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Abstract

This paper empirically examines the relationship between CO_2 emissions and corporate performance in terms of long-term performance, short-term performance, and cost of capital, using available firm-level data in the First Section of the Tokyo Stock Exchange from FY2011 to FY2019. To address potential biases in previous empirical studies, we employ double machine learning, which is one of the semiparametric models introduced by Chernozhukov et al. [2018], for our empirical analysis. We find that corporations with lower CO_2 emissions have (i) better long-term corporate performance and (ii) lower cost of equity. These results suggest that investors estimate that corporations with lower CO_2 emissions have lower business risks, setting their risk premium to be low, which results in higher market value of such corporations. In addition, our analysis indicates that corporations with lower CO_2 emissions have higher short-term performance and lower cost of debt, but also shows that the results of previous studies of these relationships may contain biases and should be evaluated with caution.

Keywords: CO_2 Emissions; Corporate Performance; Double Machine Learning
JEL classification: G30, M14, Q54

* Associate Director and Economist, Institute for Monetary and Economic Studies, Bank of Japan (E-mail: ryou.aruga@boj.or.jp)
** Assistant Professor, School of Commerce, Waseda University, and Economist, Institute for Monetary and Economic Studies, Bank of Japan (currently, UTokyo Economic Consulting and Adjunct Researcher, Research Institute of Business Administration, Waseda University, E-mail: keiichi@utecon.net)
*** Economist, Institute for Monetary and Economic Studies, Bank of Japan (currently, Sumitomo Mitsui Banking Corporation, E-mail: Chiba_Takashi@dn.smbc.co.jp)

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1. Introduction

With growing interest in the United Nations' Sustainable Development Goals (SDGs), the risks associated with climate change due to global warming are attracting greater attention. The Intergovernmental Panel on Climate Change [2014] lists eight key climate change risks: rising sea levels, inland flooding, breakdown of infrastructure networks and critical services, extreme heat, food insecurity, insufficient access to water, loss of marine and coastal ecosystems, and loss of terrestrial and inland water ecosystems. Carney [2015] also mentions the potential risks of climate change affecting the financial system through three pathways: physical risk, liability risk and transition risk. To mitigate the risks of climate change, there have been calls for many years for a reduction in greenhouse gas (GHG) emissions, especially carbon dioxide (CO_2) emissions, which are considered to be the main cause of global warming. As part of the United Nations Framework Convention on Climate Change (established in March 1994), international agreements have been reached, such as the Kyoto Protocol (February 2005) and the Paris Agreement (November 2016).

Against the backdrop of the global trend, Japan has also been taking measures to reduce CO_2 emissions, starting with the Act on Promotion of Global Warming Countermeasures (October 1998), which was introduced in response to the adoption of the Kyoto Protocol. With the government's announcement in October 2020 that it aims to become carbon neutral by 2050, it is expected that social demands for Japanese firms to reduce their CO_2 emissions will become even stronger. However, there is no academic consensus on whether firms' efforts to reduce CO_2 emissions are desirable for the firms themselves, for the financial institutions that provide credit to firms, or for investors in corporations; in other words, there is no consensus on whether firms with lower CO_2 emissions perform better or worse than those with higher emissions.

Theoretically, drawing on previous studies on corporate social responsibility (CSR) activities, which are discussed in the same context as CO_2 emissions reduction, the relationship between CO_2 emissions and a firm's performance can be positive or negative.[1] The argument that the two are positively related is based on the idea that CSR activities, such as investment in environmental measures, are additional costs to corporations, which puts downward pressure on the value of the corporations through lower profit levels (Friedman [1970]). The argument that the two are negatively related

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[1] A positive relationship means that low (high) CO_2 emissions are associated with low (high) corporate performance, while a negative relationship means that low (high) CO_2 emissions are associated with high (low) corporate performance.

is based on the idea that CSR activities increase the value of a firm through improved relationship with stakeholders and lower agency costs (Jensen and Meckling [1976], Porter and Van der Linde [1995], Ambec and Lanoie [2008], Freeman [2010]). Moreover, if reducing CO_2 emissions is considered as a preemptive response to possible future transition risks, future regulatory compliance costs and litigation risks could be curbed, thereby improving corporate performance (Ambec and Lanoie [2008]).

If a reduction in CO_2 emissions leads to an increase in the value and profitability of a firm, firms would have an incentive to voluntarily reduce their CO_2 emissions. Investors would also have an incentive to invest in firms that are reducing their CO_2 emissions, which would in turn lead to an acceleration of green investment. On the other hand, if the reduction of CO_2 emissions does not necessarily lead to an increase in value and profitability, firms would have no need to proactively reduce their CO_2 emissions, and investors would not take action to invest in corporations working to reduce their CO_2 emissions. Therefore, to mitigate the risks of climate change, a framework must be established that will induce firms to reduce their CO_2 emissions. This highlights the importance of the relationship between a firm's CO_2 emissions and its performance when considering the direction of efforts to reduce CO_2 emissions.

This study empirically examines from a variety of points of view the relationship between CO_2 emissions and corporate performance in Japan. Specifically, we analyze the relationship between corporate performance in terms of long-term performance, short-term performance, and the cost of capital, using CO_2 emissions data at the firm-level in the First Section of the Tokyo Stock Exchange from fiscal 2010 to fiscal 2019. In addition, this study applies double machine learning (DML), as proposed by Chernozhukov *et al.* [2018], to address potential biases caused by the linear regression models used in many previous studies. DML is a method for estimating policy treatment effects in a semiparametric model using machine learning and is particularly effective when a large number of candidates are considered as covariates, as is the case with corporate performance, which is the objective variable in this study. The details are explained in Section 3.

The structure of this paper is as follows: Section 2 provides an overview of previous studies on CO_2 emissions and corporate performance; Section 3 describes the models used in this study; Section 4 provides definitions of data and variables; Section 5 describes the results; Section 6 provides a summary of this paper.

2. Previous Studies

In this section, we summarize the results of previous empirical studies on the relationship between CO_2 emissions and corporate performance.[2] Previous studies have analyzed various age groups and regions, setting market-based indicators (such as Tobin's q and market capitalization) and accounting-based indicators (such as ROA and ROE) as measures of corporate performance. Some studies also focus on risk premiums and target the cost of capital (cost of equity and cost of debt).

In the following, we will introduce previous studies, roughly divided into studies for Japan, studies for other countries, and studies focusing on the relationship with capital costs. An overview of the results shows that while most of the studies for Japan report that CO_2 emissions are negatively related to corporate performance, the results of the studies for other countries are not conclusive, and there is no consensus on the relationship between CO_2 emissions and corporate performance. Studies on capital costs have reported that they are generally positively related to CO_2 emissions, i.e., corporations with lower CO_2 emissions have lower capital costs.

(1) Studies for Japan

This subsection reviews major previous studies for Japanese corporations (see Table 1 for a list of the studies). Nishitani and Kokubu [2012], Fujii *et al*. [2013] and Lee *et al*. [2015] report that CO_2 or GHG emissions and corporate performance are negatively related. Nishitani and Kokubu [2012] analyzed the relationship between sales per CO_2 emissions and Tobin's q for 641 Japanese manufacturing corporations listed on the First Section of the Tokyo Stock Exchange. To examine the impact of market norms, the paper conducted an analysis focusing on the difference in corporate performance before and after the acquisition of ISO 14001 (an international standard for environmental management systems), pointing out that corporations may have improved their sales per CO_2 emissions and increased their Tobin's q after acquiring ISO 14001. Fujii *et al* [2013] analyzed the relationship between sales per CO_2 emissions and ROA for the Japanese manufacturing industry and reported that corporations with lower CO_2 emissions have higher ROA. In

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[2] As for the explanatory variables used in the previous studies, there are two types of cases: one focuses on corporate CO_2 and GHG emissions and uses the value of each company's emissions divided by its sales or total assets, and the other focuses on corporate environmental performance and uses the value of each company's sales divided by its CO_2 and GHG emissions. However, for the sake of clarity when introducing the studies in this section, the results will be organized according to the definitions given in footnote 1, regardless of the methods used in each paper.

addition, Lee *et al*. [2015] analyzed the relationship between CO_2 emissions per total assets and Tobin's q or ROA for 362 Japanese manufacturing corporations and reported that both show a negative relationship.

On the other hand, Iwata and Okada [2011] reported different results depending on the indicators used in analysis. Their paper analyzed the relationship between GHG emissions per sales and corporate performance (e.g., ROE and Tobin's q) for the Japanese manufacturing industry, and reported that GHG emissions have a negative relationship with ROE, but a positive relationship with Tobin's q.

Most previous studies have adopted linear regression models, which assume linearity between corporate performance and control variables (explanatory variables other than CO_2 emissions). This study addresses the bias caused by the assumption of linearity between corporate performance and control variables but will continue to assume linearity in the relationship between corporate performance and CO_2 emissions (see section 3 for our model specification). One of the few studies to report the existence of a non-linear relationship between corporate performance and CO_2 emissions is Kimbara [2010], which analyzed listed corporations in the chemical and food sectors in Japan and reported an inverse U-shaped relationship between sales per CO_2 emissions and ROA.

Table 1: Summary of major previous studies for Japan

Result	Paper	Data	Period	Objective variable	
Negative	Nishitani and Kokubu [2012]	Manufacturing 641 corporations	2006 - 2008	Tobin's q	
	Fujii *et al.* [2013]	758 corporations	2006 - 2008	ROA	
	Lee *et al.* [2015]	Manufacturing 362 corporations	2004 - 2008	Tobin's q ROA	
Mixed	Iwata and Okada [2011]	Manufacturing 268 corporations	2004 - 2008	ROE Tobin's q	Negative Positive
Non-linear	Kimbara [2012]	Chemical and food 94 corporations	2006	ROA	

Note: Each paper is classified by main results according to the definition given in footnote 1. "Mixed" refers to papers with different results depending on the objective variable, and the relationship with GHG or CO_2 emissions is shown to the right of the objective variables.

(2) Studies for Other Countries

This subsection reviews major previous studies that focused on countries other than Japan (see Table 2 for a list of the studies). Major studies that reported a negative relationship between CO_2 or GHG emissions and corporate performance include Aggarwal and Dow [2012], Matsumura *et al*. [2014], Ganda and Milondzo [2018] and Tzouvanas *et al*. [2020]. Aggarwal and Dow [2012] reported a negative relationship between GHG emissions and Tobin's q for a sample of 500 U.S. corporations. Matsumura *et al*. [2014] analyzed the relationship between CO_2 emissions and stock market capitalization for corporations that make up the S&P 500 index and reported a negative relationship. They also analyzed the impact of the presence or absence of disclosure of information on CO_2 emissions on stock market capitalization and pointed out that corporations that do not disclose are additionally penalized by the market. Ganda and Milondzo [2018] conducted an analysis of 63 South African corporations included in the list published by the Carbon Disclosure Project (CDP) in 2015 and found that GHG emissions and ROE are negatively related.[3] Tzouvanas *et al*. [2020] analyzed the relationship between GHG emissions and ROA or ROE for European manufacturing corporations and reported that both show a negative relationship.

Results showing no significant relationship or mixed positive and negative relationships have been reported by Busch and Hoffmann [2011], Gallego-Álvarez *et al*. [2014] and Delmas *et al*. [2015]. Busch and Hoffmann [2011] analyzed the relationship between environmental performance defined by GHG emissions and corporate performance (Tobin's q, ROA and ROE) for the top Dow Jones Global Index constituent corporations in terms of market capitalization and reported that, while GHG emissions and Tobin's q showed a negative relationship, no significant relationship was found with ROA or ROE. Gallego-Álvarez et al. [2014] analyzed the relationship between CO_2 emissions per sales and ROA for corporations around the world and reported that there was no significant relationship. Delmas *et al*. [2015] reported different results depending on the measure of corporate performance. They analyzed U.S. corporations and reported results showing that GHG emissions are positively related to ROA, but negatively related to Tobin's q. They interpreted the results as showing that in the short run, there is a positive relationship between GHG emissions and ROA due to the costs of reducing GHG emissions, while in the long run, there will be a negative relationship between GHG

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[3] CDP is an international non-governmental organization that addresses environmental issues such as climate change. It collects and publishes climate change-related information on the world's major corporations.

emissions and Tobin's q due to the market's assessment of the corporation's competitive potential.

However, Busch *et al*. [2020] conducted an analysis that replicated the Delmas *et al.* [2015] data as closely as possible and reported that, while a positive relationship was found between GHG emissions and ROA, no significant relationship was found with Tobin's q. Regarding the difference with the results of Delmas *et al*. [2015], the paper pointed out that the results may depend on the time period of the analysis. The paper also reported a positive relationship between GHG emissions and ROA or Tobin's q by adding European corporations to its analysis. Similar to Busch *et al*. [2020], Wang *et al*. [2014] also reported a positive relationship between GHG emissions and corporate performance. They analyzed the relationship between GHG emissions and Tobin's q for 69 manufacturing corporations listed on the Australian market and reported that there is a positive relationship. The paper pointed out that the result may be influenced by Australia's unique industrial structure, where mining has a large share.

Studies reporting a non-linear relationship between corporate performance and CO_2 or GHG emissions include Misani and Pogutz [2015] and Trumpp and Guenther [2017]. Misani and Pogutz [2015] conducted an analysis of 127 listed corporations in 19 countries, as published by CDP, and reported a non-linear relationship between Tobin's q and an index calculated from CO_2 emissions and sales. Trumpp and Guenther [2017] also conducted an analysis of 696 corporations from around the world and reported a non-linear relationship between ROA and an index calculated from CO_2 emissions and sales.

Table 2: Summary of major previous studies for other countries

Result	Paper	Data	Period	Objective variable	
Negative	Aggarwal and Dow [2012]	500 U.S. corporations	2009	Tobin's q	
	Matsumura *et al.* [2014]	Corporations constituting S&P 500 Index	2006 - 2008	Market capitalization	
	Ganda and Milondzo [2018]	63 South African corporations	2015	ROE	
	Tzouvanas *et al.* [2020]	288 European manufacturing corporations	2005 - 2016	ROA ROE	
Mixed	Busch and Hoffmann [2011]	174 corporations constituting Dow Jones Global Index	2006	Tobin's q ROA ROE	Negative Not significant Not significant
	Gallego-Álvarez *et al.* [2014]	855 corporations from various countries	2006 - 2009	ROA	Not significant
	Delmas *et al.* [2015]	1,095 U.S. corporations	2004 - 2008	ROA Tobin's q	Positive Negative
	Busch *et al.* [2020]	1,095 U.S. corporations	2005 - 2008	ROA Tobin's q	Positive Not significant
		5,663 U.S. and European corporations	2005 - 2014	ROA Tobin's q	Positive Positive
Positive	Wang *et al.* [2014]	69 Australian manufacturing corporations	2010	Tobin's q	
Non-linear	Misani and Pogutz [2015]	127 listed corporations in 19 countries	2007 - 2013	Tobin's q	
	Trumpp and Guenther [2017]	696 corporations from various countries	2008 - 2012	ROA	

Note: See note in Table 1.

(3) Studies on Cost of Capital

This subsection reviews major previous studies that analyzed the relationship between CO_2 emissions and cost of capital from the perspective of the risk premium required for corporations (see Table 3 for a list of the studies).

Chen and Gao [2012] analyzed the relationship between CO_2 emissions and cost of equity or cost of debt for electricity sector corporations listed on the U.S. market and found that both are positively related to CO_2 emissions. Kim *et al*. [2015] analyzed the relationship between GHG emissions and cost of equity for 379 Korean corporations and found a positive relationship. They also analyzed the impact of voluntarily disclosing GHG emissions in sustainability reports and other documents and pointed out that the presence or absence of disclosure does not affect the relationship. Jung *et al*. [2018] reported a positive relationship between CO_2 emissions and cost of debt for Australian corporations. Bui *et al*. [2020] analyzed the relationship between GHG emissions and cost of equity for corporations in 34 countries and reported that the two are positively related. They also analyzed the impact of CDP's carbon disclosure score (CDS) on the cost of equity and found that for corporations with higher CDS, the impact of GHG emissions on the cost of equity is smaller.

Table 3: Summary of major previous studies on cost of capital

Result	Paper	Data	Period	Objective variable
Positive	Chen and Gao [2012]	U.S. electricity sector corporations	2002, 2003, 2006, 2008	Cost of equity Cost of debt
	Kim *et al.* [2015]	379 Korean corporations	2007 - 2011	Cost of equity
	Jung *et al.* [2018]	Australian corporations	2009 - 2013	Cost of debt
	Bui *et al.* [2020]	Corporations in 34 countries	2010 - 2015	Cost of equity

3. Methodology

As mentioned in section 2, although there are many previous studies on the relationship between CO_2 emissions and corporate performance, the results vary, with some pointing to a positive relationship, some to a negative relationship, some claiming no statistically significant relationship, and others claiming that positive and negative relationships are reversed depending on the conditions. In addition to differences in the target regions and time periods of each study, two biases originating from the linear regression models adopted in many previous studies are considered as factors behind the lack of conclusive results on this theme.

The first is the bias that can arise from assuming a linear relationship between an objective variable and control variables even though that relationship may be non-linear. The second is the omitted variable bias. When corporate performance is the objective variable and CO_2 emissions is the explanatory variable, there are countless candidates for confounders that should be controlled, but in linear regression models, it is not possible to simply employ all these variables. Previous studies selectively employed a limited number of control variables, but in this case, it is difficult to address sufficiently the omitted variable bias.[4]

This study will therefore attempt an analysis of covariance using linear regression models, as in many previous studies, together with semiparametric models using the DML proposed by Chernozhukov *et al.* [2018] to deal with the bias caused by the assumption of a linear relationship between the objective and control variables and the omitted variable bias.

The estimation methods of this study are explained below in (1) and (2). Incidentally, it is possible that two-way causality exists between objective and explanatory variables, but in order to focus on causality from explanatory variables to objective variables, we lag explanatory and control variables by one period with respect to the objective variables, as in many previous studies.

(1) Linear Regression Model

As the first method, we estimate a linear regression model represented by equation (1).

$$Y_{i,t} = \theta D_{i,t-1} + f(X_{i,t-1}) + e_{i,t},\ E\left(e_{i,t} \middle| D_{i,t-1}, X_{i,t-1}\right) = 0. \qquad (1)$$

[4] Most previous studies using panel data introduced time fixed effects (year dummies) and industry dummies, but not firm fixed effects, suggesting that there may still be factors to control for.

Where Y is an objective variable, corporate performance, and D represents CO_2 emissions. X is a set of control variables, and a linear function is assumed for $f(\cdot)$. Each corporation and time is represented by *i* and *t*, respectively, and cluster-robust standard errors for *i* and *t* are used to test significance of estimators. Specific control variables will be employed for X based on previous studies (see Table 6 in Section 4(4) for details).

(2) Semiparametric Model Using DML

The basic idea of DML is shared with the semiparametric model proposed by Robinson [1988]. The semiparametric model is represented as equation (2), where a linear function $f(\cdot)$ in equation (1) is replaced by a nonparametric function $g(\cdot)$.

$$Y_{i,t} = \theta D_{i,t-1} + g(X_{i,t-1}) + e_{i,t},\ E\left(e_{i,t}\middle|D_{i,t-1}, X_{i,t-1}\right) = 0. \tag{2}$$

Now, by taking conditional expectations of $X_{i,t-1}$ on both sides of equation (2), equation (3) can be obtained from the law of iterated expectations.

$$\begin{aligned} E\left(Y_{i,t}\middle|X_{i,t-1}\right) &= E\left(\theta D_{i,t-1}\middle|X_{i,t-1}\right) + E\left(g\left(X_{i,t-1}\right)\middle|X_{i,t-1}\right) + E\left(e_{i,t}\middle|X_{i,t-1}\right) \\ &= E\left(D_{i,t-1}\middle|X_{i,t-1}\right)\theta + g\left(X_{i,t-1}\right). \end{aligned} \tag{3}$$

Furthermore, by taking the differences between equations (2) and (3), equation (4) is obtained.

$$Y_{i,t} - E\left(Y_{i,t}\middle|X_{i,t-1}\right) = \left[D_{i,t-1} - E\left(D_{i,t-1}\middle|X_{i,t-1}\right)\right]\theta\ \ + e_{i,t}. \tag{4}$$

From equation (4), if we know $Y_{i,t} - E\left(Y_{i,t}\middle|X_{i,t-1}\right)$ and $D_{i,t-1} - E\left(D_{i,t-1}\middle|X_{i,t-1}\right)$, we can finally obtain the estimator $\hat{\theta}$ of θ by OLS estimation of both. Here, both are considered to be residuals $\hat{U}_{i,t}$ and $\hat{V}_{i,t}$ of nonparametric estimations of $Y_{i,t}$ and $D_{i,t-1}$ with $X_{i,t-1}$, respectively. Letting $\hat{l}(\cdot)$ and $\hat{m}(\cdot)$ be functions for the estimations, the following relationship holds.

$$Y_{i,t} = \hat{l}\,(X_{i,t-1}) + \hat{U}_{i,t}. \tag{5}$$

$$D_{i,t-1} = \hat{m}\,(X_{i,t-1}) + \hat{V}_{i,t}. \tag{6}$$

In DML, machine learning methods are used to estimate $\hat{l}(\cdot)$ and $\hat{m}(\cdot)$. Since the estimations of $\hat{l}(\cdot)$ and $\hat{m}(\cdot)$ can be regarded as tasks of predicting $Y_{i,t}$ and $D_{i,t-1}$ using $X_{i,t-1}$, it is useful to use machine learning methods, which are able to deal with the prediction problems associated with high-dimensional data. In addition, if the appropriate machine learning models are selected, they can deal sufficiently with the nonlinearity between objective and control variables. This study employs four machine learning methods: Lasso, Ridge, SVR (support vector regression), and RF (random forest). The hyper-parameters of each machine learning method will be optimized by grid search and cross-validation.

By adopting DML, it is possible to address the bias caused by the linear function and the omitted variable bias.[5] In section 5, we report the results of a method that uses the same control variables as linear regression models and addresses only the bias caused by the linear function (hereinafter referred to as DML+partial), and the results of a method that addresses as far as possible the bias caused by the linear function and the omitted variable bias by incorporating a wider range of financial and qualitative information into the control variables (hereinafter referred to as DML+all).

4. Data and Variables

This section explains the data and variables used in this study. (1) describes the data source, the analyzed corporations, and the time period, and (2) through (4) describe the objective, explanatory, and control variables. (5) shows the data processing and the basic statistics of the data.

(1) Data

The purpose of this study is to empirically clarify the relationship between CO_2 emissions and performance of Japanese corporations. Therefore, of the corporations listed on the First Section of the Tokyo Stock Exchange as of December 2020, 591 corporations for which CO_2 emissions data are available will be included in this study, and the annual CO_2 emissions provided by Bloomberg will be used. The CO_2 emissions are the sum of direct and indirect CO_2 emissions and are obtained from each corporation's annual and CSR reports.[6] We also use data provided by Bloomberg for corporate financial information.

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[5] Although the use of DML could also lead to bias due to overfitting, this is addressed by estimating the machine learning models ($\hat{l}(\cdot)$ and $\hat{m}(\cdot)$) and $\hat{\theta}$ in splitting samples (cross-fitting). For the specific estimation methodology, please refer to Appendix 1. We confirmed that the same results can be obtained by changing the initial seed values of the pseudo-random numbers used in splitting samples.

[6] Indirect emissions used in this study refer to CO_2 emissions from generation of electricity required for a company's production activities, and do not include CO_2 emissions of their supply chain.

The analysis period is from fiscal 2011 to fiscal 2019, the period for which CO_2 emissions data of the corporations included in the analysis are available.

(2) Objective Variables

In line with previous studies, this study analyzes price-to-book ratio, Tobin's q, ROE, ROA, cost of equity and cost of debt as objective variables. Price-to-book ratio and Tobin's q can be interpreted as indicators of a corporation's long-term performance because they reflect the market value of the corporation, while ROE and ROA are accounting-based indicators and can be interpreted as reflecting a corporation's short-term performance (Delmas *et al.* [2015]). In addition, cost of equity and cost of debt represent the risk premium demanded of a corporation by investors and financial institutions. By using these various indicators as objective variables, this study analyzes the relationship between CO_2 emissions and corporate performance from multiple perspectives.

The price-to-book ratio, Tobin's q, ROE, ROA, and cost of debt are calculated from corporate financial data, and the cost of equity is estimated by the conditional Fama-French three factor model (Fama and French [1997]) and CAPM (Sharpe [1964], Lintner [1965]). For the specific estimation methodology of the cost of equity, please refer to Appendix 2. The descriptions of each objective variable in this study are shown in Table 4.

Table 4: Objective Variables

Variable	Description
P/B	The natural logarithm of the price-to-book ratio. Specifically, ln (stock price / book value per share).
q	The natural logarithm of Tobin's q. Specifically, ln {(market value of equity + total liabilities + preferred equity + minority interest) / total assets}.
ROE	net income / average total common equity.
ROA	net income / average total assets.
r_{FF97}	The cost of equity estimated by the conditional Fama-French three factor model.
r_{CAPM}	The cost of equity estimated by the CAPM.
r_D	Cost of debt. Specifically, interest expense / average interest-bearing debt.

Note: Tobin's q is calculated excluding non-interest-bearing debt. The cost of debt is calculated by excluding the financial industry and samples with calculation results showing abnormal values (over 20%).

(3) Explanatory variables

For the explanatory variables, two variables related to CO_2 emissions will be used, in line with previous studies, as well as objective variables. The first is CO_2 emissions per sale, which is calculated by dividing total CO_2 emissions by sales. This value can be interpreted as the amount of CO_2 emissions generated by per unit of production activity in a corporation. In fact, many previous studies have used the ratio of CO_2 emissions to revenues, including sales, as their explanatory variables. The second is the level of CO_2 emissions. In addition to the fact that the level of CO_2 emissions itself is the focus of attention in discussions of environmental regulations, as Bolton and Kacperczyk [2021] pointed out, different results may be drawn from CO_2 emissions per sales and the level of CO_2 emissions. Therefore, this study will also conduct an analysis using the natural logarithm of CO_2 emissions as an explanatory variable. A description of each explanatory variable is shown in Table 5.

Table 5: Explanatory Variables

Variable	Description
CO_2/Sales	CO_2 emissions by sales. Specifically, total CO_2 emissions / sales
CO_2	The level of CO_2 emissions (natural logarithmic value). Specifically, ln (total CO_2 emissions)

Note: The unit for CO_2 emissions is 1,000 metric tons, and the unit for sales is 1 million yen.

(4) Control Variables

As described in section 3, in addition to the analysis using traditional linear regression models, we also conduct two analyses using DML (DML+partial and DML+all). In the linear regression model and DML+partial analysis, the control variables shown in Table 6 are employed with reference to Morck *et al.* [1988], Russo and Fouts [1997], Konar and Cohen [2001], King and Lenox [2002], Bebchuk and Cohen [2005] Francis *et al.* [2005], El Ghoul *et al.* [2011] and Valta [2012]. On the other hand, DML+all employs a wider range of financial and qualitative information as control variables, in addition to the variables listed in Table 6 (see Appendix 3 for a list of the variables). In addition, we include short-term performance (ROE, ROA) and cost of capital (cost of equity and cost of debt) as control variables in our analysis of long-term performance (Tobin's q, price-to-book ratio), long-term performance and cost of capital in our analysis of short-term performance, and long-term and short-term performance in our analysis of cost of capital.

Table 6: Control Variables (Linear Regression Model and DML+partial)

Variable	Description	Adoption by objective variable			
		P/B, q	ROE, ROA	r_{FF97}, r_{CAPM}	r_D
Total Assets	ln (total assets).	✓	✓	✓	✓
Leverage	interest-bearing debt / total common equity.	✓	✓	✓	✓
R&D Expenses	research and development expenses / total assets.	✓	✓		
Advertising Expenses	advertising expenses / total assets.	✓	✓		
Capital Expenditures	capital expenditures / total assets.	✓	✓		
Sales Growth	Year-on-year change in sales.	✓	✓		
Operating Margin	operating income / sales.	✓			
P/B	ln (stock price / book value per share).			✓	
ROA	net income / average total assets.			✓	
Volatility	The standard deviation of day-to-day logarithmic historical price changes over 360 trading days.			✓	
EBITDA/Assets	EBITDA / total assets				✓
Altman's Z-Score	1.2 * (working capital / tangible assets) + 1.4 * (retained earnings / tangible assets) + 3.3 * (EBIT / tangible assets) + 0.6 * (market value of equity / total liabilities) + (sales / tangible assets).				✓
Fixed Asset Ratio	fixed assets / total assets.				✓
Industry Dummy	Industry dummies based on MSCI's Global Industry Classification Standard.	✓	✓	✓	✓
Fiscal Year Dummy	Dummies for each fiscal year.	✓	✓	✓	✓

Note: For each objective variable, a check mark is added if it is employed as a control variable.

(5) Data Processing and Basic Statistics

To mitigate the effect of outliers, each variable will be winsorized at 0.5% points on each side. For missing value processing, instead of excluding samples with missing values, to prevent a decrease in the number of samples, missing value dummy variables are created and then the average values of the variables are entered for the missing points. In addition, control variables are standardized in the analysis by DML.

The basic statistics for each variable described in (2) through (4) are shown in Table 7. All the statistics are values after winsorizing.

Table 7: Basic Statistics

Variables	N	Mean	SD	Min.	Max.
P/B	4,194	0.0344	0.5489	-1.2537	1.7633
Q	4,190	0.0571	0.4013	-0.8844	1.5296
ROE	4,192	0.0669	0.0824	-0.4735	0.3461
ROA	4,204	0.0318	0.0327	-0.1215	0.1460
r_{FF97}	4,143	0.0151	0.0261	-0.0714	0.1120
r_{CAPM}	4,186	0.0532	0.0214	0.0072	0.1131
r_D	3,872	0.0138	0.0097	0.0012	0.0737
CO_2/Sales	4,256	0.0017	0.0049	0.8×10^{-5}	0.0355
CO_2	4,256	4.7938	2.1788	-0.5659	11.0905
Total Assets	4,256	12.8264	1.6256	9.6629	19.0563
Leverage	4,253	0.7527	1.1865	0.0000	8.7043
R&D Expenses	2,905	0.0221	0.0252	0.0000	0.1306
Advertising Expenses	730	0.0287	0.0415	0.0001	0.3449
Capital Expenditures	4,256	-0.0389	0.0271	-0.1574	-0.0003
Sales Growth	4,248	0.0410	0.0962	-0.2456	0.5227
Operating Margin	4,256	0.0720	0.0733	-0.0791	0.4843
P/B (control)	4,238	0.0442	0.5313	-1.1953	1.8020
ROA (control)	4,248	0.0316	0.0321	-0.1161	0.1489
Volatility	4,205	0.3276	0.0923	0.1400	0.6792
EBITDA/Assets	4,159	0.0882	0.0394	-0.0185	0.2257
Altman's Z-Score	4,111	0.0301	0.0197	0.0045	0.1476
Fixed Asset Ratio	4,256	0.3027	0.1679	0.0049	0.8168

Note: See Tables 4-6 for descriptions of each variable.

5. Results

This section presents the results of the analysis and provides a brief discussion. (1) gives the results of the analysis with price-to-book ratio and Tobin's q as long-term performance of corporations, (2) gives the results of the analysis with ROE and ROA as short-term performance of corporations, and (3) gives the results of the analysis with cost of capital (cost of equity and cost of debt).

(1) Long-term Performance

This subsection presents the results of the analysis of the relationship between CO_2 emissions and long-term corporate performance (price-to-book ratio and Tobin's q). Table 8 shows the results by linear regression models, Table 9 shows the results by DML+partial, and Table 10 shows the results by DML+all.

As shown in Table 8, all estimates for coefficients on CO_2 emissions by linear regression models are significantly negative, except for the combination of Tobin's q and the level of CO_2 emissions (column (4)). Table 9 also shows that in the analysis by DML+partial, regardless of combinations of objective and explanatory variables or machine learning methods, significantly negative estimates for coefficients on CO_2 emissions are obtained, and most of them are statistically significant at the 1% level.[7] Table 10 also shows that the results by DML+all are generally significantly negative, although some of the estimates using SVR as the machine learning method are not significant. In terms of the level of the estimates for coefficients on CO_2 emissions, a comparison between the analysis methods using the same combination of objective and explanatory variables shows that the levels are generally the same for all analyses.

In light of the above results, the conclusion that there is a negative relationship between CO_2 emissions and long-term corporate performance is quite robust. In other words, in addition to the conventional analysis by linear regression models, the use of DML also supports the result that corporations with lower (higher) CO_2 emissions have higher (lower) long-term performance, which is consistent with many previous studies for Japanese corporations. In addition, there was little difference in the statistical significance and level of the estimates for coefficients on CO_2 emissions between the analysis by linear regression models and by DML. This suggests that the bias associated with the use of linear regression models is not necessarily significant when analyzing the

[7] Although the results of significance tests in Table 9 are based on the method stated in Appendix 1, there is little difference in the significance level even if nonparametric bootstrap methods are used. The same applies to Tables 10, 12, 13, 15 and 16.

relationship with the long-term performance of corporations.

Table 8: Results of Analysis Using Linear Regression Model (Long-term Performance)

	(1) P/B	(2) P/B	(3) q	(4) q
CO_2/Sales	-8.3099**		-3.5667**	
	(3.9430)		(1.8032)	
CO_2		-0.0238*		-0.0088
		(0.0144)		(0.0099)
Total Assets	0.0267	0.0495*	0.0206*	0.0288
	(0.0165)	(0.0262)	(0.0119)	(0.0186)
Leverage	0.0699***	0.0680***	0.0354***	0.0346***
	(0.0217)	(0.0218)	(0.0103)	(0.0103)
R&D Expenses	3.6139***	3.7511***	3.0286***	3.0869***
	(0.7946)	(0.7889)	(0.6602)	(0.6560)
Advertising Expenses	4.1113***	3.9778***	3.6358***	3.5847***
	(1.0898)	(1.0464)	(0.9920)	(0.9705)
Capital Expenditures	-0.0129	-0.3173	-0.1058	-0.2118
	(0.5334)	(0.5650)	(0.3551)	(0.3653)
Sales Growth	0.4310***	0.4267***	0.3523***	0.3507***
	(0.0612)	(0.0622)	(0.0525)	(0.0513)
Operating Margin	2.1085***	2.0569***	1.7209***	1.7034***
	(0.4230)	(0.4115)	(0.3075)	(0.3013)
N	4,194	4,194	4,190	4,190
Adjusted R^2	0.3887	0.3879	0.3906	0.3901

Note: ***, **, and * indicate that the estimates are statistically significant with two-sided probability 1%, 5%, and 10%, respectively. Values in parentheses are standard errors. In addition to the above variables, fiscal year dummies, industry dummies, and missing value dummies are used as control variables. For standard errors, cluster-robust standard errors for corporation and year are used.

Table 9: Results of Analysis Using DML+partial (Long-term Performance)

ML Methods		(1) P/B	(2) P/B	(3) q	(4) q
Lasso	CO_2/Sales	-8.4800***		-3.9182***	
		(1.7370)		(0.9709)	
	CO_2		-0.0243***		-0.0093*
			(0.0069)		(0.0049)
Ridge	CO_2/Sales	-8.3445***		-3.7752***	
		(1.7274)		(0.9565)	
	CO_2		-0.0253***		-0.0105**
			(0.0067)		(0.0048)
SVR + Linear	CO_2/Sales	-8.2686***		-4.0931***	
		(1.7219)		(0.9134)	
	CO_2		-0.0251***		-0.0101**
			(0.0068)		(0.0049)
SVR + Gaussian	CO_2/Sales	-9.1780***		-4.5190***	
		(1.9744)		(1.0444)	
	CO_2		-0.0381***		-0.0151***
			(0.0069)		(0.0049)
RF	CO_2/Sales	-12.5695***		-6.9734***	
		(2.8398)		(1.5440)	
	CO_2		-0.0339***		-0.0222***
			(0.0073)		(0.0052)
N		4,194	4,194	4,190	4,190

Note: ***, **, and * indicate that the estimates are statistically significant with two-sided probability 1%, 5%, and 10%, respectively. Values in parentheses are standard errors. SVR+Linear and SVR+Gaussian denote SVR models with linear and Gaussian kernel functions, respectively. In the estimation, the same control variables as in the analysis by linear regression models are used.

Table 10: Results of Analysis Using DML+all (Long-term Performance)

ML Methods		(1) P/B	(2) P/B	(3) q	(4) q
Lasso	CO_2/Sales	-6.7890***		-3.0882***	
		(1.9495)		(1.0387)	
	CO_2		-0.0328***		-0.0086**
			(0.0062)		(0.0039)
Ridge	CO_2/Sales	-6.5206***		-3.2023***	
		(1.8881)		(1.0263)	
	CO_2		-0.0331***		-0.0105***
			(0.0060)		(0.0037)
SVR + Linear	CO_2/Sales	-3.5416*		-2.2861**	
		(1.9551)		(1.0128)	
	CO_2		-0.0292***		-0.0049
			(0.0063)		(0.0039)
SVR + Gaussian	CO_2/Sales	-3.4802		-2.6844**	
		(2.2683)		(1.1352)	
	CO_2		-0.0026		-0.0032
			(0.0080)		(0.0057)
RF	CO_2/Sales	-7.2650***		-2.6093**	
		(2.7158)		(1.2412)	
	CO_2		-0.0254***		-0.0105**
			(0.0069)		(0.0045)
N		4,194	4,194	4,190	4,190

Note: ***, **, and * indicate that the estimates are statistically significant with two-sided probability 1%, 5%, and 10%, respectively. Values in parentheses are standard errors. SVR+Linear and SVR+Gaussian denote SVR models with linear and Gaussian kernel functions, respectively. In the estimation, in addition to the same variables used in the analysis by linear regression models, all variables presented in Appendix 3 are employed as control variables.

(2) Short-term Performance

This subsection presents the results of the analysis of the relationship between CO_2 emissions and short-term corporate performance (ROE and ROA). Table 11 shows the results by linear regression models, Table 12 shows the results by DML+partial, and Table 13 shows the results by DML+all.

As Table 11 shows, the estimates for coefficients on CO_2 emissions by linear regression models are significantly negative regardless of the combination of objective and explanatory variables. Table 12 also shows that, in the analysis by DML+partial, regardless of the combination of objective and explanatory variables or machine learning methods, the estimates for coefficients on CO_2 emissions are significantly negative, and most of them are significant at the 1% level. However, Table 13 shows that in the analysis by DML+all, although the estimates for coefficients on CO_2 emissions are generally significantly negative, when CO_2 emissions per sales are used as the explanatory variable, the estimates are not significant in many cases, compared to the results by linear regression model and DML+partial. In terms of the level of the estimates for coefficients on CO_2 emissions, a comparison between the analysis methods using the same combination of objective and explanatory variables shows that the estimates by DML+partial are approximately the same as those by linear regression models, while the estimates by DML+all are smaller in absolute value than those by the linear regression model and DML+partial.

These results also imply the relationship that corporations with lower (higher) CO_2 emissions have higher (lower) short-term performance. However, the statistical significance and level of the estimates for coefficients on CO_2 emissions differ to some extent between DML+all and other analyses. This suggests that the effect of the omitted variable bias associated with the use of linear regression models should not be ignored when analyzing the relationship with short-term performance.[8]

[8] Comparing the control variables employed in Lasso between DML+partial and DML+all in the analysis where the explanatory variable was CO_2 emissions per sales, it was confirmed that DML+all employed additional variables such as cost of debt, sustainable growth rate, and 5-year working capital growth rate.

Table 11: Results of Analysis Using Linear Regression Model (Short-term Performance)

	(1)	(2)	(3)	(4)
	ROE	ROE	ROA	ROA
CO_2/Sales	-1.8661**		-0.5983**	
	(0.8281)		(0.2522)	
CO_2		-0.0059***		-0.0032***
		(0.0021)		(0.0009)
Total Assets	0.0026	0.0084***	-0.0010	0.0023
	(0.0022)	(0.0027)	(0.0010)	(0.0015)
Leverage	-0.0016	-0.0019	-0.0062***	-0.0062***
	(0.0027)	(0.0026)	(0.0010)	(0.0009)
R&D Expenses	0.1560	0.1843*	0.1539***	0.1625***
	(0.1165)	(0.1116)	(0.0593)	(0.0584)
Advertising Expenses	0.0429	0.0100	0.0286	0.0125
	(0.1371)	(0.1368)	(0.0670)	(0.0669)
Capital Expenditures	0.1831**	0.1084	0.0338	-0.0115
	(0.0772)	(0.0822)	(0.0388)	(0.0377)
Sales Growth	0.1078***	0.1053***	0.0600***	0.0583***
	(0.0210)	(0.0204)	(0.0091)	(0.0084)
N	4,192	4,192	4,204	4,204
Adjusted R^2	0.0801	0.0795	0.1996	0.2063

Note: See note in Table 8.

Table 12: Results of Analysis Using DML+partial (Short-term Performance)

ML Methods		(1) ROE	(2) ROE	(3) ROA	(4) ROA
Lasso	CO_2/Sales	-1.6366***		-0.5298***	
		(0.4537)		(0.1461)	
	CO_2		-0.0056***		-0.0031***
			(0.0013)		(0.0005)
Ridge	CO_2/Sales	-1.6457***		-0.5215***	
		(0.4602)		(0.1466)	
	CO_2		-0.0057***		-0.0031***
			(0.0013)		(0.0005)
SVR + Linear	CO_2/Sales	-1.8864***		-0.6060***	
		(0.4552)		(0.1470)	
	CO_2		-0.0058***		-0.0032***
			(0.0014)		(0.0005)
SVR + Gaussian	CO_2/Sales	-1.9658***		-0.6575***	
		(0.4957)		(0.1564)	
	CO_2		-0.0064***		-0.0033***
			(0.0014)		(0.0005)
RF	CO_2/Sales	-1.8272***		-0.5315**	
		(0.6998)		(0.2151)	
	CO_2		-0.0047***		-0.0025***
			(0.0016)		(0.0005)
N		4,192	4,192	4,204	4,204

Note: See note in Table 9.

Table 13: Results of Analysis Using DML+all (Short-term Performance)

ML Methods		(1) ROE	(2) ROE	(3) ROA	(4) ROA
Lasso	CO_2/Sales	-0.8575		-0.2026	
		(0.5256)		(0.1495)	
	CO_2		-0.0043***		-0.0016***
			(0.0013)		(0.0004)
Ridge	CO_2/Sales	-0.6066		-0.1496	
		(0.5110)		(0.1443)	
	CO_2		-0.0045***		-0.0016***
			(0.0013)		(0.0004)
SVR + Linear	CO_2/Sales	-1.0469*		-0.0572	
		(0.5867)		(0.1636)	
	CO_2		-0.0040***		-0.0014***
			(0.0013)		(0.0005)
SVR + Gaussian	CO_2/Sales	-1.4150*		-0.4018**	
		(0.7836)		(0.1923)	
	CO_2		-0.0044**		-0.0020***
			(0.0022)		(0.0006)
RF	CO_2/Sales	-1.4375**		-0.3119*	
		(0.7283)		(0.1842)	
	CO_2		-0.0016		-0.0013***
			(0.0015)		(0.0004)
N		4,192	4,192	4,204	4,204

Note: See note in Table 10.

(3) Cost of Capital

This subsection presents the results of the analysis of the relationship between CO_2 emissions and cost of capital (cost of equity and cost of debt). Table 14 shows the results by linear regression models, Table 15 shows the results by DML+partial, and Table 16 shows the results by DML+all. In the following, (a) presents the results of the analysis of the cost of equity and (b) presents the results of the analysis of the cost of debt.

(a) Cost of Equity

As shown in Table 14, the analysis by linear regression models for cost of equity (r_{FF97} and r_{CAPM}) confirms that all estimates for coefficients on CO_2 emissions are significantly positive, except for combinations of cost of equity by CAPM and CO_2 emissions per sales (column (3)). Table 15 also shows that in the DML+partial analysis, the estimates for coefficients on CO_2 emissions are all significantly positive, regardless of the combination of objective and explanatory variables or machine learning methods. Table 16 shows that even in the DML+all analysis, the estimates for coefficients on CO_2 emissions are significantly positive in many cases, although some of the estimates using r_{CAPM} are insignificant. In terms of the level of the estimates for coefficients on CO_2 emissions, a comparison between the analysis methods using the same combination of objective and explanatory variables shows that the levels are generally the same for all analyses.

In light of the above results, the conclusion that there is a positive relationship between CO_2 emissions and cost of equity is fairly robust. This may be due to the fact that investors set smaller (larger) risk premium for corporations with low (high) CO_2 emissions, judging that their future management risks (such as costs of complying with environmental regulations and withdrawal of funds by investors who place importance on green investments) are lower (higher). In addition, there was little difference in the statistical significance and level of the estimates for coefficients on CO_2 emissions between the analysis by linear regression models and by DML. This suggests that, as with long-term corporate performance, the bias associated with the use of linear regression models is not necessarily significant when analyzing the relationship with cost of equity.

(b) Cost of Debt

From Table 14, it can be confirmed that the estimates for coefficients on CO_2 emissions are significantly positive in the analysis by linear regression models on cost of debt (r_D), regardless of which explanatory variable is used. Table 15 shows that even in the

DML+partial analysis, the estimates for coefficients on CO_2 emissions are significantly positive, regardless of combinations of objective and explanatory variables and machine learning methods. On the other hand, Table 16 shows that in the DML+all analysis, although the estimates for coefficients on CO_2 emissions are significantly positive in many cases, some of the estimates using CO_2 emissions per sales as an explanatory variable are insignificant. There was no significant difference in the level of the estimates among the analyses.

These results imply that debt cost also has a positive relationship with CO_2 emissions. However, there was a difference in the statistical significance of the estimates between DML+all and the other analyses. This suggests that, as with short-term corporate performance, the effect of the omitted variable bias associated with the use of linear regression models should not be ignored when analyzing the relationship with cost of debt.[9]

In addition, comparing the results of the analyses on cost of equity and cost of debt when the same explanatory variables are used, the level of the estimates regarding cost of equity is clearly higher than the level of the estimates regarding cost of debt. This suggests that cost of equity has a quantitatively larger relationship with CO_2 emissions than cost of debt.

[9] Comparing the control variables employed in Lasso between DML+partial and DML+all in the analysis where the explanatory variable was CO_2 emissions per sales, it was confirmed that DML+all employed additional variables such as EBIDA growth rate, 5-year debt growth rate, cash ratio, and personnel expenses per employee.

Table 14: Results of Analysis Using Linear Regression Model (Cost of Capital)

	(1)	(2)	(3)	(4)	(5)	(6)
	r_{FF97}	r_{FF97}	r_{CAPM}	r_{CAPM}	r_D	r_D
CO_2/Sales	0.5051**		0.1829		0.1746**	
	(0.2308)		(0.1289)		(0.0805)	
CO_2		0.0010**		0.0011***		0.0007**
		(0.0005)		(0.0004)		(0.0003)
Total Assets	-0.0020***	-0.0029***	0.0037***	0.0025***	0.6×10^{-4}	-0.0006
	(0.0007)	(0.0008)	(0.0004)	(0.0006)	(0.0002)	(0.0004)
Leverage	0.0007	0.0008	0.0008	0.0008	0.0009***	0.0010***
	(0.0007)	(0.0007)	(0.0005)	(0.0005)	(0.0003)	(0.0002)
ROA	-0.0125***	-0.0126***	-0.0051***	-0.0051***		
	(0.0015)	(0.0015)	(0.0014)	(0.0014)		
P/B	-0.0587**	-0.0586**	0.0141	0.0165		
	(0.0282)	(0.0290)	(0.0143)	(0.0144)		
Volatility	0.0232*	0.0237*	0.1162***	0.1148***		
	(0.0137)	(0.0130)	(0.0066)	(0.0067)		
EBITDA/Assets					0.0020	-0.0030
					(0.0106)	(0.0116)
Altman's Z-Score					0.1314***	0.1413***
					(0.0416)	(0.0427)
Fixed Asset Ratio					-0.0066**	-0.0076**
					(0.0028)	(0.0029)
N	4,143	4,143	4,186	4,186	3,872	3,872
Adjusted R^2	0.2139	0.2112	0.5121	0.5144	0.0801	0.0811

Note: See note in Table 8.

Table 15: Results of Analysis Using DML+partial (Cost of Capital)

ML Methods		(1) r_{FF97}	(2) r_{FF97}	(3) r_{CAPM}	(4) r_{CAPM}	(5) r_D	(6) r_D
Lasso	CO_2/Sales	0.5174***		0.1960***		0.1844***	
		(0.1403)		(0.0637)		(0.0526)	
	CO_2		0.0009***		0.0011***		0.0007***
			(0.0003)		(0.0002)		(0.0002)
Ridge	CO_2/Sales	0.5003***		0.1989***		0.1802***	
		(0.1424)		(0.0638)		(0.0525)	
	CO_2		0.0009***		0.0011***		0.0007***
			(0.0003)		(0.0002)		(0.0002)
SVR + Linear	CO_2/Sales	0.4620***		0.1134*		0.1125**	
		(0.1321)		(0.0602)		(0.0551)	
	CO_2		0.0008**		0.0010***		0.0007***
			(0.0003)		(0.0002)		(0.0002)
SVR + Gaussian	CO_2/Sales	0.4909***		0.2661***		0.1544**	
		(0.1345)		(0.0603)		(0.0609)	
	CO_2		0.0006*		0.0012***		0.0008***
			(0.0003)		(0.0002)		(0.0002)
RF	CO_2/Sales	0.4416***		0.2138***		0.3642***	
		(0.1540)		(0.0804)		(0.0583)	
	CO_2		0.0007*		0.0004*		0.0008***
			(0.0004)		(0.0002)		(0.0002)
N		4,142	4,142	4,186	4,186	3,872	3,872

Note: See note in Table 9.

Table 16: Results of Analysis Using DML+all (Cost of Capital)

ML Methods		(1) r_{FF97}	(2) r_{FF97}	(3) r_{CAPM}	(4) r_{CAPM}	(5) r_D	(6) r_D
Lasso	CO_2/Sales	0.5727***		0.1927**		0.1801***	
		(0.1655)		(0.0835)		(0.0541)	
	CO_2		0.0012***		0.0002		0.0007***
			(0.0004)		(0.0003)		(0.0002)
Ridge	CO_2/Sales	0.5751***		0.1907**		0.1888***	
		(0.1605)		(0.0790)		(0.0544)	
	CO_2		0.0009**		0.0003		0.0008***
			(0.0004)		(0.0002)		(0.0002)
SVR + Linear	CO_2/Sales	0.6582***		0.3403***		0.0442	
		(0.1598)		(0.0868)		(0.0564)	
	CO_2		0.0015***		0.0005*		0.0007***
			(0.0005)		(0.0003)		(0.0002)
SVR + Gaussian	CO_2/Sales	0.7005***		0.1909**		0.1325**	
		(0.1812)		(0.0837)		(0.0630)	
	CO_2		0.0017***		0.3×10^{-4}		0.0004**
			(0.0005)		(0.0003)		(0.0002)
RF	CO_2/Sales	0.3470**		0.2941***		0.0738	
		(0.1486)		(0.0901)		(0.0540)	
	CO_2		0.0002		0.0004		0.0002
			(0.0004)		(0.0003)		(0.0002)
N		4,142	4,142	4,186	4,186	3,872	3,872

Note: See note in Table 10.

6. Summary

In this study, we evaluate the relationship between CO_2 emissions and corporate performance by empirical analysis from the perspective of long-term performance, short-term performance, and cost of capital for corporations listed on the First Section of the Tokyo Stock Exchange for which CO_2 emissions data are available from FY2011 to FY2019. As for the methods of empirical analysis, in addition to analysis of covariance by linear regression models used in many previous studies, we also conducted analysis using semiparametric models employing the DML method proposed by Chernozhukov *et al*. [2018] and compared the results among the analyses.

As a result, we confirmed that, regardless of analysis method, corporations with lower CO_2 emissions have (i) better long-term corporate performance and (ii) lower cost of equity. These results can be interpreted as indicating that in the case of corporations with low CO_2 emissions, investors estimate their future business risks to be low and set their risk premium to be low, resulting in a high market value for those corporations. In addition, our analysis indicated that corporations with lower CO_2 emissions have higher short-term performance and lower cost of debt. However, in the analysis by DML with extended control variables, unlike the analysis by linear regression models, there were several cases where the estimates were not significant. This suggests that when analyzing the relationship between CO_2 emissions and corporate short-term performance or cost of debt, the results of analysis by linear regression models may contain omitted variable biases and should be evaluated with caution.

There are three issues to be addressed in the future. First, social attention to CO_2 emissions continues to grow, and there is a possibility that stricter CO_2 emission regulations will be introduced in the future. It would be significant to observe the impact such changes may have on estimation results. Second, although the conclusions of this study are based on empirical results covering only corporations that disclose their CO_2 emissions, it should be noted that different implications may be obtained if the period of analysis and corporations covered was expanded, as shown in Appendix 4. Third, since the sensitivity of corporate performance to CO_2 emissions may differ across sectors, it may be useful to conduct additional analysis that focuses on such differences.

Appendix 1. Double Machine Learning

(1) Divide the data set randomly into two subsets.

(2) Using the first subset, estimate the machine learning models $\hat{l}_1(\cdot)$ and $\hat{m}_1(\cdot)$.

$$\begin{aligned} Y_1 &= \hat{l}_1(X_1) + \hat{U}_{1,1}, \\ D_1 &= \hat{m}_1(X_1) + \hat{V}_{1,1}. \end{aligned} \tag{A-1}$$

(3) For the second subset, apply the machine learning model estimated in (2), and obtain the residuals $\hat{V}_{1,2}$ and $\hat{U}_{1,2}$.

$$\begin{aligned} \hat{U}_{1,2} &= Y_2 - \hat{l}_1(X_2), \\ \hat{V}_{1,2} &= D_2 - \hat{m}_1(X_2). \end{aligned} \tag{A-2}$$

(4) Estimate a linear regression model with the residuals, and obtain the estimator $\hat{\theta}_1$.

$$\hat{U}_{1,2} = a + \hat{\theta}_1 \times \hat{V}_{1,2} + \hat{\varepsilon}_1. \tag{A-3}$$

(5) Repeat (2) to (4) by replacing the subsets, and obtain the estimator $\hat{\theta}_2$.

$$\hat{U}_{2,1} = b + \hat{\theta}_2 \times \hat{V}_{2,1} + \hat{\varepsilon}_2. \tag{A-4}$$

(6) Take the average of $\hat{\theta}_1$ and $\hat{\theta}_2$, and obtain the estimator $\hat{\theta}$.

$$\hat{\theta} = \left(\hat{\theta}_1 + \hat{\theta}_2\right)/2. \tag{A-5}$$

Where the standard error $\hat{se}$ of $\hat{\theta}$ is given by (Chernozhukov *et al.* [2016]).

$$\begin{aligned} \hat{se} &= \hat{\sigma}/\sqrt{N}, \\ \hat{\sigma}^2 &= (\frac{1}{N}\sum_{i=1}^{N} \hat{V}_i^2)^{-2} \frac{1}{N}\sum_{i=1}^{N} \hat{V}_i^2 \hat{\zeta}_i^2, \\ \hat{V}_i &:= D_i - \hat{m}\left(X_i, I_{k(i)}^C\right), \\ \hat{\zeta}_i &:= \left(Y_i - \hat{l}\left(X_i, I_{k(i)}^C\right)\right) - \left(D_i - \hat{m}\left(X_i, I_{k(i)}^C\right)\right)\hat{\theta}, \\ k(i) &:= \{k \in \{1,2\}: i \in I_k\}. \end{aligned} \tag{A-6}$$

The test of significance is performed assuming that the null hypothesis is $\theta = 0$ and the following statistics asymptotically follow the standard normal distribution.

$$\frac{\hat{\theta} - 0}{\hat{se}} \sim N(0,1). \tag{A-7}$$

Appendix 2. Cost of Equity

The cost of equity figures used in this study were estimated using the CAPM proposed by Sharpe [1964] and Lintner [1965], and the conditional Fama-French three-factor model proposed by Fama and French [1997]. The two models are shown in equations (A-8) and (A-9). The cost of equity for each model was calculated by substituting the parameters estimated in each model into equations (A-10) and (A-11).

$$r_{j,t} - r_{f,t} = \alpha_j + \beta_j\left(r_{M,t} - r_{f,t}\right) + \varepsilon_t. \tag{A-8}$$

$$\begin{aligned} r_{j,t} - r_{f,t} = \alpha_j &+ \beta_j\left(r_{M,t} - r_{f,t}\right) \\ &+\gamma_{0,j}SMB_t + \gamma_{1,j}\left(SMB_t \cdot \ln\left(mv_{j,t-1}\right)\right) \\ &+\delta_{0,j}HML_t + \delta_{1,j}\left(HML_t \cdot \ln\left(pbr_{j,t-1}\right)\right) + \varepsilon_t. \end{aligned} \tag{A-9}$$

$$r_{CAPM,t} = r_{f,t} + \beta_j \cdot E[MP]. \tag{A-10}$$

$$\begin{aligned} r_{FF97,t} = r_{f,t} &+ \beta_j \cdot E[MP] \\ &+\gamma_{0,j} \cdot E[SMB] + \gamma_{1,j}\left(E[SMB] \cdot ln\left(mv_{j,t-1}\right)\right) \\ &+\delta_{0,j} \cdot E[HML] + \delta_{1,j}\left(E[HML] \cdot ln\left(pbr_{j,t-1}\right)\right). \end{aligned} \tag{A-11}$$

The definitions of the variables in each equation are as follows

$r_{j,t}$	:	Return of stock *j* at time *t*.
$r_{M,t}$	:	Return of the market portfolio at time *t*.
$r_{f,t}$	:	Risk-fee rate at time *t*.
SMB_t	:	SMB factor return (the difference between returns of small and large stock portfolios) at time *t*.
HML_t	:	HML factor return (the difference between returns of value and growth stock portfolios) at time *t*.
$mv_{j,t}$	:	Market capitalization of corporation *j* at time *t*.
$pbr_{j,t}$	:	Book-to-market ratio of corporation *j* at time *t*.
$r_{CAPM,t}$	:	Cost of equity (by the CAPM) at time *t*.
$r_{FF97,t}$	:	Cost of equity (by the conditional Fama-French three-factor model) at time *t*.
$E[MP]$	:	Expected value of market premium.
$E[SMB]$	:	Expected value of SMB premium.
$E[HML]$	:	Expected value of HML premium.

To estimate the parameters of each model, we used monthly data from 36 to 60 months back from the time when cost of equity capital was estimated. The stock data of each corporation used for estimation was obtained from Bloomberg. As a proxy for the risk-free rate, average yield of long-term government bonds (10-year) for applicants was used, and the data was obtained from the Ministry of Finance Japan website.[10] Returns for the market portfolio, SMB factor, and HML factor were obtained from Kenneth R. French's website and converted to yen using exchange rate data obtained from Federal Reserve Economic Data (FRED).[11,12] In addition, the conditional Fama-French three-factor model in equation (A-9) is based on the idea that the parameters γ_j and δ_j in the Fama-French three-factor model are time-varying, and takes market capitalization and book-to-market ratio into account.[13] Market capitalization and book-to-market ratio are prepared in accordance with Fama and French [1997].

With regard to the risk premium, for the CAPM model, we adopted the estimate by Damodaran [2020] of 5.1% (annual rate). For the Fama-French three-factor model, we used the data available on Kenneth R. French's website for the period July 1990 to June 2020, and estimated the market risk premium, SMB premium, and HML premium at 0.38%, 0.49%, and 2.77%, respectively.

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[10] https://www.mof.go.jp/jgbs/reference/appendix/index.htm (accessed April 16, 2021)

[11] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html (accessed April 16, 2021)

[12] https://fred.stlouisfed.org/ (accessed April 16, 2021)

[13] The Fama-French three-factor model, a commonly used asset pricing model, is represented by equation (A-12) (Fama and French [1993]). On the other hand, in estimating the cost of equity of a company, the company's long-term historical data used. However, it has been pointed out that the model in equation (A-12) cannot reflect changes in the profitability and business model of the company (Kubota and Takehara [2007]). Therefore, in this study, we adopted the conditional Fama-French three-factor model of equation (A-9).

$$r_{j,t} - r_{f,t} = \alpha_j + \beta_j\left(r_{M,t} - r_{f,t}\right) + \gamma_j SMB_t + \delta_j HML_t. \qquad \text{(A-12)}$$

Appendix 3. Additional Control Variables Employed in DML+all

Gross Margin
EBITDA Margin
Pre-Tax Income to Net Sales
Profit Margin
Dividend Payout Ratio
Sustainable Growth Rate
EBITDA Growth (1 year)
Operating Income Growth (1 year)
Dividend per Share Growth (1 year)
Inventory Growth (1 year)
Fixed Assets Growth (1 year)
Total Assets Growth (1 year)
Working Capital Growth (1 year)
Employees Growth (1 year)
Accounts Payable Growth (1 year)
Short Term Debt Growth (1 year)
Short and Long Term Debt Growth (1 year)
Total Equity Growth (1 year)
Total Capital Growth (1 year)
Book Value per Share Growth (1 year)
Operating Cash Flow Growth (1 year)
Capital Expenditure Growth (1 year)
Free Cash Flow Growth (1 year)
Sales Growth (5 years)
EBITDA Growth (5 years)
Operating Income Growth (5 years)
Dividend per Share Growth (5 years)
Inventory Growth (5 years)
Fixed Assets Growth (5 years)
Total Assets Growth (5 years)
Working Capital Growth (5 years)
Employees Growth (5 years)
Accounts Payable Growth (5 years)
Short Term Debt Growth (5 years)
Short and Long Term Debt Growth (5 years)

Total Equity Growth (5 years)
Total Capital Growth (5 years)
Book Value per Share Growth (5 years)
Operating Cash Flow Growth (5 years)
Free Cash Flow Growth (5 years)
Total Debt / EBITDA
Net Debt / EBITDA
Total Debt / EBIT
Net Debt / EBIT
EBITDA / Interest Expense
(EBITDA - Capital Expenditure) / Interest Expense
EBIT / Interest Expense
EBITDA / Cash Paid for Interest on Debt
EBITDA after Capital Expenditure/ Cash Paid for Interest on Debt
EBIT / Cash Paid for Interest on Debt
Common Equity / Total Assets
Long Term Debt / Common Equity
Long Term Debt / Total Capital
Long Term Debt / Total Assets
Total Debt / Total Capital
Total Debt / Total Assets
Net Debt / Total Equity
Net Debt / Total Capital
Cash Ratio
Current Ratio
Quick Ratio
Operating Cash Flow / Average Current Liabilities
Operating Cash Flow / Total Debt
Accounts Receivable Turnover
Inventory Turnover
Accounts Payable Turnover Days
Cash Conversion Cycle
Free Cash Flow Yield
Shareholder Yield
Net Income per Employee
Cash Flow per Employee

Personnel Expenses per Employee
Non-Executive Director Ratio
Independent Director Ratio
Female Board Member Ratio
Female Executive Ratio
Board Age Range
Board Average Age
Independent Directors Board Meeting Attendance Ratio
Foreign Ownership Ratio
Weighted Average Cost of Capital

Note: Weighted Average Cost of Capital is used only when analyzing long-term and short-term performance.

Appendix 4. Comparison of Samples Included/Not-included in Analysis

As mentioned in section 4 (1), this study analyzes 591 of 2,186 corporations listed on the First Section of the Tokyo Stock Exchange as of December 2020, for which data on CO_2 emissions are available. The results of this study may reflect a selection bias because disclosing CO_2 emissions is currently a voluntary initiative in Japan.

Therefore, we compared the distribution of the objective variables for the corporations included in this study and the corporations not included to verify the existence of selection bias. Specifically, referring to Hoshino [2009], we examined the average treatment effect calculated from the difference in the means of the objective variables (Δ_{ATE}), as well as the average treatment effect estimated from the inverse probability weighting method and the doubly robust method (Δ_{IPW} and Δ_{DR}), with the included corporations as the treatment group and the non-included corporations as the control group. The control variables shown in Section 4 (4) were used as covariates for the calculation of the propensity score. To avoid the influence of outliers, samples with a score higher than 0.99 or lower than 0.01 were excluded.[14]

The results are shown in Table A. As for price-to-book ratio, Tobin's q, ROE and ROA, the values of the treatment group tend to be lower than those of the control group. On the other hand, for cost of capital, there is no significant difference, and the level of difference is small. Therefore, it is necessary to evaluate carefully whether the implications of this study can be generalized to include corporations outside the scope of the analysis, especially with regard to the impact of CO_2 emissions on long-term and short-term corporate performance.

Table A: Comparison Results

	(1) PBR	(2) q	(3) ROE	(4) ROA	(5) r_{FF97}	(6) r_{CAPM}	(7) r_D
Δ_{ATE}	-0.1341***	-0.1218***	-0.0232***	-0.0138***	0.0003	0.0042***	0.0003
	(0.0110)	(0.0083)	(0.0016)	(0.0007)	(0.0005)	(0.0004)	(0.0002)
Δ_{IPW}	-0.1457***	-0.1055***	-0.0160***	-0.0079***	0.0007	0.0011**	0.0001
	(0.0167)	(0.0123)	(0.0020)	(0.0012)	(0.0007)	(0.0005)	(0.0003)
Δ_{DR}	-0.1281***	-0.0955***	-0.0136***	-0.0054***	-0.0001	0.0009**	0.0002
	(0.0170)	(0.0122)	(0.0019)	(0.0010)	(0.0006)	(0.0005)	(0.0003)

Note: ***, **, and * indicate that the estimates are statistically significant with two-sided probability 1%, 5%, and 10%, respectively. Values in parentheses are standard errors. The standard errors were calculated by the nonparametric bootstrap method with resampling 1,000 times.

[14] It was confirmed that the results were generally similar even when the outliers were not excluded.

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