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OKIMOTO, Tatsuyoshi
RIETI

TAKAOKA, Sumiko
Seikei University

Research Institute of Economy, Trade & Industry, IAA
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Credit Default Swaps and Corporate Carbon Emissions in Japan*

Tatsuyoshi Okimoto†
Keio University
Research Institute of Economy, Trade and Industry

Sumiko Takaoka‡
Seikei University

Abstract

We examine the relationship between carbon emissions and the market perception of firms' default risk measured by corporate credit default swap (CDS) spreads in Japan. While corporate revenue size is the most significant factor of carbon emissions, pressure from investors has a significant decreasing effect on carbon emissions, which is greater for investment-grade companies. We find that carbon emissions have time-varying effects on corporate CDS spreads, which supports the "investor awareness" hypothesis across sectors and credit quality. The sectoral impacts indicate that carbon emissions are priced prominently in the CDS spreads of firms in sectors where the transition to carbon-free energy sources appears relatively less complicated and less expensive. Finally, we report the impacts of carbon emissions on the CDS spread curve, where they are priced in both short- and long-term CDS spreads, and high carbon emissions steepen the CDS spread curve.

Keywords: CDS spreads, Carbon emissions, Carbon risk, Climate change, Investor awareness
JEL classification: D22, E43, G12, Q54

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† Professor, Faculty of Economics, Keio University and RIETI. 2-15-45 Mita, Minato-ku, Tokyo 108-8345, Japan. E-mail: tatsuyoshi.okimoto@keio.jp

‡ Professor, Faculty of Business Administration, Seikei University. 3-3-1, Kichijoji Kitamachi, Musashino, Tokyo 180-8633, Japan. E-mail: takaoka@bus.seikei.ac.jp

1 Introduction

Environmentally friendly policies were once viewed as incompatible with a firm's objective toward maximizing its profit. For example, Friedman (1970) clearly states that a corporate executive, who is an agent of the corporation owner, serves the interests of his/her principal. This implies that his/her decision to spend toward reducing carbon emissions beyond the amount that is in the best interest of the corporation or that is required by law to contribute to the social objective of improving the environment is inconsistent with the interests of his/her employers. Moreover, if firms expand their economic activities, carbon emissions generally increase. Furthermore, although decarbonization has become an urgent priority for corporate leaders in recent years, switching to carbon-neutral or carbon-free energy sources causes fundamentally serious problems in the existing supply chain and challenges whether such a plan is commercially viable. Therefore, it is not unreasonable to consider that firms with higher carbon emissions tend to have higher growth and profitability with smaller default risk. The first goal of this study is to examine whether this is consistent with the market perception of Japanese firms based on corporate credit default swap (CDS) spreads, which is a widely recognized measure of market perception of firms' default risk.

However, the momentum for decarbonization exposes high-carbon emitters to more pressure from investors to deal with carbon taxes and regulations. Specifically, recent research on a mechanism to promote clean input and technology proposes policy intervention by means of carbon taxes and research subsidies. For example, Acemoglu et al. (2012) discuss government intervention through a system of carbon taxes and research subsidies to redirect firms' innovation toward clean inputs. Acemoglu et al. (2018) show that the policy structure depending on both carbon taxes and research subsidies help transition to clean technology. Aghion et al. (2016) emphasize the importance of carbon taxes to allow clean technologies to overtake dirty technologies using the patent data of the car industry. As more investors expect that the carbon tax levy or regulation cost on large emitters will shrink their profit and value, these investors require a carbon risk premium to invest in firms with high carbon emissions. In addition, as recent consumers have become increasingly sensitive to the firm's challenge of reducing carbon emissions with a preference to buy environmentally friendly products and/or services, the sustainable growth of high carbon emitter firms is more unlikely. This implies that the CDS spread, which is a market perception of the sustainability of firms, of the larger carbon emitters is expected to be higher if the carbon risk is recognized. Therefore, the second goal of this study is to investigate whether carbon risk is priced in Japan's CDS market. To address these questions, it is also important to recognize the global expansion of environmental, social, and governance (ESG) investing over the last decade or thereabouts. Along with the rapid development of ESG investments generating an irreversible momentum of clean energy, it is possible that investors have required a higher carbon risk premium in more recent years. While Drudi et al. (2021) state that the investor awareness of climate risk appears incomplete, studies such as Krueger et al. (2020) and Fahmy (2022) show that institutional investors incorporate climate risk in their investments and perceive it as an important investment risk. Therefore, given the ESG investment growth, we also examine the time-varying impacts of carbon emissions on CDS spreads by relaxing the assumption that investors' reactions are constant over time.

The main contribution of this study is that it examines the existence of a carbon risk premium in CDS markets. Although an increasing number of studies analyze the carbon risk premium, few studies have examined CDS markets. For example, Bolton and Kacperczyk (2021) support the carbon risk premium hypothesis in stock returns, implying that stock returns are positively related to the level of carbon emissions; Ilhan et al. (2021) find that the carbon tail risk is priced in option; Hsu et al. (2019) show a positive (negative) relationship between toxic emissions and stock returns (future profitability); In et al. (2010) indicate that investing in carbon-efficient firms can be profitable; and Delis et al. (2019) document that fossil fuel reserves are priced in the loan market. We contribute to the literature by providing new empirical evidence vis-à-vis the carbon risk premium in CDS markets.

Another contribution of this study is the investigation of the impacts of growing pressure from investors on the carbon risk premium through ESG investments. Several studies suggest that ESG investing has considerable impacts on asset prices. For example, Hong and Kacperczyk (2009) find that "sin" stocks (alcohol, tobacco, and gaming), which are disinvestment targets of ESG investing, receive less coverage from analysts and have higher returns than otherwise comparable stocks. Gibson et al. (2018) measure the portfolio-level environmental and social characteristics of institutional investors and show that the environmental and social portfolio policies can reduce the portfolio risk. A theoretical model in Colonnello et al. (2019) suggests an ethical preference-based model to study the sin-stock anomaly and discloses the non-pecuniary factors in the formation of investment decisions and asset prices. The literature on ESG and bond markets has also been recently expanding, for example, Stellner et al. (2015) on Eurozone corporate bonds, Jang et al. (2020) on ESG scores and bond returns in Korea, Huynh and Xia (2021) on climate change news risk and corporate bond returns in the US, and Okimoto and Takaoka (2021) on Japanese corporate bond spreads. Furthermore, the survey results by Stroebel and Wurgler (2021) show that respondents believe that asset prices underestimate climate risks rather than overestimate them, while Duan et al. (2022) indicate that carbon emission risk is underpriced in the corporate bond market, a phenomenon referred to as investor underreaction. One possible reason for these findings regarding underreaction is that many studies have overlooked the growth of ESG investments over the last decade or so. If the further development of ESG investments has a stronger impact on asset prices, then the accurate quantification of the impacts of ESG investments without considering their rapid growth becomes complicated. This study contributes to the literature by investigating the time-varying impacts of carbon emissions on CDS spreads. This is an interesting contribution, as most previous studies implicitly assume a constant carbon risk impact on asset prices over time.

The main findings of this study can be summarized as follows: we begin our analysis by exploring carbon emission production using data on Japanese firms. These firms have long engaged in efficient energy utilization to mitigate global warming concerns to fulfill the Japanese government's commitment under the Kyoto Protocol to reduce greenhouse gas emissions.[1] Our first finding is that the total revenue, which can be considered as the production size in monetary terms, is a significant determinant of the amount of corporate carbon emissions. This is not surprising because firms with higher revenue tend to expand their economic activities and produce more carbon emissions.

Our second finding is that investor pressure, measured by the number of signatories to the United Nations Principles for Responsible Investment (hereafter, PRI), has a decreasing effect on corporate carbon emissions. This effect is significant in the carbon emissions of investment-grade companies compared to speculative-grade companies, which implies that firms outside the target of such investors naturally underreact to their pressure and try to make more profits to survive.

Next, we examine whether carbon emissions are priced in CDS spreads, using the fractional rank of carbon emissions instead of raw carbon emission data. Our third finding is that carbon emissions have significantly negative impacts on CDS spreads before the investor awareness of

[1] For example, Japan ranks first in the share of the world's high-value inventions (international patent families with size 2 or greater) in environment-related technologies from 2009 to 2011 according to Haščič and Migotto (2015).

ESG investments grows. This is rather reasonable because firms with larger carbon emissions tend to have higher growth and profitability. Therefore, the market perception of their default risk would be smaller. However, our results also indicate a significant increase in carbon risk premium, as the investors' ESG awareness measured by the PRI signatory investors heightens. The results of this analysis reveal that investors do not incorporate the carbon emission risk in the CDS pricing in 2005, hence yielding a negative correlation between CDS spreads and carbon emissions, but ESG attention requires a positive risk premium to pull the relation in the opposite direction. This finding holds for all sectors regardless of the scope of carbon emissions. Among sectors, the carbon risk premium is larger for sectors in which the transition to carbon-neutral or carbon-free energy sources appears less complicated and less expensive, such as healthcare, telecommunications services, technology, and finance. They do not depend on industrial processes that employ extremely high temperatures for production or high-density energy sources; hence, high emitters in such sectors are regarded as not ready toward net-zero emissions. In other words, firms in such sectors can gain recognition and their CDS spreads fall by reducing carbon emissions.

Last but not least, we also show that the carbon risk affects the CDS spread curve: short-term spread, long-term spread, and the slope (difference between the short- and long-term spread). At the beginning of the sample period, the fractional rank of carbon emissions is negatively associated with the CDS spread curve; however, as the signatory to the PRI grows, the increasing carbon risk premium offsets the negative impact of carbon emissions on the short-term spread, long-term spread, and slope. These results represent the investor's perception that the high fractional rank of carbon emissions has once been a signal of business expansion; nonetheless, it is no longer a favorable signal, as achieving net-zero emissions is required. The slope of the CDS spread curve steepens as the fractional rank of carbon emissions heightens, which implies that the investor is suspicious of the high emitters' long-term sustainable growth and, in turn, that the firms bear a higher carbon risk for long-term fundraising. These findings hold for all sectors regardless of the scope of carbon emissions. The sectors whose credit spread curves are affected more remarkably by carbon risk remain the same as the previous results: healthcare, telecommunications services, technology, and finance.

The remainder of this paper is organized as follows: Section 2 introduces the datasets used in the empirical analysis. Section 3 presents the empirical results of the analysis of firms' carbon emission production. Section 4 explains our hypotheses and the empirical strategy for the analysis of CDS spreads and discusses the results. Section 5 explores the effect of carbon emissions on the CDS spread curve. Section 6 presents the concluding remarks.

2 Data and sample construction

The dataset used in this analysis mainly consists of CDS spread data, firm carbon emission data, and corporate financial data. In addition to these firm-level data, we include the data on the signatories to the PRI. Our dataset covers a time range from 2005 to 2019, imposed by the availability of firm-level carbon emission data.

Our dependent variable is the firm's CDS spreads, which are the market prices of the default probabilities for the underlying firms. As CDS contracts are made over-the-counter, their maturity is negotiable, ranging from a few months to 10 years or longer.[2] To construct the firm-level CDS spread index, we obtain year-end CDS spreads from Markit, where the original dataset contains daily spreads. We follow the approach proposed by Gilchrist et al. (2009) and Gilchrist and Zakrajšek (2012) to construct the spread index at the firm level and calculate the arithmetic average of the firm's year-end CDS spreads for its outstanding contracts. Specifically, the individual firm's CDS spread for contracts with different maturities from the same firm is given as

$$CDS_{it} = \frac{1}{N_{it}} \sum_{k} s_{it}[k], \tag{1}$$

where s is the CDS spread for contract k for the underlying firm i in year t and N_{it} is the number of contracts with different maturities.

For the company's carbon emission data, we obtain firm-level carbon emissions from Trucost's Environmental Register database, which is one of the largest carbon emission databases. Trucost's data begin in 2005 and cover listed equity companies, although not all. Data used in this analysis as corporate carbon emissions are Carbon-Scope 1 (tonnes CO2e), Carbon-Scope 2 (tonnes CO2e), Carbon-Scope 3 (tonnes CO2e), and a total of these three emissions per firm each year, where Carbon-Scope 1 (tonnes CO2e) refers to greenhouse gas emissions generated from burning fossil fuels and production processes which are owned or controlled by the company; Carbon-Scope 2 (tonnes CO2e) refers to greenhouse gas emissions from consumption of purchased electricity, heat or steam by the company; Carbon-Scope 3 (tonnes CO2e) refers to other upstream indirect greenhouse gas emissions, such as from the extraction and production of purchased materials and fuels,

[2]Refer to Longstaff et al. (2005) for a detailed explanation of credit default swaps.

transport-related activities in vehicles not owned or controlled by the reporting entity, electricity-related activities not covered in Scope 2, outsourced activities, waste disposal, and so on; total refers to the sum of Scopes 1, 2, and 3—so-called supply-chain emission. By definition, Scope 3 emissions are attributed to the largest proportion of a company's emission footprint. Each carbon emission data point is equally important, hence we use all four variables in the analysis; however, each variable is used in the estimation.

Figure 1 plots the average corporate carbon emissions for each Carbon-Scope (tonnes CO2e) against the CDS spread (%) over the sample period from 2005 to 2019. The CDS spread fluctuation corresponds to economic fluctuations, as the average credit spreads have surged around the global financial crisis. Average corporate emissions decreased in the wake of the Lehman collapse and after the Paris Agreement of 2016. The recent trend is that Carbon-Scope 1 emissions show a notably decreasing tendency.

[Figure 1 around here]

We match the firm-level CDS spread data and corporate carbon emission data with the firm's dataset, which includes credit rating and financial indicators, to control for the firm's financial health and credit quality. Following previous studies, such as Stellner et al. (2015), financial indicators include the firm's total assets, earnings before interest and taxes (EBIT) margin (EBIT/total revenue), debt/capital, capital expenditure (CapEx)/total revenue, return on invested capital (ROIC), and equity price volatility. Furthermore, the issuer's credit rating information is used to control for the credit quality of the issuer. The firm's information is taken from the Thomson Reuters database and is as of immediately prior to the year-end CDS spread point. Table 1 presents the descriptive statistics for the panel dataset used in this analysis. As noted in Appendix A, the universe in Trucost's data for Japanese firms' observations expanded in 2016, whereas that in the CDS dataset did not. This enables our sample mean for carbon emissions to remain unaffected by the sudden drop in average carbon emissions in the expanded Trucost sample.

[Table 1]

Finally, we incorporate the number of signatories to the PRI in Japan as a proxy for the number of investors who care about ESG in their investment. PRI is a United Nations-supported international network of investors working to implement its six aspiration principles, often referred to as *the Principles*. In Japan, the Government Pension Investment Fund (GPIF), the world's largest pension fund, has become a signatory to the PRI since September 16, 2015, which has made ESG issues the center of attention in Japanese financial markets. The number of signatories in Japan is collected from various issues of annual reports.

3 Carbon emission production function

We first examine a firm's carbon emission production function to understand which factor plays a key role in the corporate carbon emissions. Equation (2) shows the baseline regression specification for a firm's production function of carbon emissions. The dependent variable is firm i's carbon emissions for a total, Scope 1, Scope2, or Scope 3 in year t, where a total of carbon emissions is the sum of the amounts (tonnes CO2e) of Scope 1, Scope 2, and Scope 3. The carbon emission production function takes the following form:

$$Carbon\ emissions_{it} = \alpha_i + \beta Production\ factors_{it} + \epsilon_{it}, \tag{2}$$

where α_i is the firm fixed effect, and the production factors of firm i's carbon emissions in year t are revenue, EBIT margin, debt-to-capital ratio, CapEx-to-revenue ratio, total assets, and ROIC. We consider the revenue, which is a proxy of production size in monetary terms, as the most important factor of carbon emission production. This conjunction is based on Figure 2, which plots the firm's revenue against the total, Scope 1, Scope 2, and Scope 3 emissions (tonnes CO2e), along with the linear predicted emissions, where all variables are transformed using inverse hyperbolic sine. In each panel, we see that carbon emissions increase with the revenue. Other firm-specific control variables are also considered to potentially affect carbon emissions. For instance, the size of an asset indicates how much energy is necessary to keep a firm's assets running and updated.

[Figure 2 around here]

We transform all level variables (carbon emissions, revenue, total asset, and ROIC) using an inverse hyperbolic sine (*asinh*). Although taking the logarithm of a variable has been a common transformation to approximate a normal distribution or make the empirical interpretation useful in elasticity estimates, the inverse hyperbolic sine transformation has advantages over taking the natural logarithm of a variable. A typical advantage is that it allows us to retain zero- and negative-valued observations, while the interpretation is similar to a logarithm (Burbidge et al. (1988), MacKinnon and Magee (1990), Bellemare and Wichman (2020)).[3]

Table 2 reports the estimation results of Equation (2) based on carbon emissions for (1) Total, (2) Scope 1, (3) Scope 2, and (4) Scope 3 of a firm and the financial indicators discussed above. As expected from Figure 2, the results indicate a significantly positive relationship between total revenue and all carbon emissions, even after controlling for other variables. Specifically, the results suggest that a 1% increase in revenue tends to increase carbon emissions by 0.609% (Scope 2) to 0.838% (Scope 3). Similarly, the coefficients of the total asset are found to be significantly positive, although the magnitude is relatively small compared to the revenue. More specifically, the results imply that a 1% increase in the asset tends to increase carbon emissions by 0.095% (Scope 3) to 0.323% (Scope 1). It is reasonable that the impact of carbon emissions from running and maintaining the firm's assets is the largest on Scope 1 emissions. Other variables appear to have no strong relationship with carbon emissions, except for capital expenditure, which shows a negative relationship with the total and Scope 1 carbon emissions. This may reflect that new capital tends to have efficient carbon emissions, thereby reducing carbon emissions in production processes.

Thus far, we assume that the effect of this factor on carbon emissions is constant over time. Next, we test whether the time-variant effect is observed in the carbon emissions in the following form:

$$Carbon\ emissions_{it} = \alpha_i + \beta Production\ factors_{it} + \gamma d_t + \epsilon_{it}, \tag{3}$$

where d_t is the time-variant increase/decrease effect on carbon emissions. In this analysis, we use the number of PRI signatories in Japan as the effect d_t, or, more specifically, the inverse hyperbolic sine of the number of PRI signatories in Japan.

Table 3 presents the estimation results of Equation (3), which is an extension of (2) by adding the number of signatories to the PRI in Japan. Unsurprisingly, the results are very similar to those

[3]Inverse hyperbolic sine transformation is proposed in Johnson (1949). The advantage of retaining meaningful zero-valued observations over alternative transformations makes this transformation employed in the empirical work of applied economics, for example, Clemens and Tiongson (2017), Bahar and Rapoport (2018), Jayachandran et al. (2017), McKenzie (2017). Taking the inverse hyperbolic sine transformation yields $asinh(x) = ln(x + \sqrt{x^2+1})$ for a random variable x. Bellemare and Wichman (2020) provide derivations that the interpretation in a case with asinh (dependent variable) - asinh (explanatory variable) specification is similar to log transformation. The estimates in this study are robust to the use of log transformation, while the sample size is slightly smaller with log transformation.

of (2), documenting a strong positive relationship between firm sales size and carbon emissions. Moreover, the additional variable, PRI signatory, shows a significantly negative relationship with all carbon emissions, except for Scope 1. This implies that as the number of PRI signatories increases, which can be considered as evidence of increasing pressure from institutional investors to reduce carbon emissions, carbon emissions tend to decrease, except for Scope 1. Since the Kyoto Protocol in 1997, many Japanese companies have made efforts to reduce Scope 1 carbon emissions. Consequently, it might be difficult to reduce Scope 1 carbon emissions further, even if institutional investor pressure increases. This could be a reason why the coefficient of the PRI signatory is insignificant only for Scope 1.

A number of regulated institutional investors are supposed to invest in bonds rated BBB or higher on the major rating agencies' scales, such as that of Standard and Poor's (Baa or higher on Moody's scale). Similarly, in the CDS markets, the target for such institutional investors is an entity whose credit quality is above BBB, that is, the investment-grade category. This means that a firm whose credit quality is not investment-grade does not have an incentive to focus on the reduction in carbon emissions, even if institutional investor pressure increases. Conversely, more production without the efforts and costs to reduce carbon emissions can generate more profit for such firms. We examine whether a firm's behavior in reducing carbon emissions under investor pressure differs according to its credit quality.

The results in Table 4 confirm the difference in the response of carbon emissions to investor pressure by the firm's credit quality. The PRI signatory has a significantly negative impact on all carbon emissions except for Scope 1 for investment-grade firms but only for Scope 3 for speculative-grade firms. The results provide supportive evidence of our view that only investment-grade firms have some incentive to reduce carbon emissions in response to institutional investors' pressure to do so. Other results are fairly consistent with the previous results, showing a strong positive relationship between firm revenue and asset and carbon emissions, and a negative relationship between capital expenditure and Scope 1 emissions. The only exception is that firm asset has a much weaker positive impact on carbon emissions for speculative-grade firms.

[Tables 2, 3, 4 around here]

4 Carbon emissions and CDS spread

We have revealed that a firm's carbon emissions are mostly dependent on its total revenue, that is, production size. In this section, we empirically explore the relationship between carbon emissions and CDS spread.

4.1 Hypotheses

This subsection presents the hypotheses to be empirically examined. There are several underlying mechanisms through which carbon emissions affect CDS spreads. Given that the results of the previous section and the clientele of the CDS market are mostly institutional investors who are well-informed about the firms and market, we consider the following hypotheses. Importantly, these hypotheses are neither mutually exclusive nor necessarily in conflict with each other.

H1: Profitability hypothesis

Investors consider that the larger carbon emission is a consequence of larger production, and carbon emission reduction will lead to nonnegligible profit reduction, given Japan's relatively high decarbonization cost. Therefore, the investors regard the larger carbon emission as a favorable signal of the firm's profitability, thus lowering the CDS spreads of the firm.

This hypothesis is based on our analysis of firm-level carbon emissions in Section 3, showing a strong dependency between a firm's revenue and the amount of carbon emissions. In other words, a larger amount of carbon emissions results from the firm's higher production. Therefore, higher carbon emissions can be a by-product of better firm performance. With the long history of the Energy-Saving Act in Japan, it was repeatedly reported in the media that Japanese firms having a thoroughgoing energy conservation policy would find it difficult to reduce carbon emissions without shrinking production,[4] and that carbon emission reduction can be disadvantageous for firms that have already realized emission reduction through their efforts. Considering the relatively high decarbonization cost in Japan, as indicated in OECD (2019), investors might be concerned about profitability as the firm accelerates to decarbonize itself.

H2: Carbon risk hypothesis

[4] E.g., articles of 10 Apr. 2007 in Nikkei Sangyo Shimbun (Nikkei Industrial Newspaper) and articles of 31 Oct. 2009, 17 Nov. 2009, and 8 Mar. 2010 in The Nikkei.

As the regulation and tax system on fossil fuels are to be further tightened on a global basis, the large carbon emitters are exposed to carbon risk. The tighter regulations and higher carbon tax may decrease the net profit of the large carbon emitters, which leads to their lower asset prices. Investors less evaluate large carbon emitters about their sustainability, resulting in higher CDS spreads.

Notably, CDS market participants are mostly well-informed institutional investors, meaning that they are forward-looking and sensitive to event-specific risk. As investors expect the carbon tax levy or regulation cost on large emitters to shrink their profits and the value of those firms, the CDS spread for large carbon emitters is expected to be higher according to such carbon risk.

This hypothesis is also related to theories in which ESG-conscious investors prefer green firms' stocks, or sustainable investors prefer green firms to brown firms. Heinkel et al. (2001) theoretically indicate that the polluting firms' cost of capital can be raised by green investors. The theoretical model in Luo and Balvers (2017) considers the boycott risk premium of socially responsible investors. If the large emitters are targeted, their asset prices are required to pay extra compensation for the risk. Pastor et al. (2021) develop the theoretical model that considers ESG criteria and indicates that greener firms have higher market values, thereby lowering the cost of capital for green firms. Pedersen et al. (2021) also show that prices of green stocks are relatively higher than brown stocks' prices.

H3: Investor awareness hypothesis

The CDS spreads for firms with small carbon emissions are lower because of lower carbon risk, as the investor awareness of the dire consequences of climate change is growing.

One of the motivations for this hypothesis is the market underreaction discussed by Pedersen et al. (2021) and Duan et al. (2022). Specifically, Pedersen et al. (2021) argue that although the ESG performance could be a favorable signal of firm fundamentals, the market could underreact to this predictability of corporate ESG performance for expected future profits due to the lack of recognition. Duan et al. (2022) also argue that fewer investors underreact when investor awareness increases.

Investor awareness of climate change is also emphasized in macroeconomics and finance, as the disaster and climate crisis risks stemming from climate change are extensively recognized worldwide. Even central banks have begun to integrate climate risks into monetary policy operations. In addition to the investor's ESG preference in Pastor et al. (2021) and the taste premium in Zerbib (2019, 2022), global trends in investor awareness are pronounced over time, as reported in Drudi et al. (2021).[5] Consequently, more investors are concerned about carbon risk as investor awareness increases. The size and significance of its impacts depend on the sector characteristics and changes over time; thus, we expect the amount of firm-level carbon emissions to have a larger impact on CDS spreads, especially more recently, with increasing investor awareness. This hypothesis relaxes the constant impacts of carbon emissions on CDS spreads over time and is plausible because recent climate-related events trigger investors' awareness.

4.2 Main results

First, we convert the amount of carbon emissions per firm into a fractional rank within a year, given that the features of firm-level carbon emissions data have large differences between their ranges.[6] The rank of carbon emissions is calculated using the sample in this analysis. The advantages of using fractional rank instead of the amount of carbon emissions are: first, a fractional rank retains the order among carbon emitters in cross-sectional data. Second, the model, which includes firm fixed effects, estimates the change in CDS spreads for a change in the fractional rank of carbon emissions, thereby controlling for unobserved firm-level heterogeneity. Since cross-sectional variation is captured by fixed effects, what is left with is the time-series variation, which we assume is attributed to overall time trends, macroeconomy, and relative carbon emission performance. For example, even if a firm decreases its carbon emissions, investors naturally compare performance with other firms, not only within a firm. The fractional rank variable reflects the assessment of relative performance. Third, the fractional rank is robust to outliers. Table 1 displays the large variation in the amount of carbon emissions; nonetheless, it seems inappropriate to exclude some of the largest carbon emitters from the analysis as outliers. Using the fractional rank allows us to

[5] Fahmy (2022) shows that the rise in investors' awareness of climate risks especially after the Paris Agreement has an impact on the connection between clean energy prices and oil and technology stock prices.

[6] An alternative method is to normalize variables using z-score, minimum and maximum observations, or exponential function and mean and standard deviation. Using a standardized z-score does not solve concerns caused by the large value observations because the mean value is still affected by the very large values. By contrast, the carbon emission variables using mini-max normalization and softmax normalization at the year or sector-year level yield, quantitatively and qualitatively, similar estimates to those using fractional ranks. In this analysis, we use the fractional rank variable for its advantages in interpreting the results over the aforementioned alternatives that the mean value is 0.5, which is a feature of softmax normalization, and the range is between 0 and 1, which is a feature of min-max normalization.

incorporate such emitters in the analysis because it is less sensitive to outliers than the measures of carbon emission amounts.

Then, we estimate the following specification:

$$\begin{aligned} CDS_{it} =& \alpha_i + \beta_0 fractional\ rank_{it} + \beta_1 fractional\ rank_{it} \times signatories_t \\ & + \lambda Controls_{it} + \gamma Macros_t + \epsilon_{it}, \end{aligned} \tag{4}$$

where the dependent variable is CDS spreads on firm i in year t (asinh(CDS spread in basis point)), and the fractional rank of firm i in year t is used as a carbon emission variable. The model specification contains firm fixed effects α_i. The inverse hyperbolic sine transformation of CDS spreads is used to control for heteroskedasticity as a similar transformation, commonly taking the logarithm used in corporate bond credit spreads when the distribution of credit spreads is highly skewed. On the one hand, for the profitability hypothesis (**H1**), we focus on the coefficient of the fractional rank variable β_0 and consider that it is supported if β_0 is significantly negative. On the other hand, for the carbon risk hypothesis, we examine the coefficient of the interaction term between the fractional rank and the number of PRI signatories in Japan, β_1, as well as β_0. If the carbon risk hypothesis holds, either β_0 or β_1, or both should be significantly positive, reflecting the carbon risk premium. Finally, the investor awareness hypothesis (**H3**) concerns β_1 because it captures the increasing pressure from investors to reduce carbon emission risk by policy changes toward a zero-carbon society. If the coefficient β_1 is significantly positive, the impact of fractional rank increases with the number of PRI signatories.

To control for the factors determining CDS spreads, $Controls_{it}$ contains the firm's credit rating information, vector of financial variables, and illiquidity measure. Appendix B describes the calculation of the illiquidity measure. $Macros_t$ consists of two macroeconomic variables: annual GDP growth rate and annual inflation.

Our empirical strategy to extract the relationship between corporate carbon emissions and CDS spreads begins with the panel estimation of Equation (4). One might be concerned about the causality of the association between the carbon emission amounts and CDS spreads; however, CDS spreads are event-specific and inherently forward-looking. In this sense, the reverse causality between CDS spreads and carbon emissions seems unlikely to be present, and we can reasonably overlook this issue. Additionally, we use year-end CDS spreads to minimize simultaneity issues, making many of the explanatory variables predetermined.

Table 5 reports the estimation results of Equation (4) based on fractional rank calculated from carbon emissions for (1) Total, (2) Scope 1, (3) Scope 2, and (4) Scope 3, credit rating dummies, and financial indicators. As can be seen, the coefficient of the fractional rank is negative, ranging from -1.764 to -1.185, and is significant for all carbon emissions. The coefficient can be interpreted as the impact of fractional rank on CDS spreads in 2005 when the number of PRI signatories is zero. The results indicate that the profitability hypothesis (**H1**) is supported in the absence of pressure from investors, indicating that firms with higher carbon emission ranks pay lower CDS spreads on average, hence reflecting higher economic activities. This also implies that there is little supportive evidence for the carbon risk hypothesis (**H2**) in 2005. However, our results show that the coefficient of the interaction term between the fractional rank and the number of PRI signatories in Japan is significantly positive, at approximately 0.27 for all carbon emissions. The results support both the carbon risk hypothesis and the investor awareness hypothesis (**H3**), showing that the negative impact of the fractional rank appears to be smaller in magnitude and eventually becomes positive for Scopes 2 and 3 as investor awareness, measured by the number of PRI signatories, grows. To see this point clearly, Figure 4 plots the total impact of the fractional rank of carbon emissions on CDS spreads, which can be expressed by $\beta_0 + \beta_1 signatories_t$. As can be seen, the impact was negative around the beginning of the sample, but its magnitude of negative impact decreased over time for all emissions, while the total impact was slightly positive toward 2020 for Scopes 2 and 3. In other words, our results clearly indicate that increasing investor pressure induces a carbon risk premium in CDS markets.

Other control variables mostly have the expected effects on CDS spreads. For example, the better the credit rating of firms, the lower the CDS spread. Similarly, revenue and earnings show a significantly negative relationship with CDS spreads, suggesting that profitability generally lowers CDS spreads. On the contrary, our results indicate that CDS spreads are significantly higher with various types of risks captured by leverage, illiquidity, and price volatility. In addition, the two macroeconomic variables have expected effects on CDS spreads. Specifically, the annual GDP growth rate has a significantly negative impact on CDS spreads, as higher economic growth tends to lower firms' default risk. However, annual inflation shows significantly positive impacts, partly reflecting that higher inflation tends to increase interest rates, and, hence, default risk.

[Table 5 around here]

4.3 Sectoral impacts on CDS

We have reported evidence that although the profitability hypothesis (**H1**) is dominant in 2005 before the development of ESG investments, the carbon risk hypothesis (**H2**) and investor awareness hypothesis (**H3**) have been supported and prevailed in the relationship between carbon emissions and CDS spreads in more recent years. Because the costs of decarbonization differ substantially across sectors, this subsection examines the sectoral impacts of carbon emissions on CDS spreads and whether the carbon risk hypothesis (**H2**) and investor awareness hypothesis (**H3**) are still supported in all sectors. We modify Equation (4) with the following specification to include sectoral impacts:

$$\begin{aligned} CDS_{it} =& \alpha_i + \beta_0 fractional\ rank_{it} + \beta_k \sum_k sector_{ik} \times fractional\ rank_{it} \times signatories_t \\ & + \lambda Controls_{it} + \gamma Macros_t + \epsilon_{it}, \end{aligned} \tag{5}$$

where $fractional\ rank_{it} \times signatories_t$ is estimated by sector k to which firm i belongs, $sector_{ik}$, and the rest of the variables in the specification remain the same.

In some sectors, particularly those referred to as hard-to-abate or high-climate impact sectors, decarbonization is expected to be difficult, given costs, energy sources, and integrated industrial processes. In other sectors, reducing carbon emissions is not technically challenging in their core business operations because they do not employ extremely high temperatures for production, high-density energy sources, nor use hydrocarbons as feedstock and energy sources. Naturally, this poses the question: Should firms not in hard-to-abate sectors reduce carbon emissions more? We expect that investors more severely evaluate firms that can reduce carbon emissions by using less expensive and less complicated carbon-free approaches compared to firms in hard-to-abate sectors. This raises an interesting question to investigate: Are **H2** and **H3** prominent for such firms?

Table 6 shows the estimation results of β_0 and β_k in Equation (5), where the other estimated coefficients are not reported for brevity and remain similar in Table 5. The results indicate the negative impacts of the fractional rank of all carbon emissions in 2005, when there is no pressure from investors, indicating that **H1** is supported, as shown in Table 5. However, the significantly positive estimates of β_k for all sectors suggest that the pressure from investors rapidly reduces the lowering effect on the CDS spreads of firms, regardless of sector and carbon emission. Moreover, the sectoral impacts document that investor reactions differ among sectors, and the strongest impacts can be found in the healthcare, telecommunications services, and technology sectors. Furthermore, the utility, energy, and basic materials sectors show relatively smaller impacts, suggesting that investors' reactions to carbon emissions from firms in hard-to-abate sectors appear to be weaker. This is consistent with our view that the clientele of the CDS market are mostly informed institutional investors, and their reactions to the carbon emissions of firms in hard-to-abate sectors tend to be less demanding. Nonetheless, the estimates of β_k support **H2** and **H3** for all the sectors. The results also predict that the rise in CDS spreads, attributable to **H2** and **H3**, would be dominant in the total impact expressed as $\beta_0 + \beta_1 signatories_t$ for Scopes 2 and 3 for most of the sectors, as investors who care about carbon risk increase.

4.4 Credit quality

In this subsection, we examine the impact of carbon emissions on CDS spreads by sector and credit quality. This is reasonable because our finding on emission production in Table 4 shows that the pressure from institutional investors to reduce carbon emissions is stronger for investment-grade firms. This result suggests that investor pressure appears to be more relevant to investment-grade firms.

Table 7 reports the estimation results, including the interaction term between credit quality and the sectoral impact in Equation (5). The results support **H2** and **H3** for both investment- and speculative-grade firms. Although speculative-grade companies are assumed to be less sensitive to pressure from institutional investors, who are supposed to invest in bonds rated BBB or higher by management policy, the results in Table 4 indicate that the increasing pressure from investors has impacts on CDS spreads, even for speculative-grade firms. Moreover, the magnitude of the impact on CDS spreads tends to be larger for speculative-grade firms across all sectors. This could be because lower carbon risk can provide more precious information about the sustainability of speculative-grade firms with higher default risk, as reported by Okimoto and Takaoka (2021). Finally, the tendency for larger impacts on the CDS spreads of firms in the healthcare, telecommunications services, and technology sectors remains the same. In other words, firms in these sectors can lower their CDS spreads by reducing their carbon emissions more than those in other sectors, particularly in hard-to-abate sectors.

[Table 7 around here]

4.5 Robustness checks

4.5.1 Controlling hard-to-abate sectors

Section 4.3 reports the sectoral impacts of carbon emissions on CDS spreads because the costs of decarbonization differ substantially across sectors. However, within or among sectors, there are firms whose operations fall into the sector with relatively higher abatement costs than other sectors. The Energy Transitions Commission (2018) refers to heavy industry sectors and heavy duty transport as harder-to-abate sectors, and Teske et al. (2020) point out energy and utility sectors as key (supplier) sectors. In this section, we explicitly control for the effects of firms in such hard-to-abate sectors by classifying the firms into three groups: "non-manufacturing easier-to-abate," "manufacturing easier-to-abate," "hard-to-abate" sectors.[7] The Energy Transitions Commission (2018) refers economic sectors with relatively lower abatement costs than harder-to-abate sectors as easier-to-abate sectors. In addition, we classify firms in the easier-to-abate sector into manufacturing and non-manufacturing sectors to reflect their differences in industrial processes and products.

Table 8 shows that our empirical results are intact, even when controlling for the hard-to-abate sectors, and also reports the differences among these three groups. Specifically, the results indicate that the carbon risk premium associated with increasing pressure from investors is largest in the non-manufacturing easier-to-abate sectors, followed by manufacturing easier-to-abate, and harder-to-abate sectors. This is generally consistent with the sectoral results in the previous subsection, showing that the carbon risk premium is larger for sectors that can reduce carbon emissions relatively easily. Thus, investors require a higher risk premium for firms that can reduce carbon emissions by having less expensive and less complicated carbon-free approaches compared to firms in the hard-to-abate sectors.

[Table 8 around here]

4.5.2 Alternative measure of carbon emissions

We use the fractional rank of carbon emissions by year in the analyses by leveraging its advantages. In this section, we use the carbon intensity of each carbon emission scope as an alternative measure of carbon emissions and examine whether our variables of interest qualitatively show

[7] Following the literature, we classify heavy industry (cement, steel, chemicals, and aluminum), heavy-duty transport (shipping, trucking, and aviation), energy, and utilities as hard-to-abate sectors.

the same effects on CDS spreads. Carbon intensity variables include carbon intensity-scope 1 (tonnes CO2e/USD mn), carbon intensity-scope 2 (tonnes CO2e/USD mn), carbon intensity-scope 3 (tonnes CO2e/USD mn), and carbon intensity of all scopes (tonnes CO2e/USD mn). They are transformed using the inverse hyperbolic sine as well as other level variables.

Table 9 reports the sectoral impact of carbon intensity on CDS spreads, which corresponds to Table 6; however, carbon intensity is used to replace the fractional rank. As can be seen, the results are qualitatively similar with those in the previous subsection. The results indicate that carbon emissions significantly decrease CDS spreads, thus supporting the profitability hypothesis. Moreover, the carbon risk premium has been increasing with the growth of investor awareness, hence supporting the carbon risk and investor awareness hypotheses. However, the results based on carbon intensity also show a noticeable difference in the magnitude of the carbon risk premium. Specifically, the carbon risk premium assessed by carbon intensity is much smaller than that measured by the fractional rank of carbon emissions in the previous subsections. Moreover, the economic significance of the carbon risk premium is negligible if carbon intensity is used. This result is fairly consistent with that of Bolton and Kacperczyk (2021) who report that carbon premium is not related to carbon emission intensity.

[Table 9 around here]

5 CDS spread curve and Carbon emissions

The results in the previous section have focused on the impacts of carbon emissions on the average CDS spreads for the firm. This section extends the analysis to the CDS spread curve to investigate whether carbon emissions affect the CDS spread curve and to which factor of the CDS spread curve (short-term CDS spread, long-term CDS spread, or slope defined by the difference between long-term and short-term CDS spreads) the carbon emissions are priced. The empirical specification is the same as in Equation (5), but the dependent variable alternates according to which factor of credit spread term structure we are studying: short-term CDS spread, long-term CDS spread, or the slope.

5.1 Short-term CDS spread and long-term CDS spread

In this subsection, we study the relationship between carbon emissions and short-term and long-term CDS spreads. We assume that the short-term CDS spread reflects the firm's urgent credit risk, whereas the long-term CDS spread reflects the firm's credit risk over the long-term horizon. Using short- and long-term CDS spreads, we test whether the market regards carbon emissions as an urgent risk or risk of long-term sustainable growth for the firm.

To this end, we estimate a version of Equation (5) for short-term CDS spreads, which are the average of CDS spreads between six-month and four-year, and long-term CDS spreads, which are the average of CDS spreads between five- and thirty-years, alternatively. The results in Table 10 indicate that in 2005, the fractional rank of carbon emissions has a significantly negative impact on both the short- and long-term spreads for all Scope emissions. This means that higher carbon emissions are considered as a good signal for firms' sustainability in 2005, supporting the profitability hypothesis (**H1**). However, the significantly positive estimates of the interaction terms suggest that as the pressure to reduce carbon emissions from investors grows, this negative impact disappears for most of the sectors. The results for both short- and long-term CDS spreads support the carbon risk hypothesis (**H2**) and the investor awareness hypothesis (**H3**). The magnitude of sectoral impacts differs, for example, from 0.160 to 0.718 for total emissions on short-term CDS spreads and from 0.231 to 0.650 for total emissions on long-term CDS spreads.

[Table 10 around here]

5.2 Slope of CDS spread curve

In this subsection, we examine the impact of carbon emissions on the CDS curve slope.[8] The slope of the CDS spread curve is simply calculated as the difference between the long- and short-term CDS spreads.

Table 11 reports the estimation results of a version of Equation (5), using the slope as the dependent variable. As can be seen, the coefficient β_0 on the fractional rank is significantly negative for all carbon emissions. This implies that higher carbon emissions tend to flatten the CDS spread

[8] In addition to the level and slope of the spread curve, the term structure of the spreads is sometimes represented by the curvature component, which is referred to as a third component. Ang et al. (2006) document that a third component is important at daily and weekly frequencies and we work at yearly frequencies, hence we consider CDS spread level and slope to be sufficient to describe our CDS spread curve, leaving out the curvature from the analysis.

curve when pressure from investors is absent, thus reflecting the low default risk associated with higher economic activities, hence supporting **H1**. However, significantly positive estimates of β_k provide supportive evidence for **H2** and **H3**, indicating that the flattening effects appear to vanish in recent years once more investors start recognizing climate change risk. Consequently, the expansion of investors who care about climate change will steepen the CDS spread curve of high emitters.

[Table 11 around here]

The results in Tables 10 and 11 suggest that the impacts of carbon emissions are significant for all sectors for both short- and long-term CDS spreads, as well as the slope of the CDS curve. This means that a firm's carbon emissions play a key role in determining the CDS spread curve for the firm, and their steepening effect on the CDS spread curve predicts that they would have a greater impact on the firm's long-term fundraising costs in the near future.

6 Conclusions

In this study, we examine carbon emission production and carbon emissions in the pricing of CDS spreads at the firm level in Japan. First, we found that revenue size (production size in monetary terms) was the most significant factor affecting carbon emissions. We also showed that the recent growth in the number of PRI signatories in Japan had a decreasing effect on firms' carbon emissions. Investment-grade firms decreased carbon emissions more than speculative-grade firms in response to increasing pressure from investors. Second, our analysis of CDS spreads supports the profitability hypothesis in 2005, but the carbon risk hypothesis (**H2**) and investor awareness hypothesis (**H3**) have become dominant in recent years, regardless of carbon emissions and sectors. This means that CDS spreads for firms with smaller carbon emissions are lower as investor awareness of the dire consequences of climate change grows. Third, investors severely evaluate the CDS spreads of firms that can reduce carbon emissions using less expensive and less complicated carbon-free approaches compared to firms in hard-to-abate sectors. Last but not least, carbon emissions are a determinant of the CDS curve. The results indicate that firms' carbon emissions play a key role in the CDS spread curve for the sample firms across all sectors.

With more investors seeking action toward net-zero emissions, the firm needs to respond with a strategic plan for carbon emission reduction. The impact of carbon emissions on the CDS spread curve indicates that carbon emissions are priced in the CDS spread curve, with high carbon emissions steepening the CDS spread curve. This result implies that higher carbon emissions signal a higher risk for a firm's long-term sustainability in the market. This is relevant because the risk of a higher carbon tax and tighter regulation appears to be inevitable, given the active movement toward net-zero emissions. In addition, the change in consumer preference stemming from the consequences of climate change shifts the demand toward greener firms, which leads to the downward sales of high-carbon-emitter firms. Thus, consumer awareness of climate risk is directly linked to product sales. Ultimately, those firms regarded as not environmentally friendly might suffer from a lack of young and human resources, as the young generation becomes increasingly environmentally conscious. Consequently, more investors consider the sustainable growth of higher carbon-emitting firms to be less likely. Our findings from the CDS spread analysis suggest that decarbonization is essential not only to itself but also to its client or supplier firms, as supply-chain emissions matter in the process of calculating emissions for any involved firms.

Appendix A. Distribution and fractional rank of carbon emissions

The amount of carbon emissions is not equally distributed across sectors nor firms. Figure A1 displays the Gini coefficient for corporate carbon emissions for Scopes 1, 2, and 3 over the 2005–2019 period using the data from our analysis. The universe of Trucost's data for Japanese firm observations expanded from 563 to 1757 firms in 2016. To mitigate the effect of this large gap in the sample, we limit the sample to firms in our CDS dataset, which are constantly registered in Trucost's data. For reference, the corresponding Gini coefficient using the whole Trucost data in Japan is constantly higher by approximately 0.028 to 0.198. The Gini coefficient for Scope 1 emissions is notably high, whereas those for Scope 2 and 3 emissions are substantially high.

[Figure A1 around here]

We use the fractional rank of firm observations from Scope 1, 2, and 3 emissions in the regressions. The computation of fractional ranks is conducted by year, as follows:[9] Consider firm observations N on the carbon emissions of each scope Y with associated sampling weights, $(y_i, w_i)_{i=1}^{N}$.

[9] Refer to Van Kerm (2020) *Generalized Gini, Concentration coefficients, Factor decomposition and Gini correlations in Stata*, http://medim.ceps.lu/stata/sgini.pdf for practical calculations.

When we have K distinct values observed on Y denoted as $y_1^* < y_2^* < ... < y_K^*$, and π_k^* the corresponding weighted sample proportions for any value of y_k^*,

$$\pi_k^* = \frac{\sum_{i=1}^N w_i \mathbf{1}(y_i = y_k^*)}{\sum_{i=1}^N w_i}$$

where $\mathbf{1}(condition)$ is unity if the condition is true; otherwise, it is 0. With no tied observations and/or sample weights, we simply have $\pi_k^* = 1/N$. The fractional rank of y_k^* is

$$F_k^* = \sum_{j=0}^{k-1} \pi_j^* + 0.5\pi_{j+1}^*$$

where $\pi_0^* = 0$. Then, the fractional rank is given as

$$F_i = \sum_{k=1}^{K} F_k^* \mathbf{1}(y_i = y_k^*).$$

Here, tied observations in this analysis do not depend on the order of the data, and the sample size does not affect the sample mean of the fractional ranks.

Appendix B. Illiquidity measure

There appears to be a consensus in the literature that liquidity is a significant factor in corporate bond spreads and CDS spreads. However, unlike stocks whose trading is centrally organized on stock exchanges, intraday data on quotes and trading volumes are not available for constructing the liquidity index. Schestag et al. (2016) provide the comprehensive comparison of common liquidity measures for the US corporate bond market, for example, the ratio of daily high to daily low prices in Roll (1984), Hasbrouck (2009), and Corwin and Schultz (2012). Other measures include the issue size in Campbell and Taksler (2003), bond age in Sarig and Warga (1989), Adams and Mansi (2009), and Mansi et al. (2012), and the number of months a bond is assigned a market quote during the past 12 months in Güntay and Hackbarth (2010). Given the data availability on CDS prices and trading volumes, we construct a measure of illiquidity based on Bao et al. (2011) which does not require trading volume and intraday bid—ask quotations. This measure is a simple gauge that can be applied to the CDS market, see Guo and Newton (2013). The details are documented in Bao et al. (2011), and we briefly describe how we construct this measure using our CDS data.

The illiquidity measure γ_{it} proposed by Bao et al. (2011) for corporate bonds at time t is used for individual bond issue i. The log price of an asset, $lnP_{it} = p_{it}$, is denoted by

$$p_{it} = f_{it} + u_{it}$$

where f_{it} is the fundamental value in the absence of friction and follows a random walk, and u_{it} is transitory, which is uncorrelated with the fundamental value owing to the impact of illiquidity. The magnitude of u_{it} represents the level of illiquidity. Thus, γ_{it} is designated to extract the transitory component in p_{it}. We denote the change in price from $t-1$ to t by $\Delta p_{it} = p_{it} - p_{i,t-1}$. The illiquidity measure γ_{it} is defined by the negative autocovariance in relative price changes because transitory price movements result in negatively serially correlated price changes.

We calculate the illiquidity measure γ using daily CDS spread data based on Bao et al. (2011) as follows:

$$\gamma_{it} = cov(\Delta s_t, \Delta s_{i,t+1})$$

where s_{it} is the CDS spread for firm i at time t, that is, the illiquidity measure, γ_{it}, indicates the covariance between daily CDS spread changes. While Bao et al. (2011) denote the negative of the autocovariance for corporate bond price changes, we use the positive covariance for the CDS spread, which represents the expected default loss plus credit risk premium (Longstaff et al. (2005)) and whose transitory movements lead to positively serially correlated CDS spread changes. A higher γ value indicates lower liquidity.

We set the horizon over which we measure CDS spread changes same across firms to avoid the horizon effect that arises from the discrepancy in horizons over which we measure CDS spread changes and extract the different aspects of u_{it}. In this analysis, the CDS spread on the year-end trading day is used in the regressions, so we calculate the illiquidity measure using the daily data within a year prior to the last trading day.

References

Acemoglu, D., Aghion, P., Bursztyn, L., and Hemous, D. (2012). The environment and directed technical change. *American Economic Review*, 102(1):131–66.

Acemoglu, D., Akcigit, U., Hanley, D., and Kerr, W. (2018). Transition to clean technology. *Journal of Political Economy*, 124(1):52–104.

Adams, J. C. and Mansi, S. A. (2009). CEO turnover and bondholder wealth. *Journal of Banking & Finance*, 33:522–533.

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., and Van Reenen, J. (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. *Journal of Political Economy*, 124(1):1–51.

Ang, A., Piazzesi, M., and Wei, M. (2006). What does the yield curve tell us about GDP growth? *Journal of Econometrics*, 131:359–403.

Bahar, D. and Rapoport, H. (2018). Migration, knowledge diffusion and the comparative advantage of nations. *The Economic Journal*, 128(612):F273–F305.

Bao, J., Pan, J., and Wang, J. (2011). The illiquidity of corporate bonds. *Journal of Finance*, 66(3):911–946.

Bellemare, M. F. and Wichman, C. J. (2020). Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics*, 82(1):50–61.

Bolton, P. and Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, 142(2):517–549.

Burbidge, J. B., Magee, L., and Robb, A. L. (1988). Alternative transformations to handle extreme values of the dependent variable. *Journal of the American Statistical Association*, 83(401):123–127.

Campbell, J. Y. and Taksler, G. B. (2003). Equity volatility and corporate bond yields. *Journal of Finance*, 58(6):2321–2349.

Clemens, M. A. and Tiongson, E. R. (2017). Split decisions: Household finance when a policy discontinuity allocates overseas work. *Review of Economics and Statistics*, 99(3):531–543.

Colonnello, S., Curatola, G., and Gioffré, A. (2019). Pricing sin stocks: Ethical preference vs. risk aversion. *European Economic Review*, 118:69–100.

Corwin, S. A. and Schultz, P. (2012). A simple way to estimate bid-ask spreads from daily high and low prices. *Journal of Finance*, 67(2):719–759.

Delis, M. D., de Greiff, K., Iosifidi, M., and Ongena, S. (2019). Being stranded the carbon bubble? Climate policy risk and the pricing of bank loans. Swiss Finance Institute Research Paper Series No. 18-10.

Drudi, F., Moench, E., Holthausen, C., Weber, P.-F., Ferrucci, G., Setzer, R., Adao, B., Dées, S., Alogoskoufis, S., and Téllez, M. D. (2021). Climate change and monetary policy in the euro area. Occasional Paper Series 271, European Central Bank.

Duan, T., Li, F. W., and Wen, Q. (2022). Is carbon risk priced in the cross-section of corporate bond returns? Working Paper.

Fahmy, H. (2022). The rise in investors' awareness of climate risks after the Paris Agreement and the clean energy-oil-technology prices nexus. *Energy Economics*, 106:105738.

Friedman, M. (1970). The social responsibility of business is to increase its profits. New York Times Magazine, September 13.

Gibson, R., Krüger, P., and Mitali, S. F. (2018). The sustainability footprint of institutional investors. European Corporate Governance Institute – Finance Working Paper No. 571/2018.

Gilchrist, S., Yankov, V., and Zakrajšek, E. (2009). Credit market shocks and economic fluctuations: Evidence from corporate bond and stock markets. *Journal of Monetary Economics*, 56(4):471–493.

Gilchrist, S. and Zakrajšek, E. (2012). Credit spreads and business cycle fluctuations. *American Economic Review*, 102(4):1692–1720.

Güntay, L. and Hackbarth, D. (2010). Corporate bond credit spreads and forecast dispersion. *Journal of Banking & Finance*, 34:2328–2345.

Guo, B. and Newton, D. (2013). Regime dependent liquidity determinant of credit default swap spread changes. *Journal of Financial Research*, 36(2):279–298.

Hasbrouck, J. (2009). Trading costs and returns for U.S. equities: Estimating effective costs from daily data. *Journal of Finance*, 64(3):1445–1477.

Haščič, I. and Migotto, M. (2015). Measuring environmental innovation using patent data. OECD Environment Working Papers No. 89.

Heinkel, R., Kraus, A., and Zechner, J. (2001). The effect of green investment on corporate behavior. *Journal of Financial and Quantitative Analysis*, 36(4):431–449.

Hong, H. and Kacperczyk, M. (2009). The price of sin: The effects of social norms on markets. *Journal of Financial Economics*, 93(1):15–36.

Hsu, P.-H., Li, K., and Tsou, C.-Y. (2019). The pollution premium. Working Paper.

Huynh, T. D. and Xia, Y. (2021). Climate change news risk and corporate bond returns. *Journal of Financial and Quantitative Analysis*, 56(6):1985–2009.

Ilhan, E., Sautner, Z., and Vilkov, G. (2021). Carbon tail risk. *Review of Financial Studies*, 34(3):1540–1571.

In, S. Y., Park, K. Y., and Monk, A. (2010). Is 'being green' rewarded in the market?: An empirical investigation of decarbonization and stock returns. Stanford Global Project Center Working Paper.

Jang, G.-Y., Kang, H.-G., Lee, J.-Y., and Bae, K. (2020). ESG scores and the credit market. *Sustainability*, 12(8):1–13.

Jayachandran, S., de Laat, J., Lambin, E. F., Stanton, C. Y., Audy, R., and Thomas, N. E. (2017). Cash for carbon: A randomized trial of payments for ecosystem services to reduce deforestation. *Science*, 357(6348):267–273.

Johnson, N. L. (1949). Systems of frequency curves generated by methods of translation. *Biometrika*, 36(1/2):149–176.

Krueger, P., Sautner, Z., and Starks, L. T. (2020). The importance of climate risks for institutional investors. *Review of Financial Studies*, 33(3):1067–1111.

Longstaff, F. A., Mithal, S., and Neis, E. (2005). Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market. *Journal of Finance*, 60(5):2213–2253.

Luo, H. A. and Balvers, R. J. (2017). Social screens and systematic investor boycott risk. *Journal of Financial and Quantitative Analysis*, 52(1):365–399.

MacKinnon, J. G. and Magee, L. (1990). Transforming the dependent variable in regression models. *International Economic Review*, 31(2):315–339.

Mansi, S. A., Maxwell, W. F., and Zhang, A. (2012). Bankruptcy prediction models and the cost of debt. *Journal of Fixed Income*, 21(4):25–42.

McKenzie, D. (2017). Identifying and spurring high-growth entrepreneurship: Experimental evidence from a business plan competition. *American Economic Review*, 107(8):2278–2307.

OECD (2019). *The Costs of Decarbonisation: System Costs with High Shares of Nuclear and Renewables*. Nuclear Energy Agency, OECD Publishing, OECD Paris.

Okimoto, T. and Takaoka, S. (2021). Sustainability and credit spreads in Japan. RIETI Discussion Paper Series 21-E-052.

Pastor, L., Stambaugh, R. F., and Taylor, L. A. (2021). Sustainable investing in equilibrium. *Journal of Financial Economics*.

Pedersen, L. H., Fitzgibbons, S., and Pomorski, L. (2021). Responsible investing: The ESG-efficient frontier. *Journal of Financial Economics*, 142(2):572–597.

Roll, R. (1984). A simple implicit measure of the effective bid-ask spread in an efficient market. *Journal of Finance*, 39(4):1127–1139.

Sarig, O. and Warga, A. (1989). Bond price data and bond market liquidity. *Journal of Financial and Quantitative Analysis*, 24(3):367–378.

Schestag, R., Schuster, P., and Uhrig-Homburg, M. (2016). Measuring liquidity in bond markets. *Review of Financial Studies*, 29(5):1170–1219.

Stellner, C., Klein, C., and Zwergel, B. (2015). Corporate social responsibility and Eurozone corporate bonds: The moderating role of country sustainability. *Journal of Banking and Finance*, 59:538 – 549.

Stroebel, J. and Wurgler, J. (2021). What do you think about climate finance? *Journal of Financial Economics*, 142(2):487–498.

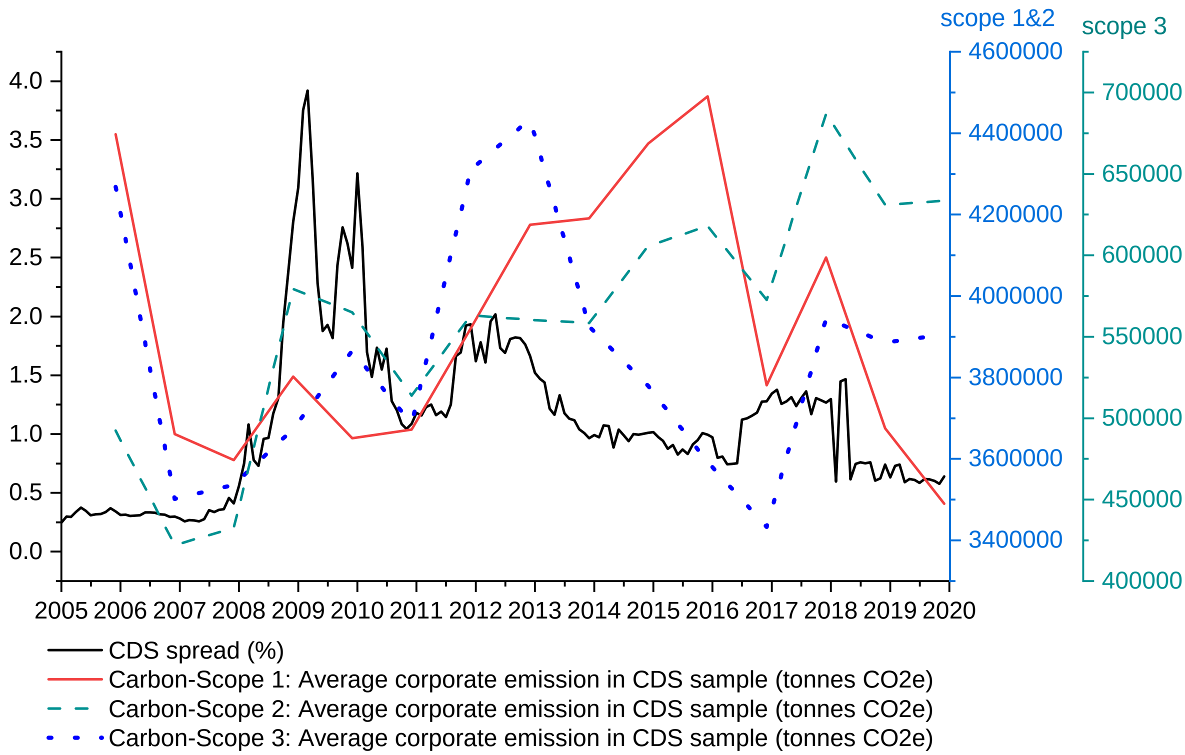
Teske, S., Niklas, S., Atherton, A., Kelly, S., and Herring, J. (2020). Sectoral pathways to net zero emissions. Report prepared by the University of Technology Sydney for the Net Zero Asset Owners Alliance.

The Energy Transitions Commission (2018). Mission possible: Reaching net-zero carbon emissions from harder-to-abate sectors. November 2018.

Zerbib, O. D. (2019). The effect of pro-environmental preferences on bond prices: Evidence from green bonds. *Journal of Banking and Finance*, 98:39–60.

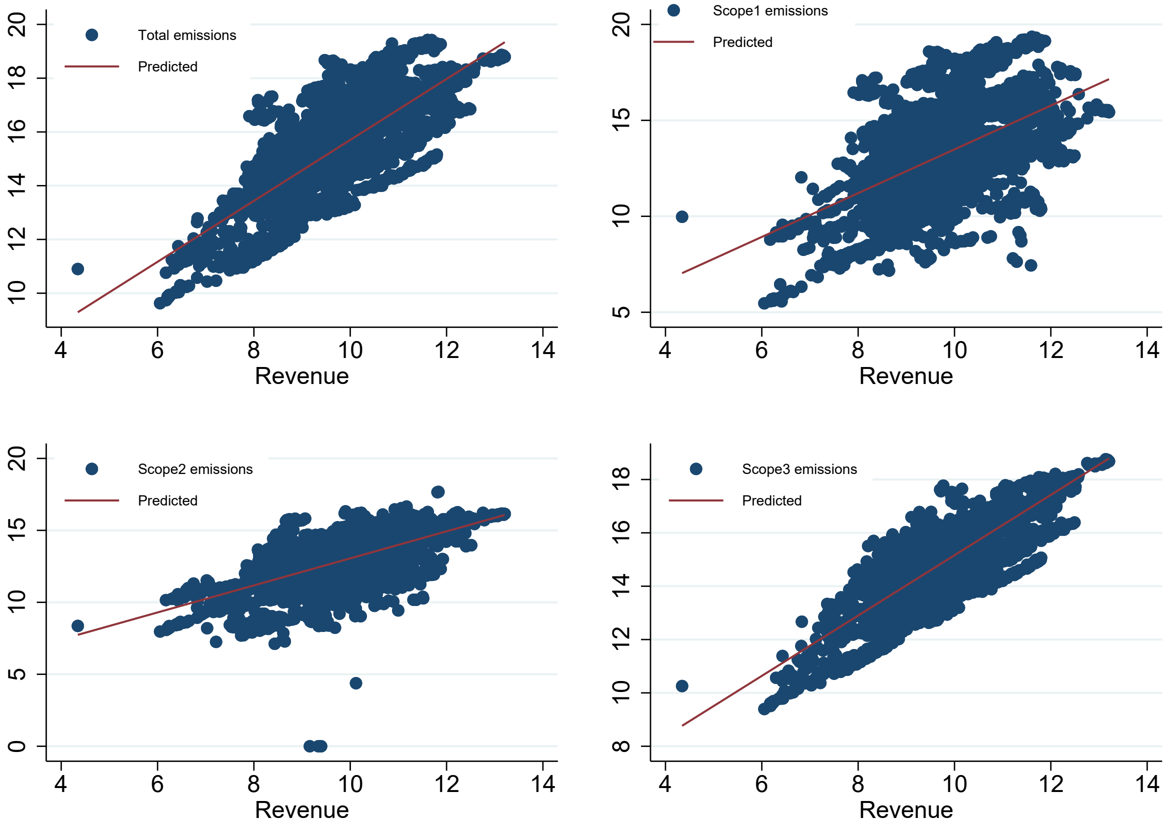
Zerbib, O. D. (2022). A sustainable capital asset pricing model (S-CAPM): Evidence from environmental integration and sin stock exclusion. Proceedings of Paris December 2020 Finance Meeting EUROFIDAI - ESSEC.

Figure 1: Carbon emissions and CDS spread in Japan: Time series



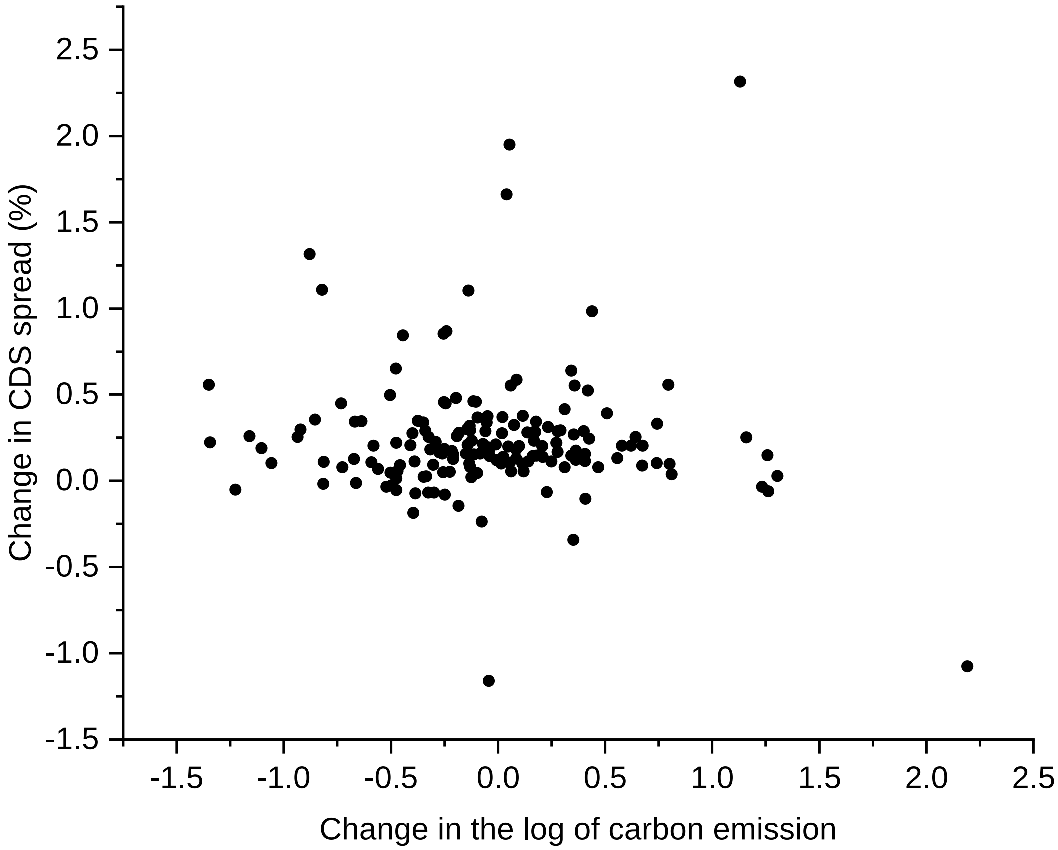
Notes: Figure 1 plots the firm-level average of the Scope 1, Scope 2, and Scope 3 carbon emissions (tonnes CO_2e) against the CDS spread (%). Observations span the years 2005–2019.

Figure 2: Carbon emissions and the revenue size



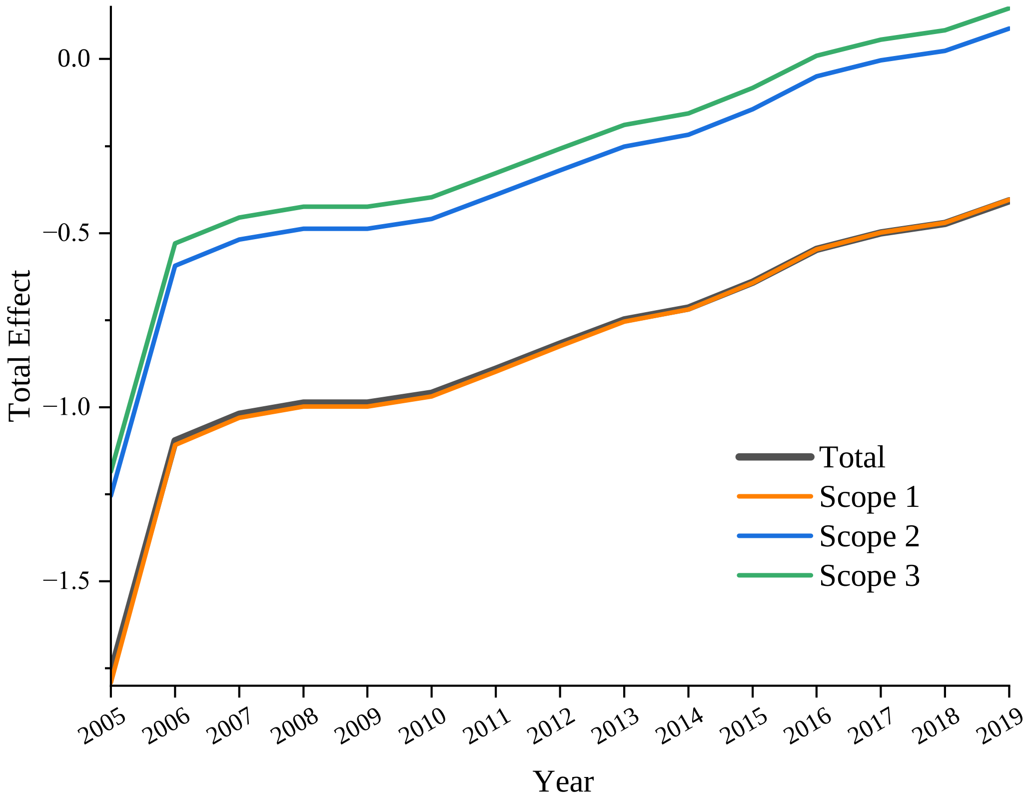
Notes: Figure 2 plots the firm's revenue against the total, Scope 1, Scope 2, and Scope 3 carbon emissions (tonnes CO2e) along with the linear predicted emissions (red line). All level values of firm's revenue and emissions are transformed using the inverse hyperbolic sine.

Figure 3: Carbon emissions and CDS spread in Japan: Variations



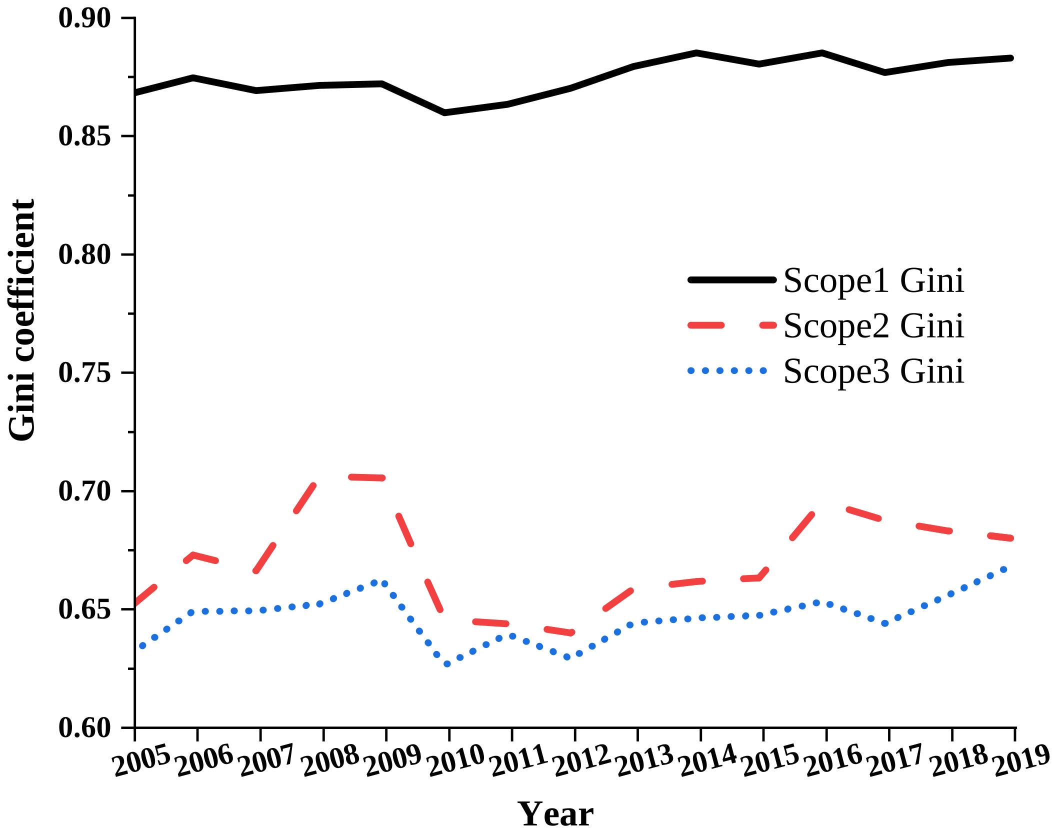
Notes: Figure 3 plots the difference of the log of the corporate carbon emissions (the sum of Scopes 1–3) against the difference of the CDS spreads in 2005 and 2019.

Figure 4: Total impacts of the fractional rank of carbon emissions on the CDS spreads



Notes: Figure 4 plots the total impacts of the fractional rank of carbon emissions on the CDS spreads based on Equation (4).

Figure A1: Gini coefficient for carbon emissions in Japan



Notes: Figure A1 displays the Gini coefficient for corporate Scope 1, Scope 2, and Scope 3 emissions in our CDS sample over the period 2005–2019.

Table 1: Descriptive statistics

		Mean	Std. Dev.	Min	Max	N/n/$\bar{T}$
CDS spread (%)	overall	0.86	2.38	0.04	97.75	3237.00
	between	.	1.47	0.11	19.51	310.00
	within	.	1.95	-18.26	79.10	10.44
Scope 1 (tonnes CO2e)	overall	4050076.39	12685983.92	117.94	1.27e+08	3237.00
	between	.	10962883.09	172.69	1.01e+08	310.00
	within	.	2165230.28	-2.27e+07	30702975.05	10.44
Scope 2 (tonnes CO2e)	overall	575211.34	1103829.31	0.00	23773922.00	3237.00
	between	.	812089.35	705.62	5521538.91	310.00
	within	.	635169.72	-3075537.91	19799959.09	10.44
Scope 3 (tonnes CO2e)	overall	3909019.37	6694630.42	6021.96	70277312.00	3237.00
	between	.	5833300.32	9042.15	60985390.13	310.00
	within	.	1532306.99	-1.46e+07	26953917.70	10.44
Total assets	overall	4.11e+09	1.66e+10	71092277.00	3.11e+11	3237.00
	between	.	1.97e+10	95840000.00	2.51e+11	310.00
	within	.	3.02e+09	-5.95e+10	6.45e+10	10.44
Capex to Revenue	overall	0.07	0.09	0.00	1.81	3237.00
	between	.	0.10	0.00	1.11	310.00
	within	.	0.05	-0.56	1.35	10.44
Debt to Capital	overall	0.56	0.46	0.00	11.97	3237.00
	between	.	0.41	0.00	3.64	310.00
	within	.	0.26	-1.00	10.58	10.44
EBIT to Revenue	overall	0.08	0.11	-1.27	0.85	3237.00
	between	.	0.09	-0.33	0.85	310.00
	within	.	0.07	-0.95	0.79	10.44
Price volatility	overall	26.22	6.99	6.88	57.90	3237.00
	between	.	6.57	7.03	46.60	310.00
	within	.	3.37	11.61	43.48	10.44
Revenue (USD mn)	overall	16584.66	24721.96	212.69	272607.72	3237.00
	between	.	21452.76	295.43	228979.66	310.00
	within	.	5664.82	-38951.41	96872.14	10.44
ROIC	overall	4.12	5.38	-62.73	63.34	3237.00
	between	.	3.23	-10.85	16.95	310.00
	within	.	4.62	-62.69	63.38	10.44

Notes: The table presents the summary statistics for the unbalanced panel data from 2005 to 2019. N, n, and $\bar{T}$ refer to the observations with firm-year data, the number of firms, and the average number of years per firm, respectively.

Table 2: Emission production function

	(1) Total	(2) Scope1	(3) Scope2	(4) Scope3
Revenue	0.736***	0.610***	0.609***	0.838***
	(0.028)	(0.072)	(0.088)	(0.027)
EBIT margin	0.009	0.031	0.005	0.005
	(0.044)	(0.138)	(0.134)	(0.033)
Debt/Capital	-0.000	-0.015	0.064	0.005
	(0.009)	(0.034)	(0.046)	(0.008)
Capex/Revenue	-0.196***	-0.626**	0.182	-0.084
	(0.075)	(0.298)	(0.224)	(0.054)
Asset	0.173***	0.323***	0.196**	0.095**
	(0.034)	(0.082)	(0.093)	(0.038)
ROIC	-0.001	-0.021**	0.007	0.007**
	(0.004)	(0.010)	(0.012)	(0.003)
Firm Fixed Effects	YES	YES	YES	YES
Observations	3324	3324	3324	3324
Adjusted R^2	0.58	0.22	0.09	0.67

$Notes$: The table presents the estimation results of Equation (2) based on carbon emissions for (1) Total, (2) Scope 1, (3) Scope 2, and (4) Scope 3 of a firm and its financial indicators. All level variables are transformed using the inverse hyperbolic sine. A year variable is included. Standard errors (SE) clustered at the firm level are in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 3: Investor pressure: Emission production function

	(1) Total	(2) Scope1	(3) Scope2	(4) Scope3
Signatory	-0.040***	0.000	-0.060***	-0.060***
	(0.004)	(0.012)	(0.021)	(0.003)
Revenue	0.744***	0.610***	0.621***	0.850***
	(0.028)	(0.072)	(0.089)	(0.027)
EBIT margin	-0.000	0.031	-0.009	-0.008
	(0.044)	(0.138)	(0.135)	(0.034)
Debt/Capital	-0.005	-0.015	0.057	-0.002
	(0.011)	(0.034)	(0.043)	(0.008)
Capex/Revenue	-0.170**	-0.626**	0.221	-0.045
	(0.071)	(0.300)	(0.230)	(0.050)
Asset	0.175***	0.323***	0.198**	0.097***
	(0.034)	(0.082)	(0.092)	(0.037)
ROIC	-0.001	-0.021**	0.006	0.006**
	(0.004)	(0.010)	(0.012)	(0.003)
Firm Fixed Effects	YES	YES	YES	YES
Observations	3324	3324	3324	3324
Adjusted R^2	0.59	0.22	0.09	0.69

Notes: The table presents the estimation results of Equation (3) based on carbon emissions for (1) Total, (2) Scope 1, (3) Scope 2, and (4) Scope 3 of a firm, its financial indicators, and the number of signatory to the PRI in Japan. All level variables are transformed using the inverse hyperbolic sine. A year variable is included. Standard errors (SE) clustered at the firm level are in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 4: Investor pressure by credit quality: Emission production function

	Investment-grade				Speculative-grade			
	Total	Scope1	Scope2	Scope3	Total	Scope1	Scope2	Scope3
Signatory	-0.045***	-0.006	-0.074***	-0.062***	-0.017	0.018	0.046	-0.053***
	(0.005)	(0.014)	(0.029)	(0.003)	(0.014)	(0.044)	(0.050)	(0.011)
Revenue	0.743***	0.587***	0.590***	0.864***	0.742***	0.820***	0.788***	0.804***
	(0.030)	(0.078)	(0.090)	(0.033)	(0.055)	(0.132)	(0.230)	(0.031)
EBIT margin	0.001	0.066	-0.074	-0.018	0.016	0.329	0.449	0.041
	(0.040)	(0.109)	(0.130)	(0.032)	(0.091)	(0.420)	(0.351)	(0.082)
Debt/Capital	-0.005	-0.014	0.066	0.003	-0.006	0.035	-0.059	-0.023
	(0.012)	(0.030)	(0.045)	(0.008)	(0.025)	(0.079)	(0.075)	(0.016)
Capex/Revenue	-0.157**	-0.620*	0.235	-0.047	-0.546**	-0.796*	-1.387	-0.141
	(0.070)	(0.318)	(0.207)	(0.051)	(0.240)	(0.435)	(1.612)	(0.145)
Asset	0.182***	0.346***	0.248**	0.087**	0.141**	0.189	-0.212	0.096
	(0.037)	(0.086)	(0.100)	(0.040)	(0.063)	(0.176)	(0.271)	(0.070)
ROIC	-0.002	-0.022**	0.008	0.007**	-0.008	-0.062***	-0.047	-0.003
	(0.004)	(0.010)	(0.014)	(0.003)	(0.008)	(0.023)	(0.029)	(0.005)
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2704	2704	2704	2704	571	571	571	571
Adjusted R^2	0.57	0.21	0.09	0.66	0.62	0.26	0.18	0.72

$Notes$: The table presents the estimation results of Equation (3) by firm's credit quality levels. The first four columns present results on carbon emission for Total, Scope 1, Scope 2, and Scope 3 of a firm, its financial indicators, and the number of signatory to PRI in Japan for firms whose credit quality is in investment-grade, while the last four columns for firms whose credit quality is in speculative-grade. All level variables are transformed using the inverse hyperbolic sine. A year variable is included. Standard errors (SE) clustered at the firm level are in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 5: CDS and carbon emissions

	(1) Total	(2) Scope1	(3) Scope2	(4) Scope3
Fractional rank	-1.764***	-1.791***	-1.254***	-1.185***
	(0.419)	(0.274)	(0.186)	(0.390)
Fractional rank × signatory	0.268***	0.274***	0.265***	0.263***
	(0.018)	(0.018)	(0.018)	(0.018)
AAA rating	-0.279***	-0.273***	-0.269***	-0.280***
	(0.092)	(0.091)	(0.090)	(0.093)
AA rating	-0.226***	-0.226***	-0.231***	-0.230***
	(0.051)	(0.051)	(0.050)	(0.050)
A rating	-0.125***	-0.128***	-0.128***	-0.126***
	(0.035)	(0.035)	(0.035)	(0.035)
Illiquidity	0.055***	0.055***	0.055***	0.055***
	(0.008)	(0.008)	(0.008)	(0.008)
EPS	-0.000*	-0.000*	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
EBIT margin	-0.539**	-0.523**	-0.614**	-0.546**
	(0.255)	(0.252)	(0.274)	(0.261)
Debt/Capital	0.098*	0.105*	0.099*	0.093*
	(0.057)	(0.056)	(0.058)	(0.056)
Capex/Revenue	-0.292	-0.323	-0.207	-0.281
	(0.222)	(0.230)	(0.222)	(0.221)
ROIC	-0.085***	-0.084***	-0.083***	-0.088***
	(0.015)	(0.015)	(0.015)	(0.015)
Price volatility	0.026***	0.026***	0.032***	0.028***
	(0.005)	(0.005)	(0.005)	(0.005)
Δ GDP	-0.093***	-0.092***	-0.090***	-0.091***
	(0.004)	(0.004)	(0.004)	(0.004)
Δ CPI	0.103***	0.102***	0.108***	0.105***
	(0.009)	(0.009)	(0.009)	(0.009)
Firm Fixed Effects	YES	YES	YES	YES
Observations	3233	3233	3233	3233
Adjusted R^2	0.28	0.28	0.27	0.27

Notes: The table presents the estimation results of Equation (4) based on fractional rank calculated from carbon emissions for (1) Total, (2) Scope 1, (3) Scope 2, and (4) Scope 3, rating dummies, and financial indicators. Baseline rating category is below BBB. All level variables are transformed using the inverse hyperbolic sine. Standard errors (SE) clustered at the firm level are in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 6: Sectoral impact of carbon emissions on CDS

	(1) Total	(2) Scope1	(3) Scope2	(4) Scope3
Fractional rank	-1.844***	-1.930***	-1.304***	-1.224***
	(0.432)	(0.296)	(0.198)	(0.406)
Fractional rank $\times$ *Signatories*				
Basic Materials	0.237***	0.234***	0.228***	0.245***
	(0.038)	(0.035)	(0.036)	(0.041)
Consumer Goods	0.288***	0.317***	0.290***	0.265***
	(0.037)	(0.038)	(0.032)	(0.031)
Consumer Services	0.266***	0.258***	0.231***	0.257***
	(0.053)	(0.049)	(0.037)	(0.051)
Energy	0.207***	0.203***	0.183***	0.195***
	(0.049)	(0.051)	(0.062)	(0.040)
Financials	0.312***	0.295***	0.237***	0.298***
	(0.096)	(0.108)	(0.056)	(0.088)
Healthcare	0.648***	0.730***	0.666***	0.561**
	(0.232)	(0.273)	(0.159)	(0.224)
Industrials	0.267***	0.282***	0.271***	0.256***
	(0.035)	(0.036)	(0.036)	(0.036)
Technology	0.342***	0.389***	0.286***	0.320***
	(0.080)	(0.097)	(0.070)	(0.074)
Telecommunications Services	0.374***	0.401***	0.328***	0.351***
	(0.071)	(0.072)	(0.057)	(0.052)
Utilities	0.240***	0.238***	0.331***	0.267***
	(0.021)	(0.021)	(0.059)	(0.029)
Firm Fixed Effects	YES	YES	YES	YES
Observations	3233	3233	3233	3233
Adjusted R^2	0.28	0.28	0.28	0.27

$Notes$: The table presents the estimation results of β_0 and β_k in Equation (5) based on fractional rank calculated from carbon emissions for (1) Total, (2) Scope 1, (3) Scope 2, and (4) Scope 3. We do not report the estimated coefficients of $Controls_{it}$ for brevity. All level variables are transformed using the inverse hyperbolic sine. Baseline rating category is below BBB. Firm fixed effects are included. Standard errors (SE) clustered at the firm level are in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 7: CDS and carbon emissions by credit quality

	Total		Scope1		Scope2		Scope3	
Fractional rank	-1.869***	(0.436)	-1.928***	(0.296)	-1.297***	(0.198)	-1.267***	(0.413)
Fractional rank × *Signatories*								
Speculative-grade × Basic Materials	0.264***	(0.044)	0.263***	(0.040)	0.257***	(0.040)	0.273***	(0.049)
Investment-grade × Basic Materials	0.224***	(0.039)	0.220***	(0.036)	0.215***	(0.037)	0.232***	(0.042)
Speculative-grade × Consumer Goods	0.288***	(0.045)	0.302***	(0.052)	0.286***	(0.039)	0.265***	(0.035)
Investment-grade × Consumer Goods	0.287***	(0.036)	0.320***	(0.035)	0.289***	(0.033)	0.263***	(0.033)
Speculative-grade × Consumer Services	0.434***	(0.121)	0.407***	(0.098)	0.302***	(0.075)	0.425***	(0.115)
Investment-grade × Consumer Services	0.249***	(0.052)	0.243***	(0.047)	0.216***	(0.036)	0.242***	(0.050)
Speculative-grade × Energy	0.227***	(0.055)	0.222***	(0.053)	0.202***	(0.057)	0.214***	(0.044)
Investment-grade × Energy	0.208***	(0.055)	0.208***	(0.058)	0.180***	(0.065)	0.198***	(0.045)
Speculative-grade × Financials	0.489***	(0.128)	0.477***	(0.131)	0.359***	(0.073)	0.445***	(0.120)
Investment-grade × Financials	0.289***	(0.098)	0.274***	(0.104)	0.220***	(0.059)	0.283***	(0.090)
Speculative-grade × Healthcare	0.849***	(0.182)	0.343	(0.491)	0.794*	(0.450)	0.746***	(0.101)
Investment-grade × Healthcare	0.596*	(0.359)	0.780**	(0.306)	0.654***	(0.184)	0.504	(0.337)
Speculative-grade × Industrials	0.323***	(0.040)	0.335***	(0.041)	0.315***	(0.039)	0.301***	(0.040)
Investment-grade × Industrials	0.243***	(0.035)	0.257***	(0.037)	0.248***	(0.037)	0.237***	(0.036)
Speculative-grade × Technology	0.589***	(0.080)	0.642***	(0.121)	0.447***	(0.065)	0.545***	(0.075)
Investment-grade × Technology	0.332***	(0.084)	0.371***	(0.100)	0.267***	(0.073)	0.314***	(0.077)
Speculative-grade × Telecommunications Services	0.517***	(0.066)	0.552***	(0.076)	0.407***	(0.050)	0.453***	(0.063)
Investment-grade × Telecommunications Services	0.355***	(0.066)	0.383***	(0.066)	0.314***	(0.056)	0.338***	(0.049)
Speculative-grade × Utilities	0.290***	(0.041)	0.283***	(0.039)	0.601**	(0.244)	0.342***	(0.053)
Investment-grade × Utilities	0.222***	(0.024)	0.221***	(0.024)	0.328***	(0.054)	0.245***	(0.031)
Firm Fixed Effects	YES		YES		YES		YES	
Observations	3233		3233		3233		3233	
Adjusted R^2	0.28		0.29		0.28		0.28	

$Notes$: The table presents the estimation results of β_0 and impacts of credit quality on β_k in Equation (5). We do not report the estimated coefficients of $Controls_{it}$ for brevity. The credit quality is referred as investment-grade when the firm's credit rating is above BBB, while the credit quality is referred as speculative-grade when the firm's credit rating is below BB. Firm fixed effects are included. Standard errors (SE) clustered at the firm level are in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 8: CDS and carbon emissions controlling for hard-to-abate sectors

	(1) Total	(2) Scope1	(3) Scope2	(4) Scope3
Fractional rank	-1.822***	-1.891***	-1.265***	-1.227***
	(0.429)	(0.284)	(0.186)	(0.395)
Fractional rank × Signatories				
Non-manufacturing easier-to-abate	0.334***	0.339***	0.327***	0.316***
	(0.041)	(0.040)	(0.033)	(0.037)
Manufacturing easier-to-abate	0.255***	0.303***	0.250***	0.228***
	(0.026)	(0.029)	(0.023)	(0.024)
Hard-to-abate	0.249***	0.236***	0.234***	0.276***
	(0.026)	(0.024)	(0.030)	(0.029)
Firm Fixed Effects	YES	YES	YES	YES
Observations	3233	3233	3233	3233
Adjusted R^2	0.28	0.28	0.28	0.27

$Notes$: The table presents the estimation results of β_0 and β_k in Equation (5) based on fractional rank calculated from carbon emissions for (1) Total, (2) Scope 1, (3) Scope 2, and (4) Scope 3. Firms are classified into three sectors according to GICS Sub Industry Code: Non-manufacturing easier-to-abate, Manufacturing easier-to-abate, and Hard-to-abate sectors. We do not report the estimated coefficients of $Controls_{it}$ for brevity. All level variables are transformed using the inverse hyperbolic sine. Baseline rating category is below BBB. Firm fixed effects are included. Standard errors (SE) clustered at the firm level are in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 9: Sectoral impact of carbon intensity on CDS

	(1) Total	(2) Scope1	(3) Scope2	(4) Scope3
Carbon intensity	-1.309***	-0.372***	-0.357***	-1.500***
	(0.138)	(0.038)	(0.042)	(0.311)
Carbon intensity × Signatories				
Basic Materials	0.013***	0.025***	0.037***	0.013***
	(0.004)	(0.004)	(0.006)	(0.004)
Consumer Goods	0.022***	0.040***	0.051***	0.021***
	(0.004)	(0.006)	(0.004)	(0.004)
Consumer Services	0.016***	0.032***	0.038***	0.015***
	(0.004)	(0.007)	(0.006)	(0.005)
Energy	0.018***	0.026***	0.035***	0.025
	(0.005)	(0.008)	(0.011)	(0.018)
Financials	0.017***	0.057***	0.041***	0.019***
	(0.006)	(0.016)	(0.009)	(0.007)
Healthcare	0.038***	0.058**	0.094***	0.040***
	(0.011)	(0.023)	(0.017)	(0.012)
Industrials	0.015***	0.034***	0.045***	0.016***
	(0.004)	(0.004)	(0.005)	(0.005)
Technology	0.022***	0.045***	0.052***	0.020***
	(0.006)	(0.013)	(0.010)	(0.008)
Telecommunications Services	0.034***	0.066***	0.065***	0.031***
	(0.005)	(0.008)	(0.011)	(0.006)
Utilities	0.019***	0.023***	0.078***	0.027***
	(0.003)	(0.002)	(0.013)	(0.004)
Firm Fixed Effects	YES	YES	YES	YES
Observations	3233	3233	3233	3233
Adjusted R^2	0.36	0.31	0.31	0.36

$Notes$: The table presents the estimation results of β_0 and β_k in Equation (5) based on firm-level carbon intensity in replace of fractional rank for (1) Total, (2) Scope 1, (3) Scope 2, and (4) Scope 3. We do not report the estimated coefficients of $Controls_{it}$ for brevity. All level variables are transformed using the inverse hyperbolic sine. Baseline rating category is below BBB. Firm fixed effects are included. Standard errors (SE) clustered at the firm level are in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 10: CDS spread curve and carbon emissions

	Short-term spread				Long-term spread			
	Total	Scope1	Scope2	Scope3	Total	Scope1	Scope2	Scope3
Fractional rank	-1.532***	-1.685***	-1.101***	-0.898**	-1.990***	-1.989***	-1.352***	-1.332***
	(0.474)	(0.336)	(0.212)	(0.456)	(0.401)	(0.274)	(0.190)	(0.375)
Fractional rank × *Signatories*								
Basic Materials	0.224***	0.223***	0.218***	0.227***	0.243***	0.240***	0.232***	0.253***
	(0.043)	(0.039)	(0.040)	(0.047)	(0.035)	(0.031)	(0.033)	(0.038)
Consumer Goods	0.232***	0.262***	0.238***	0.215***	0.296***	0.325***	0.295***	0.271***
	(0.042)	(0.047)	(0.038)	(0.036)	(0.034)	(0.036)	(0.029)	(0.029)
Consumer Services	0.201***	0.198***	0.182***	0.193***	0.278***	0.270***	0.241***	0.269***
	(0.051)	(0.054)	(0.039)	(0.048)	(0.050)	(0.046)	(0.035)	(0.049)
Energy	0.172***	0.174***	0.154**	0.158***	0.231***	0.223***	0.204***	0.217***
	(0.061)	(0.060)	(0.074)	(0.054)	(0.042)	(0.044)	(0.054)	(0.033)
Financials	0.160	0.151	0.165**	0.152	0.345***	0.318***	0.244***	0.329***
	(0.128)	(0.117)	(0.074)	(0.117)	(0.084)	(0.095)	(0.052)	(0.076)
Healthcare	0.718***	0.719**	0.654***	0.613***	0.650***	0.714**	0.678***	0.557**
	(0.212)	(0.284)	(0.176)	(0.212)	(0.234)	(0.280)	(0.166)	(0.223)
Industrials	0.219***	0.233***	0.229***	0.208***	0.276***	0.289***	0.279***	0.265***
	(0.040)	(0.042)	(0.041)	(0.040)	(0.032)	(0.033)	(0.033)	(0.033)
Technology	0.316***	0.365***	0.262***	0.299***	0.358***	0.405***	0.300***	0.326***
	(0.087)	(0.104)	(0.077)	(0.082)	(0.076)	(0.085)	(0.065)	(0.071)
Telecommunications Services	0.327***	0.337***	0.296***	0.309***	0.389***	0.421***	0.336***	0.360***
	(0.069)	(0.086)	(0.055)	(0.052)	(0.076)	(0.069)	(0.059)	(0.054)
Utilities	0.198***	0.198***	0.261***	0.215***	0.258***	0.253***	0.356***	0.289***
	(0.027)	(0.027)	(0.064)	(0.037)	(0.020)	(0.021)	(0.060)	(0.028)
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	3173	3173	3173	3173	3233	3233	3233	3233
Adjusted R^2	0.28	0.29	0.28	0.28	0.28	0.29	0.28	0.27

$Notes$: The table presents the estimation results of β_0 and β_k in Equation (5) using the short- and long-term CDS spreads as a dependent variable. We do not report the estimated coefficients of $Controls_{it}$ for brevity. The first four columns present effects of firm's fractional rank of Total, Scope 1, Scope 2, and Scope 3 emissions on short-term CDS spreads, while the last four columns present those on long-term CDS spreads. Firm fixed effects are included. Standard errors (SE) clustered at the firm level are in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 11: Slope of CDS spread curve and carbon emission

	(1) Total	(2) Scope1	(3) Scope2	(4) Scope3
Fractional rank	-2.292***	-2.013***	-1.434***	-1.672***
	(0.376)	(0.270)	(0.200)	(0.369)
Fractional rank × Signatories				
Basic Materials	0.248***	0.249***	0.229***	0.257***
	(0.035)	(0.033)	(0.037)	(0.037)
Consumer Goods	0.323***	0.348***	0.313***	0.296***
	(0.035)	(0.036)	(0.029)	(0.030)
Consumer Services	0.330***	0.307***	0.279***	0.319***
	(0.062)	(0.049)	(0.041)	(0.062)
Energy	0.239***	0.227***	0.195***	0.228***
	(0.043)	(0.048)	(0.061)	(0.032)
Financials	0.482***	0.545***	0.267***	0.417***
	(0.090)	(0.093)	(0.078)	(0.092)
Healthcare	0.524	0.710**	0.727***	0.485
	(0.348)	(0.297)	(0.185)	(0.331)
Industrials	0.290***	0.304***	0.283***	0.274***
	(0.040)	(0.037)	(0.043)	(0.045)
Technology	0.340***	0.382***	0.289***	0.292***
	(0.073)	(0.072)	(0.063)	(0.069)
Telecommunications Services	0.345***	0.366***	0.291***	0.308***
	(0.058)	(0.051)	(0.050)	(0.051)
Utilities	0.345***	0.333***	0.518***	0.394***
	(0.033)	(0.031)	(0.062)	(0.042)
Firm Fixed Effects	YES	YES	YES	YES
Observations	3173	3173	3173	3173
Adjusted R^2	0.24	0.24	0.23	0.23

$Notes$: The table presents the estimation results of β_0 and β_k in Equation (5) using the slope as dependent variable. We do not report the estimated coefficients of $Controls_{it}$ for brevity. Firm fixed effects are included. Standard errors (SE) clustered at the firm level are in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10%.