarded as a proxy for the efficiency of each firm in terms of GHG emissions and economic performance. It should be noted that intensity differs majorly across sectors.

For both measures, we estimate models with- and without- firm fixed effect, denoted by $FirmFE_i$. Firm FEs control the variation in the average emission level or intensity in each industry but still allow us to exploit the effect of any deviation from the industry and firm averages. $BankFE_j$ and $Time_t$ are the bank and time FEs, respectively. As a robustness check, we also estimate an alternative model with time-varying bank and industry FEs.

As control variables, we specify bank book leverage (BLEV), the bank return on assets (ROA), bank size (size), firm sales growth, firm book leverage, firm ROA, and distance-to-default (D-to-D).

3 Estimation Results

3.1 Does the Level of GHG Emissions Matter?

First, focusing on the allocation effect across all sectors, we employ the logarithm of the level of GHG emissions as independent variables. Columns 1 to 3 in Table 3 provide the estimation results without firm FEs, indicating that firms with larger GHG emissions are provided with a smaller amount of loans. All three emission variables from scopes 1 to 3 have statistically significant coefficients. In addition, the effect of GHG emissions on loans is economically significant. For example, a one-standard-deviation increase in the GHG emissions (+2.3) of a firm decreases loans to that firm by 2.9 percentage points. To control the effect of unobserved firm-side factors, we include firm FEs, as shown in Columns 4 to 6. The estimated coefficients on scopes 1 and 3 are statistically significant at the 1% and 10% significance level, respectively, whereas that on scope 2 is not significant. This suggests that scope 1 GHG emissions play an important role in the supply of bank loans. The size of the coefficient in column 4 with firm FEs is quite large, compared with that in column (1) without firm FEs. This is partly because the average effect in industry and for each firm is fully controlled by firm FEs. In other words, the larger coefficient in the specification with firm FEs implies that any deviation from the industry average level is heavily penalized in terms of the provision of bank loans. We also estimate the model with time-varying bank FEs, as shown by Columns 7 to 9 in Table 3. The estimation result confirms that bank loans to firms with high GHG emissions decreased more and that scope 1 GHG emissions are the most relevant indicator for bank lending.

As a robustness check, we control for sector-specific shocks by including time-varying industry FEs, as shown in Table 4. Columns 1 to 3 and 4 to 6 report the results without and with time-varying bank FEs, respectively. The estimation results for all of the specifications in Table 4 indicate that firms with larger scope 1 GHG emissions are provided with fewer bank loans. We should note that in this specification with time-varying industry FEs, the variation in deviation of GHG emission from the time-varying sector average is still used to detect the effects of GHG emission. In other words, the average effect of GHG emissions in each industry is controlled, but the deviation from the industry mean that varies substantially across industries is exploited in the identification. In this way, we can still at least partly exploit any variation in GHG emissions across industries even when including time-varying industry FEs.

In summary, firms with larger GHG emissions are likely to obtain a smaller amount of bank loans if we consider the level of the firm's GHG emission without considering any industry difference. Furthermore, this result holds even if we control for the characteristics of each industry. In addition, GHG emissions based on scope 1 are the most informative variable in the provision of bank loans.

3.2 Does GHG Intensity Matter?

In the previous analysis, we employ the level of GHG emissions as the main independent variable, which allows us to understand whether banks decreased loans to firms with high GHG emissions compared with firms across all sectors. However, if a firm becomes more energy efficient while increasing output along with its GHG emissions, and if banks increased loans to this more efficient firm, the behavior of such banks could contribute to a "greener" economy. The previous specification does not reveal whether this is the case because the level of GHG emissions does not include any information about energy efficiency. To address this, we specify the intensity variable, which is the log of the ratio of GHG emissions to sales, as the primary explanatory variable.

Columns 1 to 3 in Table 5 provide the estimation results without firm FEs, indicating that bank loans to firms with higher GHG emissions intensity decrease more across all three types of GHG emissions. Importantly, GHG intensity has an economically significant effect on bank lending in that a one-standard-deviation increase in the intensity of GHG emissions of scope 1 implies a decrease in loans by 2.2 percentage points. Columns 4 to 9 providing the estimation results including firm FEs and time-varying bank FEs indicate that the intensity for scopes 1 and 3 GHG emissions significantly affect bank lending, even when we control for unobserved firm effects.

As a robustness check, we include the time-varying industry FEs and bank FEs, as shown in Table 6. The estimation results suggest that firms with a higher intensity of scopes 1 or 2 GHG emissions are granted fewer bank loans.

Overall, we conclude that the intensity of GHG emissions has a significant effect on the provision of bank loans.

Table 3: Effect of GHG emissions on bank loans

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Without Firm FE			With Firm FE			With Bank *Year FE		
GEL1	−1.252***			−5.903***			−5.499***		
	(0.204)			(1.234)			(1.279)		
GEL2		−1.025***			0.420			0.984	
		(0.340)			(1.504)			(1.534)	
GEL3			−1.555***			0.031			−0.0786
			(0.247)			(2.111)			(2.170)
Bank BLEV	0.730	0.751	0.649	0.473	0.304	0.301			
	(0.664)	(0.664)	(0.664)	(0.674)	(0.673)	(0.673)			
Bank ROA	2.036	2.090	1.955	1.649	1.506	1.504			
	(1.589)	(1.591)	(1.590)	(1.588)	(1.593)	(1.593)			
Bank size	1.333	1.314	1.198	0.747	0.243	0.232			
	(1.994)	(1.995)	(1.994)	(2.019)	(2.024)	(2.023)			
Firm sales growth	0.00240*	0.00288*	0.00237*	0.001	0.001	0.001	0.002	0.001	0.00109
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.00237)
Firm BLEV	−0.107***	−0.106***	−0.118***	−0.984***	−0.928***	−0.928***	−0.959***	−0.908***	−0.909***
	(0.032)	(0.032)	(0.032)	(0.122)	(0.121)	(0.121)	(0.126)	(0.125)	(0.125)
Firm ROA	0.053	0.056	0.044	0.177	0.135	0.134	0.144	0.108	−0.104
	(0.110)	(0.110)	(0.110)	(0.153)	(0.155)	(0.154)	(0.156)	(0.157)	(0.156)
Firm size	1.368***	1.235***	1.429***	−13.85***	−16.94***	−17.21***	−16.82***	−19.42***	−20.06***
	(0.394)	(0.431)	(0.390)	(4.223)	(4.238)	(4.209)	(4.294)	(4.326)	(4.275)
Firm D-to-D	0.257	0.230	0.326	0.020	0.019	0.025	0.046	0.036	−0.0508
	(0.223)	(0.223)	(0.225)	(0.377)	(0.379)	(0.377)	(0.396)	(0.397)	(0.395)
N	19484	19489	19489	19266	19271	19271	19056	19061	19061
Firm fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	—	—	—
Bank * Year fixed effects	No	No	No	No	No	No	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	—	—	—

Note: Robust standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table provides the estimation results for the panel regression with the growth rate of bank loans as the dependent variable. GEL*i* is the logarithm of the GHG emissions level for scope *i* GHG emissions.

Table 4: Robustness check: Effect of GHG emissions on bank loans

	(1)	(2)	(3)	(4)	(5)	(6)
GEL1	-6.460***			-6.116***		
	(1.750)			(1.778)		
GEL2		-2.541			-3.289	
		(2.173)			(2.211)	
GEL3			5.276			5.379
			(3.703)			(3.799)
Bank BLEV	0.203	0.162	0.120			
	(0.663)	(0.662)	(0.662)			
Bank ROA	0.808	0.744	0.695			
	(1.590)	(1.590)	(1.588)			
Bank size	0.429	0.610	0.648			
	(2.050)	(2.054)	(2.053)			
Firm sales growth	-0.00539	-0.00315	-0.00142	-0.00522	-0.00322	-0.00139
	(0.00445)	(0.00436)	(0.00446)	(0.00486)	(0.00474)	(0.00481)
Firm BLEV	-1.235***	-1.114***	-1.081***	-1.240***	-1.132***	-1.096***
	(0.205)	(0.199)	(0.202)	(0.210)	(0.204)	(0.207)
Firm ROA	-0.710***	-0.666**	-0.648**	-0.721***	-0.689**	-0.666**
	(0.267)	(0.267)	(0.266)	(0.267)	(0.268)	(0.267)
Firm size	-24.81***	-26.94***	-30.45***	-26.12***	-27.73***	-31.76***
	(5.935)	(5.921)	(6.023)	(6.045)	(6.027)	(6.152)
Firm D-to-D	0.175	0.313	0.252	0.129	0.270	0.197
	(0.543)	(0.545)	(0.544)	(0.569)	(0.571)	(0.570)
N	19242	19247	19247	19031	19036	19036
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	—	—	—
Bank * Year fixed effects	No	No	No	Yes	Yes	Yes
Industry * Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table provides the estimation results for the panel regression with the growth rate of bank loans as the dependent variable. GEL*i* is the logarithm of the GHG emission level for scope *i* GHG emissions.

Table 5: Effect of GHG intensity on bank loans

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Without Firm FE			With Firm FE			With Bank *Year FE		
GEI1	−1.450***			−7.450***			−6.798***		
	(0.270)			(1.343)			(1.406)		
GEI2		−1.766***			1.314			1.594	
		(0.453)			(1.611)			(1.630)	
GEI3			−2.289***			−28.25***			−26.09***
			(0.543)			(5.804)			(5.777)
Bank BLEV	0.183	0.148	0.164	0.116	0.064	0.019			
	(0.722)	(0.722)	(0.722)	(0.716)	(0.716)	(0.716)			
Bank ROA	1.072	1.064	1.074	0.844	0.718	0.664			
	(1.758)	(1.759)	(1.760)	(1.730)	(1.739)	(1.731)			
Bank size	0.306	0.430	0.212	0.272	0.836	0.719			
	(2.107)	(2.107)	(2.104)	(2.099)	(2.101)	(2.102)			
Firm sales growth	0.002	0.00223*	0.002	0.00351**	0.00320**	0.00434***	0.00406**	0.00379**	0.00480**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.00191)
Firm BLEV	−0.128***	−0.127***	−0.150***	−0.943***	−0.886***	−0.871***	−0.908***	−0.858***	−0.847***
	(0.033)	(0.033)	(0.034)	(0.123)	(0.122)	(0.123)	(0.127)	(0.126)	(0.126)
Firm ROA	0.017	0.017	0.037	0.124	0.082	0.050	0.082	0.046	−0.0161
	(0.112)	(0.113)	(0.113)	(0.155)	(0.156)	(0.156)	(0.158)	(0.160)	(0.159)
Firm size	0.663	0.509	0.581	−17.25***	−16.84***	−19.51***	−20.08***	−19.83***	−22.10***
	(0.408)	(0.411)	(0.410)	(4.824)	(4.850)	(4.851)	(4.892)	(4.917)	(4.928)
Firm D-to-D	0.306	0.302	−0.416*	0.486	0.419	0.448	0.421	0.359	−0.391
	(0.238)	(0.237)	(0.242)	(0.403	(0.402)	(0.402)	(0.423)	(0.423)	(0.422)
N	17488	17493	17493	17468	17473	17473	17252	17257	17257
Firm fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	—	—	—
Bank * Year fixed effects	No	No	No	No	No	No	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	—	—	—

Note: Robust standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table provides the estimation results for the panel regression with the growth rate of bank loans as the dependent variable. GEI*i* is the logarithm of GHG emission intensity for scope *i* GHG emissions.

3.3 Paris Agreement

In this section, we investigate whether the effect of the GHG emissions of firms on bank lending changed before the Paris Agreement. To do so, we run the same estimation using only samples before the Paris Agreement (Mar. 2006 – Mar. 2015).

Table 7 provides the estimation results for the shorter sample period. Similar to the previous estimation results including after the Paris Agreement periods, coefficients for GHG emissions, particularly those for Scope 1 emissions, are significantly negative. This suggests that Japanese banks had continuously taken account of the borrowing firms' GHG emissions in their lending behavior even before the Paris Agreement.[5]

3.4 Supply vs Demand Effect

In the previous section, we demonstrated that loans to firms with high GHG emissions decrease more than those with low GHG emissions in terms of both level and intensity of GHG emissions. However, although we demonstrate the effect of GHG emissions, it is not clear whether the supply of or demand for bank loans is more important. For example, firms with high GHG emissions might demand fewer bank loans for some reason. Alternatively, banks might decrease loans to firms with high GHG emissions given their higher climate risk. In this section, we show that supply-side factors primarily drive the effect of GHG emissions on bank loans.

3.4.1 Credit Demand and GHG Emissions

To assess whether the effect of GHG emissions on bank loans is driven by supply-side factors, we estimate the baseline model by restricting the sample conditioning on firm-side variables. In other words, we provide evidence that loan demand is not the main driving force behind the estimation results of the previous section.

First, following Becker and Ivashina (2014), we use loan data for borrowing firms that increased their outstanding amount of corporate bonds. All firms with increasing

[5]As a robustness check, we constructed balanced panel data for firms whose data are available both before and after the Paris Agreement. We obtained a quantitatively similar result for the subsamples. The estimation result is available on request.

Table 6: Robustness check: effect of intensity

	(1)	(2)	(3)	(4)	(5)	(6)
GEI1	-7.868^{***}			-7.527^{***}		
	(2.034)			(2.126)		
GEI2		-6.098^{**}			-6.885^{**}	
		(2.745)			(2.817)	
GEI3			-14.79^{*}			-15.80^{**}
			(7.871)			(7.968)
Bank BLEV	–0.155	–0.200	–0.181			
	(0.705)	(0.705)	(0.706)			
Bank ROA	0.278	0.216	0.230			
	(1.733)	(1.731)	(1.731)			
Bank size	1.093	1.352	1.316			
	(2.134)	(2.139)	(2.140)			
Firm sales growth	–0.00567	–0.00361	–0.00447	–0.00404	–0.00202	–0.00298
	(0.00424)	(0.00421)	(0.00422)	(0.00471)	(0.00466)	(0.00468)
Firm BLEV	-1.044^{***}	-0.870^{***}	-0.888^{***}	-1.046^{***}	-0.883^{***}	-0.901^{***}
	(0.203)	(0.200)	(0.200)	(0.208)	(0.206)	(0.206)
Firm ROA	-0.604^{**}	-0.569^{**}	-0.507^{*}	-0.611^{**}	-0.587^{**}	-0.518^{*}
	(0.271)	(0.272)	(0.272)	(0.274)	(0.276)	(0.276)
Firm size	-29.76^{***}	-30.83^{***}	-32.38^{***}	-30.89^{***}	-31.83^{***}	-33.50^{***}
	(7.088)	(7.121)	(7.195)	(7.247)	(7.275)	(7.353)
Firm D-to-D	–0.0414	0.236	0.130	0.00104	0.271	0.157
	(0.572)	(0.570)	(0.569)	(0.597)	(0.594)	(0.594)
N	17247	17252	17252	17032	17037	17037
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	—	—	—
Bank * Year fixed effects	No	No	No	Yes	Yes	Yes
Industry * Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table provides the estimation results for the panel regression with the growth rate of bank loans as the dependent variable. GEIi is the logarithm of GHG emissions intensity for scope i GHG emissions.

Table 7: Before Paris Agreement

	(1)	(2)	(3)	(4)	(5)	(6)
GEL1	-6.540***					
	(1.779)					
GEL2		0.385				
		(2.245)				
GEL3			2.979			
			(2.927)			
GEI1				-7.721***		
				(1.731)		
GEI2					-1.314	
					(2.021)	
GEI3						-20.16***
						(7.636)
N	11068	11068	11068	11265	11265	11265
Firm control variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank * Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Firm-side control variables are included in the equation, but the estimated coefficients are not shown. The table provides the estimation results for the panel regression with the growth rate of bank loans as the dependent variable for subsamples from 2006 to 2015. GEI*i* and GEL*i* are the logarithms of the GHG emissions level and the intensity of scope *i* GHG emissions, respectively.

corporate bonds should have some demand for credit. If loans to a firm with the increasing issuance of corporate bonds are likely to decrease as the firm's GHG emissions increase, it suggests that the firm's lower demand for credit is not the main driving force of the negative effect of GHG emissions on loans. Thus, for firms with increasing corporate bond issuance, the negative effect of GHG emissions on loans is primarily driven by supply factors.

Second, we estimate the effect on loans using only the loan data of firms whose growth rate of total debt is positive, which provides evidence of a strong demand for debt. If GHG emissions have a negative impact on loans to firms with increasing debts, it implies that banks are unwilling to increase loans to firms with higher GHG emissions.

Column 1 in Table 8 indicates that the negative effect of GHG emissions is evident, even for firms with strong credit demand. This implies that the negative effect of higher GHG emissions is not driven by the weaker credit demand of borrowing firms. We then infer that lending banks are less likely to increase loans to firms with high GHG emissions. Column 2 in Table 8 shows that loans to firms with increasing total debt decrease as GHG emissions increase, which also suggests that banks are likely to decrease loans owing to GHG emissions.

We repeat the analysis for GHG intensity and obtain a significantly negative coefficient on GHG emissions intensity, as shown in Columns 3 and 4 in Table 8. In addition, the coefficients are quantitatively similar to the estimates including the full samples. These results suggest that the negative effect of GHG variables on bank loans is primarily driven by the supply-side factors.

3.4.2 GHG and Firm Variables

In this section, we show that the GHG emission level and intensity are not correlated with the firm-side variables that capture the credit demands of firms. In other words, if GHG emissions are negatively associated with a firm's growth or credit demand, our result in the previous section might be driven by the low (high) credit demand of a high (low) GHG emissions firm. However, we demonstrate that this is not the case. More specifically, we examine whether high GHG emissions are a proxy for i) weak demand for capital

Table 8: Effect of GHG emissions on firms with loan demand

	(1)	(2)	(3)	(4)
	Inc. CB issue	Inc. total debt	Inc. CB issue	Inc. total debt
GEL1	–8.077***	–4.739**		
	(1.776)	(2.281)		
GEI1			–9.600***	–6.619***
			(2.014)	(2.565)
Firm sales growth	-0.000340	-0.00483	-0.000476	-0.00475
	(0.00252)	(0.00337)	(0.00249)	(0.00339)
Firm BLEV	-1.262***	-1.045***	-1.277***	-1.037***
	(0.199)	(0.199)	(0.200)	(0.197)
Firm ROA	-0.260	0.226	-0.283	0.196
	(0.225)	(0.254)	(0.225)	(0.254)
Firm size	-14.09**	-24.17***	-18.88***	-26.92***
	(6.475)	(6.617)	(6.429)	(6.479)
Firm D-to-D	-0.389	-1.126*	-0.472	-1.176*
	(0.529)	(0.642)	(0.529)	(0.642)
N	11290	10659	11290	10659
Firm fixed effects	Yes	Yes	Yes	Yes
Bank * Year fixed effects	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table provides the estimation results for the panel regression with the growth rate of bank loans as the dependent variable. GEL1 and GEI1 are the logarithms of the GHG emission level and the intensity of scope 1 GHG emissions, respectively.

expenditure, ii) weak funding needs for working capital, and iii) highly indebted firms. To do this, we regress a proxy for the funding demand variable y for firm i on the GHG emissions variable as follows,

$$y_{it} = \beta_1 GE_{it} + \beta_2 X_{it} + u_i + e_{it}. \tag{2}$$

As a proxy for funding demand, we use i) the growth rate of fixed assets, ii) sales growth, and iii) the interest coverage ratio (ICR), defined as the ratio of EBIT over interest expense. In this regression, we investigate the contemporaneous correlation between GHG emissions and these variables.

Table 9 details the estimation results. The results in the first two columns suggest that GHG emissions are positively correlated with the growth rate of fixed assets. Therefore, the negative coefficient for GHG emissions in the loan equation does not capture low funding demand for capital expenditure. Rather, firms with high GHG emissions have greater credit demand for capital expenditure. This implies that the negative effect of GHG emissions on bank loans is primarily through the supply-side effect.

Columns (3) and (4) provide the estimation result for sales growth. Higher sales growth is associated with greater demand for working capital. A positive coefficient on the GHG emission level and an insignificant coefficient on the GHG intensity indicate that higher GHG emissions are not associated with weaker demand for funding working capital. Thus, the negative effect of GHG emissions on bank loans does not reflect a weak demand for funding to finance working capital.

Finally, we investigate whether firms with high GHG emissions are highly indebted and therefore have lower demand for bank loans. Columns (5) and (6) in Table 9 show that the ICR is not significantly correlated with GHG emissions, indicating that firms with high GHG emissions do not suffer from high interest payments, such that they refrain from bank borrowing. Therefore, the negative coefficient for GHG emissions in the loan equation does not capture the weak loan demand of firms due to the interest burden of existing debt.

In sum, a higher level and intensity of GHG emissions are not associated with weak demand for capital expenditure or working capital. In addition, the effect of the GHG emissions does not reflect the greater debt burden of borrowing firms. These results suggest that the negative effect of GHG emissions on the provision of bank loans is not driven by the weak demand of borrowing firms for loans.

Table 9: Firm variable and GHG emissions

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable					
	Growth Rate of Fixed Assets$_t$		Sales Growth$_t$		ICR$_t$	
GEL1$_t$	2.209***		2.482***		–53.19	
	(0.639)		(0.814)		(293.3)	
GEI1$_t$		1.088*		–0.558		–197.2
		(0.591)		(0.825)		(273.3)
Firm sales growth$_{t-1}$	–0.000282	–0.000262	0.000910	0.000843	0.545	0.559
	(0.000789)	(0.000767)	(0.00282)	(0.00282)	(0.427)	(0.422)
Firm BLEV$_{t-1}$	–0.0251	–0.0383	0.0987	0.0708	–180.6***	–181.4***
	(0.0719)	(0.0725)	(0.0796)	(0.0800)	(44.77)	(44.70)
Firm ROA$_{t-1}$	0.425***	0.425***	–0.313**	–0.317**	23.76	23.25
	(0.0904)	(0.0910)	(0.126)	(0.127)	(57.61)	(57.59)
Firm size$_{t-1}$	–14.86***	–13.68***	–19.80***	–18.28***	1899.9	1892.3
	(3.213)	(3.236)	(2.865)	(2.810)	(1460.0)	(1437.6)
Firm D-to-D$_{t-1}$	–0.249	–0.223	0.311	0.318	204.5*	204.4*
	(0.201)	(0.201)	(0.303)	(0.299)	(113.3)	(113.3)
N	2516	2516	3419	3419	3349	3349
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry * Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table provides the estimation results for the panel regression where the dependent variable is a proxy for firm funding demand (growth rate of fixed assets and sales growth) and firm financial distress (ICR).

3.5 Interaction Effect with Bank Characteristics

In the previous section, we find that the level and intensity of GHG emissions affect bank lending and that supply factors drive the results. Furthermore, the effect can be heterogeneous among banks with different characteristics. For example, if banks consider that firms with high GHG emissions are exposed to larger physical and transitional climate risks that bring with them additional costs, banks with low profitability or unsound balance sheets may be less willing to lend to these highly risky firms to avoid incurring further losses from risky lending. Alternatively, less financially sound banks may lend more to firms with high GHG emissions, with the expectation that such a highly risky lending would entail high returns thus work as "gamble" on its own survaival.

To investigate the effect of banks' financial soundness on the impact of GHG emissions, we estimate the following panel regression with the interaction terms between GHG emissions and degree of lending banks' financial soundness:

$$\begin{aligned}\Delta LOAN_{ijt} = \beta_0^m GE_{it-1}^m + \beta_1^m GE_{it-1}^m \times BankFIN\_Dum_{jt} \\ + FirmFE_i + BankFE_{tj} + Control_{ijt} + \varepsilon_{ijt}.\end{aligned} \tag{3}$$

All variables other than $BankFIN\_Dum_{jt}$ are same as those in the baseline model (1). $BankFIN\_Dum_{jt}$ is a dummy variable that takes one or zero, depending on bank j's financial condition at t. More specifically, we consider a bank's leverage ratio and profitability as measurements of its financial condition. As for leverage, we defined two dummies that take a value of one when the bank's BLEV ratio in time $t-1$ is more than the 75th (HighLev75) and 90th (HighLev90) percentiles. As for profitability, we define two dummies that take one if the bank's ROA in time $t-1$ is less than the 25th (LowRoa25) and 10th (LowRoa10) percentiles in all samples.

The estimated coefficient, β_1^m, on the interaction term of GHG emmissions and the dummy variables defined above is of special interest. By investigating the heterogeneous behavior of banks in lending to greener firms, we uncover a mechanism through which the firm's GHG emissions affect bank loans. The leverage ratio captures the risk-taking stance along with the solvency risk of banks. If banks with a higher leverage ratio (or lower profitability) are more likely to increase loans than those with a lower leverage ratio (or higher profitability), we infer that banks decrease loans to brown firms through concern about the credit risks of these firms.

Columns 1 and 2 in Table 10 indicate that the interaction terms between the high-leverage bank dummies and GHG emissions for scope 1 GHG emissions exhibit a significantly negative coefficient, indicating that highly leveraged banks are more likely to decrease loans to firms with higher GHG emissions than otherwise.[6] This suggests that banks with a weak financial base are more sensitive to the GHG emissions of borrowing firms. The impact of GHG emissions (GEL1) increases by 18% (–5.6 to –6.6) for loans from highly leveraged banks compared with lowly leveraged banks. Columns 3 and 4 in Table 10 indicate that firms with banks with low profitability are more likely to decrease loans to firms with high GHG emissions than highly profitable banks. The effect of bank profitability is also economically significant.

We undertake the same exercise for GHG emissions intensity and obtain quantitatively similar results to those as the GHG emissions level, as shown in Columns (5) to (8) in Table 10.

These results suggest that the effect of GHG emissions on bank loans arises through the credit risk channel. This is because banks with high leverage and low profitability are more sensitive to the credit risks of borrowing firms. Therefore, these banks are more likely to decrease loans to firms with high GHG emissions.

[6]The estimates of the coefficients on the firm-side control variables are included in the model, but not reported in the table.

Table 10: Bank-side interaction effects

	Dependent variable: $\Delta LOAN$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High Leverage		Low ROA		High Leverage		Low ROA	
GEL1	-5.251^{***}	-5.302^{***}	-5.291^{***}	-5.419^{***}				
	(1.276)	(1.279)	(1.279)	(1.275)				
HighLev75 × GEL1	-0.882^{*}							
	(0.467)							
HighLev90 × GEL1		-0.998^{**}						
		(0.498)						
LowRoa25 × GEL1			-0.929^{*}					
			(0.498)					
LowRoa10 × GEL1				-1.520^{*}				
				(0.859)				
GEI1					-6.735^{***}	-6.886^{***}	-6.721^{***}	-6.941^{***}
					(1.350)	(1.352)	(1.354)	(1.346)
HighLev75 × GEI1					-1.181^{*}			
					(0.648)			
HighLev90 × GEI1						-0.804		
						(0.690)		
LowRoa25 × GEI1							-1.505^{**}	
							(0.703)	
LowRoa10 × GEI1								-3.096^{***}
								(1.145)
N	19056	19056	19056	19056	19056	19056	19056	19056
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank * Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Firm-side control variables are included in the equation, but the estimated coefficients are not shown. The table provides the estimation results for the panel regression with the growth rate of bank loans as the dependent variable. GEL1 and GEI1 are the logarithms of the GHG emission level and the intensity of scope 1 GHG emissions, respectively. HighLev75 and HighLev90 indicate highly leveraged bank dummy variables that take a value of one if the book leverage ratio is larger than the 75th and 90th percentiles of the samples, respectively. LowRoa25 and LowRoa10 indicate low profitability bank dummies that take a value of one if the ROA is lower than the 25th and 10th percentiles of the samples, respectively.

3.6 Credit vs Reputation Risk

The existing literature has tried to confirm two main hypotheses to explain why investors care about the climate exposure of firms: the credit risk and reputation risk hypotheses. The credit risk hypothesis considers that firms with high GHG emissions are exposed to higher transition and physical risks. Reputation risk emphasizes that investors with greater exposure to high GHG emissions firms are not preferred in capital markets and thereby incur higher costs of funding. Although those two hypotheses are not mutually exclusive, it does provide some policy implications to investigate which of these two channels dominates.

To investigate the credit risk channel, we test whether the effect of GHG emissions on bank loans differs across firms with varying levels of financial stress. More specifically, we run the panel regression as follows,

$$\begin{aligned} \Delta LOAN_{ijt} = {} & \beta_1^m GE_{it-1}^m \times FirmRisk_{it} \\ & + FirmFE_i + BankFE_{jt} + Control_{ijt} + \varepsilon_{ijt}. \end{aligned} \tag{4}$$

The coefficient of interest is that on the interaction term, β_1^m. As the firm credit risk variable, we use ICR. We divide firms in our sample into three groups based on their ICR and make three dummy variables, each of which takes one if a bank is in the associated group and zero otherwise. The first group includes firms whose ICR is negative, which means that these firms have a negative EBIT. The second group includes firms whose ICR is lower than the median in our sample and the third covers those with an ICR that is higher than the median. We should note that the sign on the interaction effect could be positive or negative, i.e., it is not determined ex ante. For example, if the effect of high GHG emissions is small, it could be the case that GHG emissions only matter for firms whose default rate is sufficiently high. In that case, loans to firms with high credit risks are more sensitive to climate-related risks that can be captured by GHG emissions. Alternatively, if GHG emissions capture credit risks not captured by conventional measures such as ICR, GHG emissions will have a larger impact on firms that are more stable in terms of measures of conventional financial soundness. This is because, for firms with high credit risks in terms of conventional measures, the additional information on GHG emissions will not significantly change the risk assessment of banks of those firms.

The estimation result is shown in Columns 1 and 2 in Table 11, indicating that the effect of GHG emissions is larger for loans to high ICR firms, or low credit risk firms. We test the null hypotheses that the coefficient on GHG emissions for low ICR is not different from that for middle ICR firms, and that the coefficient for low ICR is not different from that for high ICR firms. The *p*-value for the Wald test in the bottom rows in Table 11 shows that for the GHG emission level, the difference between a low ICR and a middle ICR is statistically significant at the 5% level. Although the estimated coefficients are larger for firms with lower credit risks than those with higher credit risks, the difference is not statistically significant. However, the results suggest that GHG emissions exert effects on the provision of bank loans through the credit risk channel and that banks consider these differently from conventional financial risks.

We also investigate whether the reputation channel is dominant by focusing on the degree of lending banks' disclosure of information related to climate risks. More specifically, banks with more transparency in terms of disclosure of the banks' exposure to climate risks would be under higher pressure to avoid misconduct than those that do not disclose any information. Although there is an issue of the self-selection problem, it is plausible to consider that banks with high transparency are exposed to larger reputation risk. Therefore, if reputation risk is a main driving force, more transparent banks are more sensitive to borrowing firms' GHG emissions than non-transparent ones. To test this hypothesis, we use the Bloomberg ESG environment disclosure score, which takes a value from 0 to 100 and summarizes how well a firm discloses information related to climate risks compared to the industry standards. A large environment score corresponds to the associated firm's high transparency.

More particularly, we estimate a regression model which is based on (3) but introduce new variables $BankDISC_{jt}$ and $BankDISC\_Dum_{jt}$ in place of $BankFIN\_Dum_{jt}$. $BankDISC_{jt}$ is bank j's raw ESG environment score at t. $BankDISC\_Dum_{jt}$ is a dummy variable taking one if the ESG environment score is more than 0.[7] It should be noted that for Japanese banks

[7] We set the disclosure score as zero when it is not available to keep a sufficient sample size.

Table 11: Effect of firm credit risks

Dependent variable: $\Delta LOAN$		
	(1)	(2)
LowICR × GEL1	–3.865***	
	(1.440)	
MidICR × GEL1	–5.666***	
	(1.366)	
HighICR × GEL1	–5.633***	
	(1.412)	
LowICR × GEI1		–5.903***
		(1.586)
MidICR × GEI1		–7.283***
		(1.432)
HighICR × GEI1		–7.048***
		(1.510)
N	18507	18507
R^2	0.200	0.200
LowICR = MidICR (p-value)	0.01	0.13
LowICR = HighICR (p-value)	0.10	0.39
Firm controls	Yes	Yes
Firm fixed effect	Yes	Yes
Bank * Year fixed effect	Yes	Yes

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Firm-side control variables are included in the equation, but the estimated coefficients are not shown. The table provides the estimation results for the panel regression with the growth rate of bank loans as the dependent variable. GEL1 and GEI1 are the logarithms of the GHG emissions level and the intensity of scope 1 GHG emissions, respectively.

in our samples this score becomes available in 2015 thus we use the subsamples from 2015 to 2018.

The estimation result in Table 12 indicates that the interaction effect is not significant for both continuous and dummy variables. In other words, banks did not change their behavior depending on the degree of their own transparency. This result is suggestive evidence that the reputation risk would not be a main driving factor for the effect of GHG emissions on lending even though the estimation errors on the interaction effects are not small.

Table 12: Effect of Bank Disclosure

	(1)	(2)	(3)	(4)
	Δ LOAN	Δ LOAN	Δ LOAN	Δ LOAN
GEL1	-6.098**	-5.005*		
	(3.109)	(2.969)		
GEL1 × BankDISC	-0.904			
	(0.860)			
GEL1 × BankDISC_Dum		-0.419		
		(0.546)		
GEI1			-6.818**	-6.360**
			(3.006)	(3.029)
GEI1 × BankDISC			0.815	
			(1.260)	
GEI1 × BankDISC_Dum				-0.354
				(0.859)
N	8830	8824	8824	8824
Firm controls	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
Industry * Year fixed effect	Yes	Yes	Yes	Yes
Bank * Year fixed effect	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Firm-side control variables are included in the equation, but the estimated coefficients are not shown. The table provides the estimation results for the panel regression with the growth rate of bank loans as the dependent variable. GEL1 and GEI1 are the logarithms of the GHG emissions level and the intensity of scope 1 GHG emissions, respectively. *BankDISC* indicate the bank's ESG environment score and *BankDISC_Dum* is a dummy variable that takes one if the ESG environment score is more than 0.

4 Conclusion

In this paper, we investigate the effect of GHG emissions on bank loans using loan-level data for Japanese listed firms. We find that loans to firms with higher levels of GHG emissions and intensity are likely to decrease more than those to firms with lower GHG emissions. This effect of GHG emissions appears to have been significant even before the signing of the Paris Agreement in 2015. In addition, the effect of GHG emissions on loans is larger for loans from banks with high leverage and low profitability, which implies that lending banks consider high GHG emissions as being associated with higher future credit costs. Moreover, banks are more sensitive to the GHG emissions of borrowing firms with low credit risk, suggesting that the GHG emission effect is driven by the banks' view that high GHG emissions imply high credit risk in the longer term. These results have some policy implications. First, banks were very keen to know about the environmental consequences of their lending even before the introduction of "Green operations" by the BOJ in 2021. Second, lending behavior to brown firms significantly varies across banks. This implies that when a new policy related to green finance is introduced, it is likely to affect the lending behavior of banks heterogeneously.

Finally, it should be noted that, while we exploit listed firm data in this paper, half of all bank loans in Japan are to small and medium-sized enterprises (SMEs). Therefore, investigating the effects of GHG emissions on SMEs would be a useful future research topic.

References

ARUGA, R., K. GOSHIMA, T. CHIBA, ET AL. (2022): "CO2 Emissions and Corporate Performance: Japan's Evidence with Double Machine Learning," Tech. rep., Institute for Monetary and Economic Studies, Bank of Japan.

BECKER, B. AND V. IVASHINA (2014): "Cyclicality of credit supply: Firm level evidence," *Journal of Monetary Economics*, 62, 76–93.

Bolton, P. and M. Kacperczyk (2021): "Do investors care about carbon risk?" *Journal of financial economics*, 142, 517–549.

Chava, S. (2014): "Environmental externalities and cost of capital," *Management science*, 60, 2223–2247.

Ehlers, T., F. Packer, and K. de Greiff (2022): "The pricing of carbon risk in syndicated loans: which risks are priced and why?" *Journal of Banking & Finance*, 136, 106180.

Fujii, H., K. Iwata, S. Kaneko, and S. Managi (2013): "Corporate environmental and economic performance of Japanese manufacturing firms: Empirical study for sustainable development," *Business Strategy and the Environment*, 22, 187–201.

Garvey, G., M. Iyer, and J. Nash (2018): "Carbon footprint and productivity: does the "E" in ESG capture efficiency as well as environment?" *Journal of Investment Management*, 16, 59–69.

Goss, A. and G. S. Roberts (2011): "The impact of corporate social responsibility on the cost of bank loans," *Journal of Banking & Finance*, 35, 1794–1810.

Hasan, I., C. K. Hoi, Q. Wu, and H. Zhang (2017): "Social capital and debt contracting: Evidence from bank loans and public bonds," *Journal of Financial and Quantitative Analysis*, 52, 1017–1047.

Hauptmann, C. (2017): "Corporate sustainability performance and bank loan pricing: It pays to be good, but only when banks are too," *Saïd Business School WP*, 20.

Houston, J. F. and H. Shan (2022): "Corporate ESG profiles and banking relationships," *The Review of Financial Studies*, 35, 3373–3417.

Kacperczyk, M. T. and J.-L. Peydró (2021): "Carbon emissions and the bank-lending channel," .

Kleimeier, S. and M. Viehs (2018): "Carbon disclosure, emission levels, and the cost of debt," *Emission Levels, and the Cost of Debt (January 7, 2018)*.

Nishitani, K. and K. Kokubu (2012): "Why does the reduction of greenhouse gas emissions enhance firm value? The case of Japanese manufacturing firms," *Business Strategy and the Environment*, 21, 517–529.

Okimoto, T. and S. Takaoka (2021): "Sustainability and Credit Spreads in Japan," Tech. rep., Research Institute of Economy, Trade and Industry (RIETI).

Ongena, S., M. Delis, and K. de Greiff (2018): "Being stranded on the carbon bubble? Climate policy risk and the pricing of bank loans," .

Reghezza, A., Y. Altunbas, D. Marques-Ibanez, C. R. d'Acri, and M. Spaggiari (2022): "Do banks fuel climate change?" *Journal of Financial Stability*, 62, 101049.

Scatigna, M., D. Xia, A. Zabai, and O. Zulaica (2021): "Achievements and challenges in ESG markets," .

Sharfman, M. P. and C. S. Fernando (2008): "Environmental risk management and the cost of capital," *Strategic management journal*, 29, 569–592.

Trucost (2018): "Trucost Environmental Register: Methodology FAQs," .

Previous volumes in this series

1077 February 2023	Understanding post-COVID inflation dynamics	Martín Harding, Jesper Lindé and Mathias Trabandt
1076 February 2023	The shape of business cycles: a cross-country analysis of Friedman's plucking theory	Emanuel Kohlscheen, Richhild Moessner and Daniel M Rees
1075 February 2023	Overcoming original sin: insights from a new dataset	Mert Onen, Hyun Song Shin and Goetz von Peter
1074 February 2023	Non-bank lending during crises	Iñaki Aldasoro, Sebastian Doerr and Haonan Zhou
1073 February 2023	Constrained Liquidity Provision in Currency Markets	Wenqian Huang, Angelo Ranaldo, Andreas Schrimpf, and Fabricius Somogyi
1072 February 2023	Climate tech 2.0: social efficiency versus private returns	Giulio Cornelli, Jon Frost, Leonardo Gambacorta and Ouarda Merrouche
1071 January 2023	Financial access and labor market outcomes: evidence from credit lotteries	Bernardus Van Doornik, Armando Gomes, David Schoenherr and Janis Skrastin
1070 January 2023	Theory of supply chains: a working capital approach	Se-Jik Kim and Hyun Song Shin
1069 January 2023	Global financial cycle and liquidity management	Olivier Jeanne and Damiano Sandri
1068 January 2023	Forecasting swap rate volatility with information from swaptions	Amanda Liu and Jinming Xie
1067 January 2023	Signaling with debt currency choice	Egemen Eren, Semyon Malamud and Haonan Zhou
1066 January 2023	The Technology of Decentralized Finance (DeFi)	Raphael Auer, Bernhard Haslhofer, Stefan Kitzler, Pietro Saggese and Friedhelm Victor
1065 January 2023	The Bank of Amsterdam and the limits of fiat money	Wilko Bolt, Jon Frost, Hyun Song Shin and Peter Wierts
1064 January 2023	Monetary policy and credit card spending	Francesco Grigoli and Damiano Sandri

All volumes are available on our website www.bis.org.