Assessing the impact of carbon emissions on firm default risk: A global perspective

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Abstract

This study assesses the impact of carbon emissions on firms' default risk in 44 major countries. To this end, we develop a methodology for stepwise logistic regression to find the financial ratios related to firms adhering to their countries' emission regulations, in addition to international agreements. The results for countries in the top four regarding firm numbers show that carbon emissions can directly increase a firm's default risk, except in Japan and China. Notably, carbon emission reduction activities do not necessarily contribute to a firm's default risk reduction depending on each country's emission regulations and the attained level of reduction activities. Overall, this study provides an effective credit risk analysis methodology that considers carbon emissions for related entities such as firms, lenders, and investors.

Keywords: Carbon emissions, climate change, default risk, stepwise logistic regression
JEL classification: G24; G33; C33; Q54.

1. Introduction

Global climate change is currently one of the most significant risks firms face. Endless emissions of greenhouse gases (GHG)[1] would accelerate the rise in temperature and intensify the frequency and severity of extreme weather events, with disruptive effects on businesses and communities. To limit the

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[1]GHG comprises gases such as CO2, CH4, N2O, HFCs, PFCs, SF6, and NF3. Thus, carbon emissions hereafter correspond to "CO2 equivalent" calculated as total amount by converting these gas emissions into CO2 emissions.

increase in emissions, various national and international initiatives have been implemented to comply with national and international treaties and principles. For example, the Paris Agreement entered into force in 2016, and calls for signatories to reduce carbon emission such that global warming level can be reduced to 1.5 degrees Celsius compared to pre-industrial levels (Kabir et al., 2021).

In the international context of ESG investment and financing, the Principles for Responsible Investment, issued by the United Nations in April 2006, commit signatories not only to financial conditions but also to incorporating challenges for ESG tasks. Based on the "Statement on ESG in credit risk and ratings" issued by the United Nations in May 2016, credit rating agencies and fixed income investors should commit to incorporating ESG into credit ratings and analysis in a systematic and transparent manner (PRI Association, 2016; Kanno, 2023).

The likelihood and magnitude of the physical impacts of climate change affect firms and their supply chains, depending on their geographical position (Huang et al., 2018). Thus, physical risk can vary substantially even among firms in a given industry or market. However, climate risk also involves transition risks, which are related to the transition of the economic system to lower GHG emissions. Transition risks are mostly imputable to regional legislation and industry affiliations, including corporate environmental performance (Lee et al., 2015), market contraction (Gerged et al., 2021), and corporate performance (Bătae et al., 2021). This transition can affect a firm's business outlook via various channels (NGFS, 2021). Hence, climate change affects a firm's risk profile through physical and transitional climate risks.

A critical management issue related to the enhancement of firm value is the extent to which each environmental factor contributes to borrowers' credit risk reduction. A recent study indicates that higher emission scores enhance firms' default risk (Kanno, 2023). This positive relationship between carbon risk and credit risk is also substantiated by other recent research (e.g., Capasso et al., 2020). Given the importance of a firm's regulatory environment for transitional climate risk (NGFS, 2021), it is important to examine the relationship between carbon and credit risks.

There are three open issues to examine regarding the relationship between ESG investment and firm credit risk: (a) investment effects, (b) the possibility of cost collapse, and (c) the risk of inferior returns on investment relative to the market average (Kanno, 2023). In terms of (a), for example, even if the usage of funds raised through green bonds were clarified, there would be a concern that the funds might be appropriated for highway construction instead of green investment (i.e., greenwashing) (Flammer, 2021; Xinwen et al., 2023). In terms of (b), the biggest bottleneck in ESG investment is the costs incurred (Jeongseok et al. (2023)). In addition, even if the performance of an investee firm improves by investing costs and the return-on-investment increases, the debt investor can only earn income corresponding to the credit risk exposure; the return on the remaining exposure is received by other debt investors at no cost (i.e., the free-rider problem) (for reference, see Liang et al. 2023). In terms of (c), although many empirical studies find that ESG investment is superior to other investments, there is no consensus as some studies show no significant differences. Better-performing firms devote resources to ESG activities, and as a result, ESG activities and asset prices seem to be linked, indicating that these firms incorrectly estimate the superiority of ESG investments (Hartzmark and Sussman, 2019).

Thus, in this study, we analyze the impact of carbon emission factors on firms' default risk, mainly relating to the open issue (b) of the possibility of cost collapse. To this end, we refer to the methodology proposed by rating agencies such as Moody's Investor Service (Marty and Hunter, 2021). This methodology is based on the concept that ESG factors including emissions directly affect a firm's default risk.

We explore the relationship between firms' credit risk and carbon risk performance in 44 major countries and four constituent countries: the US, the UK, Japan, and China, which countries have top four rankings in terms of the annual cumulative number of firms during fiscal year (FY) 2017–FY2022. For each country, we examine the heterogeneity in the global market by comparing the results of the top four countries with those in the global market.

In response to the lack of understanding of the relationship between default risk and carbon emission factors (i.e., Scope 1, 2, and 3)[2], we aim to answer the following research question.

[2]Scope 1 relates to direct emissions from the firm owned or controlled sources, mainly produced by manufacturing processes, transportation, and fugitive emissions. Scope 2 covers indirect emissions from the generation of electricity, steam, heating, and cooling. Scope 3 includes all other indirect emissions that result from the supply chain. Large listed firms generally report Scope 1 and 2 emissions in their carbon emission footprint disclosure. Scope 3 emissions are more complex to quantify and are disclosed by some firms, posing significant challenges when comparing GHG intensities among firms.

RQ. Do carbon emission factors affect a firm's default risk directly?

To answer this research question, this study adopts a methodology detailed in Subsection 3.2. This methodology estimates both carbon emission factors and financial ratios simultaneously using a logistic regression model (Kleinbaum and Klein, 2010; Kanno, 2023).

Our findings at the global level demonstrate that carbon emissions differ depending on the risk horizon and emission type, as in Scope 1, 2, and 3. By contrast, at the country level, carbon emissions boost firms' default risk in the UK for almost all risk horizons, whereas they depress risk in Japan for all risk horizons. Additionally, the findings can help lenders and investors provide more appropriate criteria for reducing credit risk by investing in more environmentally responsible firms. Furthermore, our results can help regulators and policymakers revise ESG criteria for their loans and investments.

The remainder of this paper is organized as follows: Section 2 reviews the literature on emissions-related analyses. Section 3 presents the empirical analysis results. Section 4 concludes the paper.

2. Literature review

This section presents an overview of the literature on carbon emission-related credit risk management issues. Extant studies have mainly focused on climate risk-related issues regarding firms' credit fundamentals (financial leverage: Nguyen and Phan, 2020; profitability: Caby et al., 2022; financial performance: Huang et al., 2018; corporate investments: Phan et al., 2022; cost of debt financing: Caragnano et al.,2020; green bond issuance: Flammer, 2021; Wang et al., 2023; disclosure of carbon emissions: Jung et al., 2016; Gerged et al., 2021). However, the extent to which a firm's carbon risk factors affect its credit (default) risk remains underexplored.

In contrast, in terms of the relationship between exposure to climate change and firm credit risk, this positive link between carbon risk and credit risk is substantiated by recent research (e.g., Capasso et al., 2020; Dumrose and Höck, 2023). Some studies (e.g., Capasso et al., 2020; Kabir et al., 2021) use the distance-to-default as a market-based measure of corporate default risk.

However, because Merton's (1974) credit risk model, introduced by Capasso et al. (2020), is a classic model for judging a default only at maturity, their study was originally exposed to model bias. Although Dumrose and Höck (2023) analyze the effect of carbon risk on corporate bond credit spreads, they do not consider liquidity risk, which is more important than carbon risk. In addition, although Dumrose and Höck (2023) assume that the USD and EUR swap curve is a proxy of the risk-free yield curves, the validity of such an assumption is not supported.

Kabir et al. (2021) use a panel dataset over the long period 2004–2018 from 42 economies. Despite the existence of systemic risk in the data during the 2007-09 global financial crisis, their analyses do not consider heterogeneity inherent in the panel dataset. As a result, although they report a negative impact of emissions on firms' distance-to-default, their claim does not ensure validity in terms of the possibility that the direction of the impact can differ according to each country's environmental policy and the carbon emission mitigation responses of firms that establish a head office in the country. We offer a counterexample later in this study.

In terms of ESG and credit risk, the PRI Association (2017) abstracts studies in the early days on ESG and firm credit risk (environment: Bauer and Hann, 2010; Muriel, 2015).

In addition, regarding the hypotheses in our study, some rating agencies show credit rating philosophies that consider the relationship between ESG factors and credit ratings. Marty and Hunter (2021) explain how ESG factors are considered when they are not explicitly described in a sector-specific methodology.

3. Empirical analysis

This section describes the empirical analysis of the impact of ESG factors on firms' default risk using panel regression.

3.1. Data

We use firm-level physical probability of default (PD) data obtained from the Credit Research Initiative of the National University of Singapore[3], in addition to carbon emission and financial ratio data for the panel analysis (Table 1). The odds ratio is calculated using PDs (Figure 1).

[3]See NUS-CRI (2021) for details. The quantitative model currently used by the CRI is a forward-intensity model introduced in Duan et al. (2012).

Carbon emission data are obtained from the ASSET4 ESG database provided by Refinitiv, which has been used extensively in CSR and environmental studies (e.g., Dyck et al., 2019; Hörisch et al., 2015). The ASSET4 ESG database also provides the estimated total carbon emissions for firms that do not report their actual carbon emissions. According to Greenhouse Gas Protocol, supply chain emissions comprise direct emissions (Scope 1), indirect emissions (Scope 2), and other indirect emissions (Scope 3) (Table 1). Scope 3 includes indirect emissions from a variety of sources such as the production and transportation of materials, waste disposal, employee commuting, and use of firm-owned vehicles.

Financial ratios and beta are obtained from the Refinitiv Datastream. Financial ratios comprise three typical categories: size ratios (ln(Total assets), ln(Net assets per share), and ln(EBITDA)), safety ratios (Current Ratio, Quick Ratio, Interest Coverage Ratio, Total Debt to Total Assets Ratio, and Tangible Assets to Total Assets Ratio), and profitability ratios (ROA, Gross Profit Margin, Operating Profit Margin, Capital Turnover Ratio).[4] Beta is the value after adjustment calculated on monthly data for five years, which expresses the extent of the equity cost of capital and controls for the systematic risk of firms.

Table 3 shows the cumulative number of firms by GICS industry group for FY 2017–FY2022. Although the carbon intensity of capital goods, such as building materials and capital goods, is relatively low, the emissions are the largest because financed emissions (Scope 3) are the largest. Because materials such as metals and mining have relatively large carbon intensities, their emissions are ranked second.

The dataset includes a set of endogenous variables comprising financial ratios and a set of exogenous variables, including carbon emission data, as instrumental variables. Table 4 shows the descriptive statistics by variable for the expected sign, observations, mean, standard deviation, and minimum and maximum with regard to the variables, including the annual dataset. Table 5 lists the correlations among the variables. The correlations among carbon emissions are large, from 60% to 67%, in contrast to a range of −30% to 47% regarding cross-correlations between carbon emissions and financial ratios, and a range of −37% to 37% among financial ratios. The sign (±)

[4] In financial analysis conducted for firm creditworthiness evaluation, all three categories of financial ratios are generally considered. For example, see Kanno, 2019, 2023.

indicates that any expected sign can be predicted.

3.2. Methodology

We incorporate a panel regression methodology. This methodology assumes that carbon emission factors directly affect a firm's default risk.

In terms of a quantitative model for credit rating evaluation by credit rating agencies such as Moody's Investors Service, exogenous variables such as carbon emission factors are directly reflected in the firm's issuer rating with financial ratios (Marty and Hunter, 2021).

With reference to this methodology, we adopt an alternative modelling approach in which carbon emission risks, financial ratios, and market beta are simultaneously reflected in the default risk analysis. This approach corresponds to the research question in the Introduction.

Using a panel dataset with yearly observations comprising firms in 44 major countries with carbon emission data (Scope 1, 2, and 3) in FY2017 to FY2022, we estimate a logistic regression model for panel data as follows:

$$\ln \frac{PD_{i,t}}{1 - PD_{i,t}} = \alpha + \boldsymbol{\delta}\ Z_{i,t} + \mu_i + \epsilon_{i,t}, \tag{1}$$

where the odds ratio (logarithm) on the left-hand side expresses the logarithm of the proportion of the physical probability of default $PD_{i,t}$ to the physical probability of survival $(1 - PD_{i,t})$ of firm i at the end date t from FY2017 to FY2022. The risk horizons for the PD employed are one, two, three, and five years. On the right-hand side, $Z_{i,t}$ represents a vector of financial ratios and carbon emission factors. These variables correlate with $\epsilon_{i,t}$. μ_i indicates the time-invariant firm-specific effects, controlling for common shocks that may affect all firms from FY2017 to FY2022. $\epsilon_{i,t}$ is an idiosyncratic error term that satisfies the standard assumptions of a zero mean and constant variance. To account for possible heteroskedasticity, the standard errors are clustered at the firm level. We estimate the coefficients $\boldsymbol{\delta}$. To this end, the fixed-effects (within) regression estimator is used to introduce firm- and time-fixed effects on panel data.

To avoid multicollinearity among the variables comprising financial ratios and carbon-emission factors, we select a set of variables without multicollinearity using a stepwise method.

3.3. Analysis results

Tables 6–8 report the results of the logistic regression for the panel data comprising financial ratios and carbon emission factors. The preliminarily predicted signs of the independent variables are all as expected from Table 4. First, the signs for the direct carbon emission factor (Scope 1) as a control variable depend on the country. However, the signs are positive in the global market, US, and UK over all risk horizons, whereas they are negative in Japan and China over all risk horizons. This means that direct carbon emissions boost firms' PDs in the global market, the US, and the UK, whereas they depress firms' PDs in Japan and China.

Second, the signs for the indirect carbon emission factor (Scope 2) are positive in the UK for all risk horizons and in the global market and China for three and five years, whereas those for the other combinations of countries and risk horizons are negative. Specifically, the signs are positive in the UK for all risk horizons, whereas those in Japan are negative for all horizons. Third, the signs for other indirect carbon emission factors (Scope 3) are negative in the global market, Japan, and China for all risk horizons, in the US for one and two years, and in the UK for one year, whereas they are negative in other combinations of countries and risk horizons.

Higher carbon emission factors do not necessarily mean a higher level of default risk for firms disclosing Scope 1–Scope 3. This indicates that carbon emission reduction does not necessarily contribute to a firm's default risk reduction; the emission reduction cost may exceed the profit produced by the greenhouse gas reduction activities. This result resolves the open issue of (b), the possibility of cost collapse incorporated in the introduction and is also inconsistent with the results of the literature (Henisz and McGlinch, 2019; Li et al., 2022). Thus, the answer to the research question in the introduction is that carbon emission factors affect a firm's default risk, but the direction of the impact differs depending on the country and risk horizon.

In addition, statistically significant variables are selected from financial ratios and beta in consideration of multicollinearity using the stepwise method. Although the selected variables differ depending on the country, they are selected to be well-balanced in three categories: safety, profitability, and size.

The estimates in Tables 6–8 are almost all significant at the 1% level. The differences among the adjusted R-squared values in a specific country are small, regardless of the risk horizons in almost all countries except China, for 5 years. In addition, because the values are highest in Japan and lowest in the global market, it is apparent that firm heterogeneity is highest in the global market.

4. Conclusion

This study contributes to the literature by evaluating the credit risk of firms reporting carbon emissions. To this end, we develop a methodology and estimate statistically significant credit risk factors from the data for firms in 44 major countries with Scope data provided by Refinitiv.

The estimates show that the adjusted R-squared values are almost flat over the risk horizon. Consequently, carbon emission factors contribute to the prediction of default risk regardless of the risk horizon. The contribution level differs notably depending on the policy used to reduce carbon emissions.

In terms of whether higher carbon emissions result in higher levels of default risk for firms, we add to the body of evidence that emission reduction activities do not necessarily contribute to a firm's default risk reduction. This conclusion is acceptable if we recognize heavy cost burdens such as emission control regulations.

Finally, credit risk analyses from the perspective of scope data can hopefully serve as a point of reference for proper risk management by related entities such as firms and institutional investors, for example, banks and insurers. In addition, we encourage further research to explore the potential role of emission information in understanding credit risk dynamics, as this would help to formulate climate-sensitive investment and hedging strategies over different risk horizons (Kabir et al., 2021). Furthermore, as few firms disclose Scope 3 data that constitute supply chain emissions, it would be effective to apply the methodology in consideration of the supply chain network to develop a new credit risk analysis framework.

Table 1: Data items for panel analysis

Item	Description	Updating cycle	Sources
Odds ratio	Ratio using 1, 2, 3, and 5-year PD	Monthly	NUS-CRI
Carbon emissions	Natural logarithm of Scope 1, Scope 2, and Scope 3 in million tonnes	Yearly	ASSET4 ESG
Financial ratios	Current ratio (%), Quick ratio (%), Interest Coverage Ratio (%), Total debt to total assets ratio, Tangible assets to total assets ratio, ROA, Gross profit margin, Operating profit margin, Capital turnover ratio, ln(EBITDA) (USD), ln(TA) (USD), ln(NAV) (USD)	Yearly	Datastream
Equity risk sensitivity	Beta after adjustment calculated on monthly data for 5 years	Yearly (Fixed with latest)	Datastream

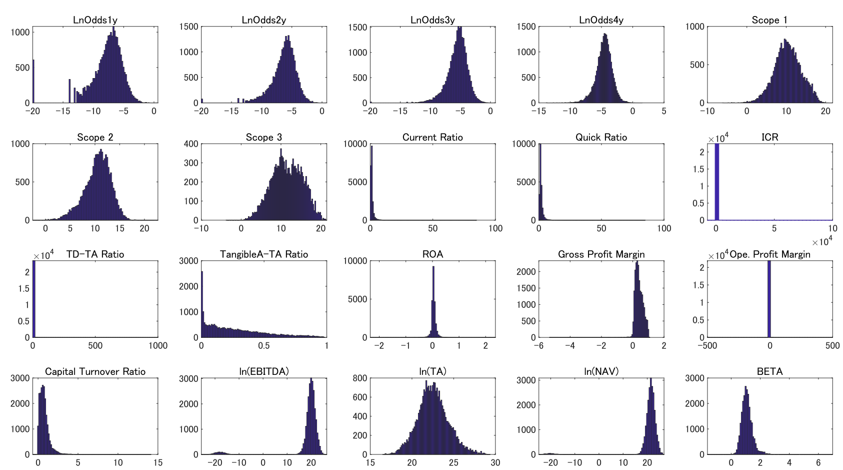

Figure 1: Histograms of loglogits by risk horizon for PDs and Carbon emissions, the end of FY2017–the end of FY2022

Table 2: Cumulative number of firms by country, FY2017–FY2022, 44 countries

Country	N	Share	Country	N	Share
US	4549	0.189	Netherlands	284	0.012
UK	2213	0.092	Turkey	283	0.012
Japan	2133	0.089	Finland	265	0.011
China	1577	0.066	Denmark	244	0.010
Canada	980	0.041	Mexico	221	0.009
Australia	828	0.034	Indonesia	197	0.008
Germany	779	0.032	New Zealand	192	0.008
Sweden	745	0.031	Ireland	190	0.008
France	728	0.030	Belgium	184	0.008
Hong Kong	722	0.030	Austria	167	0.007
India	641	0.027	Poland	159	0.007
Taiwan	639	0.027	Russia	156	0.006
Korea	582	0.024	Phillipines	120	0.005
Switherland	526	0.022	Luxenburg	113	0.005
Italy	519	0.022	Greece	102	0.004
South Africa	518	0.022	UAE	89	0.004
Malasia	455	0.019	Portugal	71	0.003
Thailand	399	0.017	Israel	62	0.003
Brasil	381	0.016	Saudi Arabia	54	0.002
Spain	330	0.014	Hungary	24	0.001
Singapore	309	0.013	Egypt	10	0.000
Norway	298	0.012	Vietnam	9	0.000

Table 3: Cumulative number of firms by GICS industry group, FY2017–FY2022

Industry Group	ID	N	Share
Capital Goods	2010	3,020	0.126
Materials	1510	2,803	0.117
Energy	1010	1,311	0.055
Banks	4010	1,216	0.051
Food, Beverage & Tobacco	3020	1,193	0.050
Utilities	5510	1,156	0.048
Diversified Financials	4020	1,138	0.047
Transportation	2030	997	0.041
Technology Hardware & Equipment	4520	952	0.040
Equity Real Estate Investment Trusts (REITs)	6010	931	0.039
Pharmaceuticals, Biotechnology & Life Sciences	3520	820	0.034
Consumer Durables & Apparel	2520	812	0.034
Retailing	2550	809	0.034
Real Estate Management & Development	6020	809	0.034
Health Care Equipment & Services	3510	674	0.028
Commercial & Professional Services	2020	665	0.028
Automobiles & Components	2510	664	0.028
Software & Services	4510	652	0.027
Consumer Services	2530	628	0.026
Insurance	4030	626	0.026
Media & Entertainment	5020	566	0.024
Telecommunication Services	5010	514	0.021
Semiconductors & Semiconductor Equipment	4530	480	0.020
Food & Staples Retailing	3010	378	0.016
Household & Personal Products	3030	233	0.010

Note: GICS® is a four-tiered, hierarchical industry classification system. The four tiers are: Sectors, Industry Groups, Industries and Sub-Industries.

Table 4: Descriptive statistics

Variable	Sign	Obs.	Mean	Std. dev	Min	Max
lnOdds_{1y}		24047	-7.85	2.93	-20.00	0.65
lnOdds_{2y}		24047	-6.33	2.09	-20.00	0.79
lnOdds_{3y}		24047	-5.51	1.69	-20.00	0.82
lnOdds_{5y}		24047	-4.59	1.29	-13.82	1.56
ln(Scope1)	±	23367	10.39	3.38	-6.21	21.79
ln(Scope2)	±	21338	10.53	2.65	-2.58	22.72
ln(Scope3)	±	12973	11.50	3.84	-3.77	21.51
Current ratio (%)	−	21210	1.44	2.12	0.00	85.04
Quick ratio (%)	−	21210	1.85	2.20	0.00	85.04
Int Cov Ratio (%)	−	22560	375.77	29,488.38	-7,291.70	3,247,782.38
TD to TA ratio	+	23591	1.47	14.83	0.00	1,835.89
TangibleA to TA ratio	+	23816	0.27	0.24	0.00	0.98
ROA	−	23975	0.05	0.10	-2.34	2.37
Gross profit margin	−	20646	0.41	0.25	-5.32	1.09
Operating profit margin	−	21974	0.07	11.48	-1,248.18	873.84
Capital turnover ratio	−	21892	0.75	0.60	-0.67	14.15
ln(EBITDA) (USD)	−	23975	18.63	7.50	-25.69	26.52
ln(TA) (USD)	±	24037	22.54	1.83	16.51	29.38
ln(NAV) (USD)	±	22748	20.90	5.38	-24.91	26.96
Beta (after adj.)	+	23641	1.08	0.37	-1.63	6.98

Note: $\ln(\cdot)$ is expressed as the natural logarithm of a variable. The expected sign is positive if the PD increases with the variable. ± indicates that the variable can be either positive or negative.

Table 5: Correlations among variables

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	lnOdds_{1y}																		
2	lnOdds_{2y}	.96**																	
3	lnOdds_{3y}	.94**	.99**																
4	lnOdds_{5y}	.88**	.95**	.98**															
5	ln(Scope1)	0.01	.05**	.07**	.11**														
6	ln(Scope2)	-.02**	0.01	.03**	.06**	.67**													
7	ln(Scope3)	-.05**	-.02*	0.00	.03**	.62**	.60**												
8	Quick ratio (%)	-.16**	-.17**	-.18**	-.17**	-.17**	-.20**	-.13**											
9	Int Cov Ratio (%)	-0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	.02**										
10	TD to TA ratio	.04**	.05**	.05**	.05**	0.01	0.00	0.00	-.02**	-0.00									
11	TangibleA to TA ratio	.03**	.05**	.07**	.08**	.45**	.27**	.28**	-.09**	-0.00	.01*								
12	ROA	-.27**	-.28**	-.29**	-.28**	.02**	.04**	.05**	.04**	0.01	-.04**	-.02*							
13	Gross profit margin	-.19**	-.20**	-.20**	-.19**	-.30**	-.27**	-.22**	.04**	0.00	0.01	-.08**	.15**						
14	Ope. profit margin	-0.01	-0.01	-0.01	-0.01	0.01	0.01	0.00	-.05**	0.00	-0.00	-.01*	.07**	.02**					
15	Cap. turnover ratio	.05**	.05**	.05**	.05**	.03**	.05**	.07**	-.08**	-0.00	-0.01	-.05**	.21**	-.37**	0.00				
16	ln(TA) (USD)	-0.00	.03**	.04**	.06**	.33**	.47**	.34**	-.18**	-0.01	.02**	-.13**	-.07**	-0.01	.02*	-.22**			
17	ln(NAV) (USD)	-.08**	-.09**	-.10**	-.10**	.10**	.16**	.09**	.02**	-0.00	-.09**	-.04**	.07**	-0.00	0.01	-.11**	.28**		
18	ln(EBITDA) (USD)	-.13**	-.14**	-.13**	-.12**	.19**	.26**	.19**	-.19**	0.00	-.04**	0.01	.37**	.11**	.05**	.07**	.30**	.14**	
19	Beta (after adj.)	.27**	.31**	.32**	.33**	.02**	-.02*	-0.01	0.01	-0.01	.02**	.11**	-.10**	-.09**	-0.01	-0.01	-.06**	-.09**	-.09**

Note: Data period: 2017–2022. S: Score.

Table 6: Global: Logistic regression for panel data comprising carbon smissions and financial ratios, stepwise method

	Dependent variable: (ln) Odds Ratio			
	1yr	2yrs	3yrs	5yrs
ln(Scope1)	0.0222***	0.0222***	0.0339***	0.0364***
	(0.0066)	(0.0066)	(0.0037)	(0.0029)
ln(Scope2)	-0.0148*	-0.0148*	0.005	0.008**
	(0.0089)	(0.0089)	(0.005)	(0.0039)
ln(Scope3)	-0.0568***	-0.0568***	-0.0244***	-0.0144***
	(0.0069)	(0.0069)	(0.0039)	(0.003)
Quick ratio (%)	-0.216***	-0.216***	-0.1289***	-0.0911***
	(0.00829)	(0.00829)	(0.0047)	(0.00362)
TD to TA ratio	0.0038***	0.0038***	0.0031***	-0.0052***
	(0.0011)	(0.0011)	(0.0006)	(0.0011)
ROA	-5.9347***	-5.9347***	-3.6174***	-2.6359***
	(0.1866)	(0.1866)	(0.1059)	(0.0816)
Gross profit margin	-1.6422***	-1.6422***	-0.8488***	-0.5534***
	(0.0766)	(0.0766)	(0.0435)	(0.0335)
ln(EBITDA) (USD)	-0.0065***	-0.0065***	-0.0057***	0.0026***
	(0.0025)	(0.0025)	(0.0014)	(0.0005)
ln(NAV) (USD)	-0.0137***	-0.0137***	-0.0148***	-0.0145***
	(0.0032)	(0.0032)	(0.0018)	(0.0014)
Beta (after adj.)	1.929***	1.929***	1.2941***	1.0134***
	(0.0459)	(0.0459)	(0.0261)	(0.0201)
Const	-6.9369***	-6.9369***	-5.6087***	-4.9565***
	(0.1309)	(0.1309)	(0.0743)	(0.0572)
Observations	24047	24047	24047	24047
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.2355	0.2597	0.2551	0.2423

Note: Robust standard errors clustered at firm level are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 7: US (upper) and UK (lower): Logistic regression for panel data comprising carbon smissions and financial ratios, stepwise method

	Dependent variable: (ln) Odds Ratio			
	1yr	2yrs	3yrs	5yrs
ln(Scope1)	0.0304	0.0392***	0.0429***	0.0486***
	(0.0201)	(0.0134)	(0.0102)	(0.0075)
ln(Scope2)	-0.0385	-0.0071	-0.0108	-0.0038
	(0.0293)	(0.0203)	(0.0149)	(0.0109)
ln(Scope3)	-0.02	-0.0022	0.0015	0.0127
	(0.0222)	(0.0149)	(0.0113)	(0.0083)
Quick ratio (%)	-0.1746***	-0.1223***	-0.0921***	-0.0513***
	(0.02959)	(0.01974)	(0.01503)	(0.01103)
Int Cov Ratio (%)	-0.0001***	-0.0001***	0***	0***
	(0)	(0)	(0)	(0)
TD to TA ratio	0.0132**	0.01***	0.0083***	0.0066***
	(0.0057)	(0.0038)	(0.0029)	(0.0021)
ROA	-7.6208***	-5.3202***	-4.0598***	-2.8054***
	(0.4401)	(0.2938)	(0.2236)	(0.164)
Gross profit margin	-2.3502***	-1.4164***	-1.1832***	-0.9204***
	(0.2299)	(0.1555)	(0.1168)	(0.0857)
ln(EBITDA) (USD)		0**		
		(0)		
ln(NAV) (USD)	-0.0236***	-0.0166***	-0.0156***	-0.0141***
	(0.0055)	(0.0037)	(0.0028)	(0.0021)
Beta (after adj.)	4.1833***	2.9089***	2.2821***	1.6393***
	(0.1332)	(0.0892)	(0.0677)	(0.0497)
Const	-10.6665***	-8.6999***	-7.3676***	-6.2398***
	(0.4147)	(0.2848)	(0.2106)	(0.1546)
Observations	4549	4549	4549	4549
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.3674	0.3671	0.3621	0.3429

	Dependent variable: (ln) Odds Ratio			
	1yr	2yrs	3yrs	5yrs
ln(Scope1)	0.0075	0.0146	0.0153	0.0169*
	(0.0158)	(0.0131)	(0.0113)	(0.0091)
ln(Scope2)	0.0261	0.0314**	0.0289**	0.0272***
	(0.0176)	(0.0146)	(0.0125)	(0.01)
ln(Scope3)	-0.0015	0.001	0.0012	0.0012
	(0.0119)	(0.00984)	(0.0085)	(0.0068)
Quick ratio (%)	-0.0928***	-0.0804***	-0.0672***	-0.0527***
	(0.0099)	(0.0082)	(0.00692)	(0.00554)
TD to TA ratio	0.0085**	0.0069**	0.006**	0.0047**
	(0.0034)	(0.0028)	(0.0024)	(0.0019)
TangibleA to TA ratio	0.9431***	0.7373***	0.6457***	0.4968***
	(0.1531)	(0.1266)	(0.1086)	(0.087)
ROA	-3.2641***	-2.1845***	-1.8299***	-1.3588***
	(0.2313)	(0.1914)	(0.1601)	(0.1282)
Gross profit margin	-1.2015***	-1.0315***	-0.9218***	-0.7385***
	(0.1382)	(0.1143)	(0.0984)	(0.0788)
ln(EBITDA) (USD)	-0.0045	-0.0062	-0.0155***	-0.0129***
	(0.0047)	(0.0039)	(0.0037)	(0.003)
ln(NAV) (USD)	-0.019***	-0.017***	0.0000	0.0000
	(0.0052)	(0.0043)	0.0000	0.0000
Beta (after adj.)	1.1111***	0.9314***	0.8054***	0.6341***
	(0.0685)	(0.0566)	(0.0489)	(0.0392)
Const	-7.2561***	-6.1935***	-5.6528***	-4.9277***
	(0.2054)	(0.1699)	(0.1431)	(0.1146)
Observations	2,213	2,213	2,213	2,213
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.4078	0.3929	0.3868	0.3785

Note: Robust standard errors clustered at firm level are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Japan (upper) and China (lower): Logistic regression for panel data comprising carbon smissions and financial ratios, stepwise method

	Dependent variable: (ln) Odds Ratio			
	1yr	2yrs	3yrs	5yrs
ln(Scope1)	-0.0501**	-0.0388***	-0.0372***	-0.0353***
	(0.0198)	(0.014)	(0.0109)	(0.0082)
ln(Scope2)	-0.1213***	-0.0957***	-0.0807***	-0.0672***
	(0.0321)	(0.0227)	(0.0178)	(0.0134)
ln(Scope3)	-0.0505**	-0.0385**	-0.0333***	-0.028***
	(0.0214)	(0.0151)	(0.0118)	(0.0089)
Quick ratio (%)	-0.4284***	-0.308***	-0.2547***	-0.1913***
	(0.0299)	(0.0211)	(0.0165)	(0.0124)
Int Cov Ratio (%)	0***			
	(0)			
TD to TA ratio	0.2053***	0.166***	0.1418***	0.1142***
	(0.0222)	(0.0157)	(0.0123)	(0.0092)
ROA	-12.49***	-10.1492***	-7.9624***	-5.9758***
	(1.114)	(0.7883)	(0.616)	(0.4633)
Gross profit margin	-1.6516***	-1.1871***	-1.0126***	-0.7475***
	(0.3197)	(0.226)	(0.1766)	(0.1328)
Ope. profit margin	-4.8255***	-2.7177***	-2.0964***	-1.3313***
	(0.521)	(0.3691)	(0.2884)	(0.2169)
ln(NAV) (USD)	0.5257***	0.4128***	0.3541***	0.2941***
	(0.0439)	(0.0311)	(0.0243)	(0.0183)
Beta (after adj.)	2.5592***	1.9937***	1.6082***	1.2164***
	(0.1649)	(0.1169)	(0.0913)	(0.0687)
Const	-17.5322***	-14.4566***	-12.6104***	-10.6856***
	(0.9125)	(0.6465)	(0.5052)	(0.3799)
Observations	2,133	2,133	2,133	2,133
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.4880	0.4916	0.5092	0.5108

	Dependent variable: (ln) Odds Ratio			
	1yr	2yrs	3yrs	5yrs
ln(Scope1)	-0.0015	-0.0101	-0.0144	-0.0178**
	(0.0139)	(0.0111)	(0.0097)	(0.0084)
ln(Scope2)	-0.0171	-0.0012	0.0083	0.017
	(0.0224)	(0.0179)	(0.0156)	(0.0136)
ln(Scope3)	-0.068**	-0.0469**	-0.032	-0.0127
	(0.0281)	(0.0224)	(0.0195)	(0.0168)
Quick ratio (%)	-0.4508***	-0.3598***	-0.3027***	-0.2347***
	(0.0251)	(0.0201)	(0.0175)	(0.0152)
TD to TA ratio	0.0457***	0.0391***	0.0351***	0.031***
	(0.009)	(0.0072)	(0.0063)	(0.0054)
ROA	-5.2255***	-4.1928***	-3.4556***	-3.0054***
	(0.409)	(0.3266)	(0.2849)	(0.2711)
Gross profit margin	-0.4451**	-0.4055***	-0.3442***	-0.2963***
	(0.1773)	(0.1416)	(0.1235)	(0.1001)
Ope. profit margin				0.2978***
				(0.0907)
Cap. turnover ratio	-0.2155***	-0.1547**	-0.1054*	
	(0.0795)	(0.0635)	(0.0554)	
Beta (after adj.)	0.4295***	0.3635***	0.335***	0.3096***
	(0.0896)	(0.0716)	(0.0624)	(0.0535)
Const	-3.9042***	-3.5189***	-3.3895***	-3.2837***
	(0.3796)	(0.3031)	(0.2644)	(0.2256)
Observations	1,577	1,577	1,577	1,577
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.4092	0.3970	0.3705	0.3151

Note: Robust standard errors clustered at firm level are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

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