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SASAKI, Takafumi
Chuo University

USHIJIMA, Tatsuo
Keio University

Research Institute of Economy, Trade & Industry, IAA

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Takafumi SASAKI
Chuo University
Tatsuo USHIJIMA
Keio University

Abstract

Achieving the Paris Agreement's goals requires substantial decarbonization investments by companies. This paper investigates the impact of corporate industrial diversification on environmental performance by focusing on the role of cash flow coinsurance. Corporate diversification may ease financing constraints and promote decarbonization investments by facilitating external financing and reallocating resources through internal capital markets across segments. Using a sample of Japanese firms from 2006 to 2019, we find that corporate diversification mitigates carbon intensity, especially among diversified firms with low cash flow correlation among business segments (high coinsurance). The relationship between coinsurance and carbon intensity is particularly evident among firms operating in carbon-intensive industries and during the period following the Paris Agreement. We also find that cash flow coinsurance does not significantly impact Scope 2 emissions but that it has a significant impact on Scope 1 emissions, for which large investments are required. Our results suggest that industrial diversification lowers carbon intensity by mitigating the financing constraints associated with decarbonization projects.

Keywords: corporate diversification, coinsurance, internal capital markets, decarbonization
JEL classification: G32, Q54, L25

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1. Introduction

Climate change is one of the most important challenges in modern society, and trillions of dollars are required yearly to achieve the goal set by the Paris Agreement. According to the climate policy initiative (2023), the current annual level of climate finance has reached 1.3 trillion dollars, which has doubled in the past years. However, this level is far below the required amount of climate finance to achieve the net-zero target specified in the Paris Agreement. Climate Policy Initiative (2023) estimates that annual climate finance needed through 2030 will increase from $8.1 to $9 trillion annually. Other institutions also estimate that the total amount invested in establishing the zero-emission target until 2050 amounts to 100 trillion dollars or more (McKinsey & Company, 2021; BloombergNEF, 2024).

To address climate change, firms must make large amounts of decarbonization investment, including R&D investment to develop green innovation and capital expenditure to replace fixed assets. For example, Nippon Steel, the largest steel company in Japan, is planning to invest at least 400 billion yen in R&D and 4-5 trillion yen in capital expenditure to replace existing fixed assets. Given the huge amount of money required to achieve the net zero emission target, even large companies face difficulties financing investment opportunities for decarbonization.

A considerable amount of external finance, including green bonds, is required to finance investment in combating climate change. Extant research investigates the impact of external financing on decarbonization investment. Green bonds can mitigate financing constraints associated with decarbonization investment mainly through two channels: greenium and duration matching.[1] Regardless of the mixed results for greenium and duration

[1] Investors incur lower costs to firms issuing green bonds (GB) because the carbon risk of these firms may be lower than other firms. In addition, investors' preference for corporate environmental performance may also decrease the costs of issuing green bonds. Consistent with these arguments, several studies find lower financing costs (greenium) for GB issuance. Wang et al. (2020) provide

mismatch, many studies find that issuing green bond improves corporate carbon performance (Cheng and Wu, 2024, Flammer, 2021, Wang et al., 2022b, Wang et al., 2023).[2] These results suggest that external green financing enhances decarbonization mainly through mitigating financing constraints.

On the other hand, few studies focus on the role of internal cash flows in decarbonization investment. Lee et al. (2023) show that firms with high climate risk save more cash from cash flows (cash flow sensitivity of cash). Noailly and Smeets (2022) show that innovation for decarbonization faces more severe financing constraints than other innovation projects. However, to our knowledge, no paper has investigated the role of internal capital markets and coinsurance effects among diversified firms on financing decarbonization investment. We fill this gap by investigating the impact of corporate diversification on corporate environmental performance by paying attention to carbon performance.

Corporate diversification can support decarbonization investment through two mechanisms. First, diversification stabilizes a firm's overall cash flow by balancing cash flow fluctuations across segments, enhancing its capacity for external financing, such as issuing green bonds. Second, internal capital markets within diversified firms allow cash-rich segments to fund decarbonization investment opportunities in other segments with fewer cash

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evidence consistent with this greenium argument. However, other studies do not find significant differences in yield between green bonds and ordinary debt (Flammer, 2021, Larcker and Watt, 2020, Tang and Zhang, 2020, Zerbib, 2019). On the other hand, issuing green bonds may mitigate the mismatch in duration between invested assets and liabilities (Cheng and Wu, 2024, Li et al., 2023). As discussed before, decarbonization projects are long-term projects in that it will take several years or more to gain a return from decarbonization projects. GBs are suitable for financing them because their duration might be longer than that of ordinary debt. However, several studies find that the maturity of green bonds is not substantially different from that of ordinary bonds (Zerbib, 2019).

[2] Issuing green bonds may also enhance decarbonization because doing so can be a commitment to engage in decarbonization investment. Flammer (2021) finds that corporate environmental performance improves after green bond issuance.

resources, facilitating decarbonization. Thus, we expect that diversified firms, especially those with low correlation among segment cash flows, can reduce carbon intensity.

We verify this hypothesis by empirically examining the impact of corporate diversification on corporate environmental performance by using a sample of Japanese firms from 2006 to 2019. The merits of analyzing Japanese companies are as follows. First, since the Great East Japan Earthquake in 2011, Japan's dependence on fossil fuels has increased, making efforts toward decarbonization particularly crucial for Japanese companies. Second, because the manufacturing industry comprises a large portion in the Japanese economy, reducing greenhouse gas emissions in manufacturing processes and products is a significant management issue. Third, the high proportion of diversified firms presents a unique opportunity to analyze the impact of financing within diversified firms on decarbonization investments.

We find that diversification reduces carbon intensity, defined as the ratio of greenhouse emissions from scope 1 & 2 divided by total revenues. Importantly, among diversified firms, low cash flow correlation among segments within a firm (high cash flow coinsurance) decreases carbon intensity significantly. These results remain significant in regressions addressing the endogeneity of diversification variables and self-selection concerns.

To provide further evidence on our hypotheses, we compare the impact of coinsurance on carbon intensity between cases in which firms are more (versus less) likely to face financing constraints associated with decarbonization investment. We find that the impacts of cash flow coinsurance on carbon intensity are particularly found among firms in carbon-intensive industries, and in the post-Paris Agreement period. We also find that cash flow coinsurance significantly affects Scope 1 emissions, whose reduction requires substantial investment, but not Scope 2 emissions, which can be reduced without such investment. In addition, we find that cash flow coinsurance reduces carbon intensity only when firms have an environmental or CSR committee, suggesting that firms deliberately use the financing slack created by coinsurance to lower carbon intensity. Overall, our results suggest that coinsurance mitigates carbon intensity mainly through mitigating financing constraints associated with decarbonization projects.

This paper brings several contributions to the literature. First, this paper contributes to the literature investigating the impact of financing constraints on improving corporate environmental performance, especially on carbon performance. Whereas extant studies mainly focus on the role of external climate finance, such as green bonds, we also focus on the role of internal cash flows. Our evidence suggests that corporate diversification can improve corporate environmental performance through more debt capacity and enhanced internal capital markets.

Second, this paper contributes to the literature investigating the relationship between corporate diversification and social performance. Although previous studies found a positive relationship between corporate diversification and social performance (Kang, 2013, Attig et al., 2016), little is known about the impact of corporate diversification on environmental performance. We show that corporate diversification may improve corporate environmental performance.

Finally, this paper is also related to the literature investigating the link between corporate diversification and corporate value. Given that recent studies show that investors demand higher risk premium for high carbon emission firms (Bolton and Kacperczyk, 2021, 2023, Huynh et al., 2020, Kim et al., 2015, Pastor et al., 2022), our results indirectly suggest that corporate diversification may increase corporate value when investors incorporate carbon risk in evaluating share prices.

The remainder of the paper is structured as follows. Section 2 briefly reviews the literature and develops hypotheses. Section 3 describes the data and methodology used. Section 4 presents the empirical results, and Section 5 concludes.

2. Literature and hypotheses

2.1 Characteristics of decarbonization investment

Investment in decarbonization has several characteristics that should be considered when financing projects. First, as discussed in the introduction section, the amount of money required to establish net zero emission is so huge that even firms less likely to face financing constraints in financing ordinary projects may face severe financing constraints to finance projects to reduce GHG emissions. Thus, for firms to reduce GHG emissions substantially, using various sources of money including government subsidies, is crucial (Aghion et al., 2023, Xiang et al., 2022). The role of governments in promoting climate finance is important to help firms enhance decarbonization (Huang et al., 2022, Wang et al., 2022). Second, projects aimed at decarbonization require long-term investment (Bhutta et al., 2020, Lee and Min, 2015, Noailly and Smeets, 2022, Owen et al., 2018, Xiang et al., 2022). Relatedly, it should also be noted that green innovation takes several years to contribute to the company's profits (Rezende et al., 2019). Third, returns from these projects are very uncertain (Bhutta, 2020, Xiang et al., 2022). This is especially the case with initial investment for decarbonization, in which R&D investment constitutes the majority of investment. It is well known that returns from R&D investment are associated with higher uncertainty than capital expenditures (Hall, 2002). Some studies even argue that R&D for green innovation has higher uncertainty than other types of R&D projects (Noailly and Smeets, 2022; Restrepo and Uribe, 2023). In addition, returns from capital investment on decarbonization might be riskier than ordinary capital investment because technological changes affect the availability of newly installed equipment.

2.2 Hypotheses development

Corporate diversification may enhance decarbonization investment in three ways.

First, diversification in general makes the firm's overall cash flow more stable, which in turn enhances its external financing capacity (the "more money effect" as discussed in Stein, 2003). This effect is particularly important for decarbonization investment because long-term debt financing, such as issuing green bonds, plays a crucial role in funding investment opportunities to reduce GHG emissions. Second, internal capital markets within a diversified firm facilitate the financing of investment opportunities in segments that lack sufficient cash flow (the "smarter money effect" as discussed in Stein, 2003). This effect can be especially beneficial for decarbonization investment when some segments have opportunities to advance decarbonization but lack the necessary cash flows.

H1: Industrial diversification decreases carbon intensity by alleviating financing constraints associated with decarbonization investment.

The two aforementioned mechanisms will effectively work, especially when correlations among segment cash flows are low. The more money effect of diversification will be especially effective among those diversified firms. The lower the correlations among segment cash flows, the more stable the overall cash flows, and, as a result of this, firms will have easier access to issuing green bonds. Furthermore, low correlations among segment cash flows would increase the opportunities for internal capital markets to work. Thus, we expect that the carbon performance of diversified companies improves when the coinsurance effect of segment cashflows is high (i.e., correlations among segment cash flows are low).

H2: Cash flow coinsurance mitigates carbon intensity by enhancing internal capital market efficiency and easing financing constraints for decarbonization investment.

3. Methodology and data

3.1 Methodology and variables

We estimate the following regression to verify whether industrial diversification improves corporate environmental performance, with an emphasis on carbon performance.

$$CEP_{it} = \alpha + \beta_1 DIVVAR_{it} + \beta_2 ROA_{it} + \beta_3 Size_{it} + \beta_4 BM_{it}$$
$$+ \beta_5 Fsales_{it} + \beta_6 Lev_{it} + \beta_7 Inst_{it} + \gamma_j + \delta_t + \varepsilon_{it},$$

where, CEP denote corporate environmental performance. As our main dependent variable, we use carbon intensity, defined as the sum of direct greenhouse gas emissions (Scope 1) and indirect GHG emissions associated with energy consumption (Scope 2), scaled by total revenue. This data is provided by Toyo-Keizai. As a robustness test, we also use emission data from CDP (formerly, Carbon Disclosure Project).

As for diversification variable (DIVVAR), we use two variables. The first one is diversification dummy (Diversification), a binary variable indicating whether a firm operates multiple segments with distinct primary industries (JSIC 4-digit level). The second one, which is a more appropriate proxy to verify our hypothesis regarding financing constraints, we use the coinsurance measure of cash flows (cfcoins) developed by Duchin (2010) and Tong (2012). This is a measure of inter-segment risk reduction, calculated using the standard deviation and correlation of segmental cash flows.

$$\mathrm{cfcoins_{it}} = \sqrt{\sum_j \sum_k \mathrm{w_j w_k} \sigma(\mathrm{x})_\mathrm{j} \sigma(\mathrm{x})_\mathrm{k}} - \sqrt{\sum_j \sum_k \mathrm{w_j w_k} \rho(\mathrm{x})_\mathrm{jk} \sigma(\mathrm{x})_\mathrm{j} \sigma(\mathrm{x})_\mathrm{k}}$$

The second term on the right-hand side denotes the SD of a firm's cash flow when it operates in industry j, with sales-weight ww_{jt}. The first term is the SD when the firm's industries are fully synchronized in cash flow fluctuations (i.e., $\rho = 1$ for all j and k). Thus, the difference between these terms estimates a reduction in SD because of the imperfect correlation of industry cash flow. For focused firms, this is zero by construction. As the estimate of σ , we use the ten-year SD of focused firms' average EBITDA/sales in [t-10, t-1] for each 3-digit industry. ρ is estimated as the correlation of this ratio during the same ten-year interval. Higher values indicate a greater ability to stabilize performance through diversification.

Following Kang (2013) and Attig et al. (2016), we include several control variables that may affect corporate environmental performance. Return on assets (ROA) is defined as operating income divided by total assets. Firm size (Size) is the logarithm of total assets, and book-to-market ratio (BM) is calculated as the book value of equity divided by the market value of it. We expect that firms with high ROA have plentiful cashflows to finance decarbonization investment opportunities. We also expect that large firms and low book-to-market ratio firms are more likely to have enough access to finance decarbonization projects. In addition, we include the percentage of foreign sales (fsales) as a control variable. Attig et al. (2016) state that international diversification improves corporate social performance. We also consider financial leverage (lev) as a covariate because existing debt may deter firms from taking decarbonization projects as argued in Myers (1977). However, it should be noted that financial leverage can be a bad control in that it might be an outcome of diversification. Therefore, we estimate the regression with and without leverage (Lev) to confirm the robustness of our results. We also include industry fixed effects (γ_j) and year fixed effects (δ_t). We do not include firm fixed effects because most of the variation of diversification variables and carbon intensity comes from cross-sectional dimensions, and time-series variation of carbon intensity may reflect measurement error of GHG emissions. The definitions of variables are summarized in Table 1.

3.2 Data

Our sample firms consist of non-financial listed firms on the Tokyo Stock Exchange between 2006 and 2019. We require observations to have non-missing data for diversification dummy, firm size, book-to-market ratio, return on assets, and leverage. We collect data required for the estimation from the following databases. As for GHG emission data, we employ two sources, Toyo-Keizai data (CSR-Kigyo-Souran) and CDP data (formerly, Carbon Disclosure Project). Toyo-Keizai is one of the leading publishing companies in Japan and its CSR database covers a wide range of Japanese firms. In the editions published in 2019, the number of firms included in this database is 1593. This mitigates the self-selection concerns for the availability of emission data. Also importantly, Toyo-Keizai database collect emissions data directly from companies. Busch et al. (2022) argue that emission data estimated by third-parties are less consistent as compared to data collected from corporate reports. We also use GHG emission data from CDP, which is used in many previous studies to confirm the robustness of our findings. We drop observations where greenhouse gas emissions data cannot be obtained from either Toyo Keizai or CDP data. To measure the industrial scope of these firms, we obtain industry segment data from the Nikkei NEEDS Financial Quest database. Nikkei assigns up to three Japan Standard Industry Classification (JSIC) codes to each segment. When a segment has multiple JSIC codes, we define the industry based on its primary code. We exclude firms with a financial segment (JSIC 6111-6759) or an unclassifiable segment (JSIC 9999) and firms with irregular reporting, such as negative equity and accounting period less than twelve months. We also exclude firms when the sum of segmental sales (assets) deviates from firm sales (assets) by 5% (25%) or more. When the magnitude of deviation is less than this cutoff level, we adjust the value of each segment by the same percentage such that the sum of the segmental values matches the value of the entire firm. Financial data is also collected from Nikkei Financial Quest.

Table 2 presents the descriptive statistics of our sample. The average of the diversification dummy (diversification) is 0.76, indicating that the majority of our sample consists of diversified firms. GHG emission data from Toyo-keizai (ghg_ems12_toyo) is available for the majority of the sample whereas that from CDP (ghg_ems12_cdp) is small.[3] This is because low annual coverage in each year and our CDP data is available from fiscal year 2012 onward. This table also reports the statistics for Scope 1 and Scope 2 emissions from CDP data. The standard deviation of Scope 1 emissions is significantly larger than Scope 2 emissions. The ownership ratio of domestic institutional investors is only available from 2016 onward, resulting in a smaller sample size. To mitigate the influence of outliers, all continuous used in regressions are winsorized at the top and bottom 1%.

4. Empirical results

4.1 Basic regression

Table 3 presents the results of regressions in which we use diversification dummy (diversification) as the main explanatory variable. We first check the estimated results of the basic control variables to confirm the validity of our model. The coefficients on BM are positive and statistically significant, suggesting that firms with lower market valuations face tighter financing constraints, which hinder decarbonization investment. On the other hand, the coefficients on firm size (Size) are positive and statistically significant. Although large firms are less likely to face financing constraints, the results here indicate that firms with large production facilities tend to have higher carbon intensity. The coefficients on ROA are not statistically significant. The coefficients on foreign sales ratio (Fsales) are negative as expected, but they are not statistically significant in most specifications. The coefficients on shareholdings by institutional investors (Inst) are negative as expected but are not statistically

[3] This is partly because our CDP data is available from fiscal year 2012.

significant, although the number of observations is quite small because of data restriction.

Next, we examine the impact of the diversification dummy (diversification) on carbon intensity. In the estimation with basic control variables (Column 1), the coefficient is negative and statistically significant at the 5% level. When we exclude leverage (Column 2), the coefficient remains negative and statistically significant at the 10% level. Column 3 presents the results excluding the foreign sales ratio, which may be the outcome of industrial diversification. In this case, the coefficient on the diversification dummy remains negative and statistically significant, similar to Column 1. Columns 4 and 5 include additional control variables: the R&D investment ratio (RD) and the standard deviation of ROA (std_ROA), respectively. While these variables could be considered bad controls, we include these variables because differences in risk-taking may influence both corporate diversification and carbon intensity. Even in these specifications, the coefficient on the diversification dummy remains negative and significant. Finally, we also conduct an estimation using the ownership ratio of domestic institutional investors (Column 6). Despite the significant reduction in sample size, the coefficient on the diversification dummy remains negative but is no longer statistically significant.

It should be noted that the results regarding the diversification dummy in Table 3 may reflect mechanisms other than financing constraints, such as operational or technological synergies related to emissions reduction. To more closely align with the underlying logic of our hypothesis, we use cash flow coinsurance (cfcoins) defined in the previous section, as our primary explanatory variable.

Table 4 presents the estimation results of regressions in which we use cash flow coinsurance (cfcoins) instead of diversification dummy. The results for control variables are similar to those reported in Table 3 except that Fsales has negative and statistically significant coefficients. This result is consistent with the findings of Attig et al. (2016) for overall corporate social performance and suggests that international diversification mitigates carbon intensity.

The coefficients on cfcoins are negative and statistically significant, suggesting that low correlations among segment cash flows reduce carbon intensity. The results are robust to the choice of control variables. The results for cash flow coinsurance are consistent with our hypothesis and suggest that enhanced debt capacity or internal capital markets among firms with high coinsurance effects enable firms to finance investment opportunities to reduce GHG emissions. The results related to cash flow coinsurance are clearer than those for diversification. This suggests that among functions associated with diversification, enhanced financing abilities due to cash flow coinsurance mitigate financing constraints to exploit decarbonization projects.

4.2 Remaining diversified firms

Next, we consider the impact of endogeneity. The results of the previous analysis may be subject to endogeneity issues through two potential channels. The first is reverse causality. Carbon intensity may influence corporate portfolio decisions. For instance, firms with high carbon intensity may seek to enter new businesses as a strategy to adapt to a decarbonized society. Additionally, unobserved firm characteristics could affect both carbon intensity and diversification. For example, managerial risk attitudes may influence decarbonization efforts and diversification strategies simultaneously. Similarly, long-term managerial thinking could play a role in these decisions.

We first address the endogeneity issue by estimating the regressions by confining the sample firms to those remain diversified throughout the sample period. Since these firms do not change their diversification decisions in the sample period, they are less likely influenced by the reverse causality of omitted variable issue. Table 5 presents the results. The coefficients on cfcoins are negative and statistically significant in all specifications. These results confirm the negative association between cash flow coinsurance and carbon intensity among diversified firms.

4.3 Impacts of the Paris Agreement

Next, we address the endogeneity issue by utilizing exogenous changes in demand for decarbonization investments. This method is similar to that of Lins et al. (2017). In exploiting exogenous changes in corporate values associated with the 2008 financial crisis to estimate the impact of CSR on corporate value, Lins et al. (2017) state that

"In our natural experiment, the exogenous financial shock disrupts the equilibrium, while levels of CSR remain fixed, at least in the short term. This allows us to directly observe how investors adjust their valuations of firms with differing attitudes toward CSR."

Since cash flow coinsurance exhibits limited variation over time, examining its interaction with the Paris Agreement dummy, which represents changes in investment demand, may provide a way to estimate the impact of diversification on carbon intensity. This analysis is also important from the viewpoint of practical implication in that addressing climate change risk has become one of the most important managerial issues after the Paris Agreement.

Table 6 presents the estimation results with the interaction between cash flow coinsurance and the Paris Agreement dummy that is equal to 1 after the Paris Agreement period and 0 otherwise. Although coinsurance is a variable calculated for diversified firms, we also conduct analyses using the full sample by assigning a value of zero to cfcoins for stand-alone firms. The coefficients on the interaction term are negative and statistically significant in three of the four specifications, suggesting that cash flow coinsurance plays an important role in reducing carbon intensity after the Paris Agreement period. As our hypothesis predicts, this can be interpreted as a suggestive evidence consistent with a causal interpretation. The results also bring an important practical implication that corporate diversification can be a good measure to address climate risk.

4.4 Carbon-intensive industries

Next, we address endogeneity concerns by conducting a subsample analysis that differentiates between cases where our hypothesis is more likely to hold and those less applicable. Specifically, we divide the sample into firms from high-carbon-intensity industries and those from low-carbon-intensity industries and perform the same analysis as before. In high-carbon-intensity industries, significant capital investment is required to reduce greenhouse gas emissions, making firms more likely to face financial constraints when investing in decarbonization.

Table 7 presents the analysis results. Looking at the results for carbon intensive industries (Panel A), the coefficients on cfcoins are negative and statistically significant and negative for high carbon-intensity industries. Given that these firms are likely to face financing constraints to alleviate carbon intensity, the results here confirm our argument that the coinsurance effect within diversified firms mitigates financial constraints related to decarbonization investments. In contrast, for firms in low carbon intensity industries (Panel B), the coefficients on coinsurance are not statistically significant. This result implies that firms in these industries are less likely to face financial constraints, as large-scale decarbonization investments are not as necessary. Overall, the fact that a clear pattern emerges only in high-carbon-intensity industries supports our hypothesis and suggests that the coinsurance effect within diversified firms may reduce financial constraints related to decarbonization through improved external financing capacity and the functioning of internal capital markets.

4.5 2SLS and selection model

To address the endogeneity issue, we next employ several econometric approaches in explaining the endogeneity of diversification decision. Specifically, we employ Two-Stage Least Squares (2SLS) and the treatment effect model of Villalonga (2004) in explaining diversification decision. As excluded instrumental variables, we use the industry-level share of diversified firms and the Herfindahl-Hirschman Index (HHI) of industry sales concentration.[4] The attractiveness of diversification within an industry is likely to influence a firm's diversification strategy. It might be that firms in industries with a higher percentage of diversified firms face fewer difficulties entering a new segment by utilizing already developed resources to produce other products. Additionally, the intensity of competition in the industry is also expected to affect the decision to diversify. Firms in competitive industries may choose to diversify in order to produce new products or services that are not subject to fierce competition. On the other hand, it is unlikely that these variables have a direct impact on carbon intensity because they capture industry-level characteristics that affect diversification decisions but are unlikely to directly influence firm-level carbon intensity. Meanwhile, in the analysis where cash flow coinsurance is the explanatory variable, we apply the Heckman (1979) self-selection model. In the first stage, we estimate the likelihood of diversification using the same excluded instruments and control variables.[5]

Panel A of Table 8 presents the analysis results examining the effect of the diversification dummy on carbon intensity. The first two columns of Panel A present the results of two-stage least squares regressions. In the first-stage regression, the coefficient on the share

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[4] It is difficult to control for differences in firm attributes using propensity score matching (PSM), because the sample is skewed towards large firms and the proportion of diversified firms in the dataset is high, accounting for approximately three-fourths of the total.

[5] It should be noted that cash flow coinsurance (c*fcoins*) is derived based on data from specialized firms, making it difficult to find a suitable instrumental variable.

of diversified firms in each industry (avg_diversification) is positive and statistically significant, suggesting that diversification decision is significantly affected by the attractiveness of diversification in the industry. On other hand, the Herfindahl-Hirschman Index of sales in each industry does not have a statistically significant coefficient. In the second-stage regression, the coefficient on the diversification dummy is negative and statistically significant, suggesting that diversification can mitigate financing constraints to invest in decarbonization projects. The results for the treatment effect model reported in the last two columns of Panel A are similar to those of the 2SLS regression with the coefficient on Lambda (inverse mills ratio) being statistically significant.

Panel B presents the results for cash flow coinsurance using the self-selection model (Heckman, 1979). We first regress diversification decision on the excluded instruments and control variables, and regress carbon intensity on cash flow coinsurance, controls, and Lambda in the second stage regression. The results for the first stage regression are similar to that of the treatment model in Panel A, although the sample size become smaller due to the availability of cash flow coinsurance. In the second stage regression, the coefficient on Lamda is statistically significant and we find a similar result for cash flow coinsurance as in Table 4. The negative and statistically significant coefficient on cfcoins suggests that low cash flow correlations among segments (high coinsurance effect) mitigate financing constraint associated with decarbonization investment. Overall, the results in Table 8 indicate that our analysis is relatively robust to the issue of endogeneity.

4.6 Motivation to reduce greenhouse gas emissions

One important question arising from our baseline results is whether the reduction in carbon intensity associated with coinsurance reflects a deliberate decarbonization strategy or an unintended byproduct of relaxed financial constraints. Firms with plentiful financial resources brought by coinsurance may use them for purposes other than decarbonization, such as ordinary investment, advertising, or payouts to shareholders. Especially, because newer capital is generally more energy-efficient than older assets, carbon intensity may decline mechanically as firms upgrade their capital stock, even in the absence of explicit environmental intentions. This raises the possibility that the observed coinsurance effect is not necessarily driven by decarbonization investment. Given that direct measures of decarbonization investment are unavailable, we conduct an additional analysis focusing on firms' motivation for decarbonization. Specifically, we focus on the presence of an Environmental or CSR Committee as a proxy for a firm's commitment to environmental initiatives. Firms with such committees are likely to have stronger incentives and organizational structures for pursuing decarbonization. We construct a dummy variable (committee) that equals one if a firm has an Environmental or CSR Committee and zero otherwise, and interact this variable with the cash flow coinsurance measure. If the coinsurance effect reduces carbon intensity only among firms with strong environmental motivation, it would suggest that coinsurance primarily alleviates financial constraints on decarbonization-related investment.

The estimation results provide evidence consistent with this interpretation. As shown in Table 9, the coefficient on the interaction term (cfcoins × committee) is negative and statistically significant across several specifications, while the standalone coefficient on cfcoins is statistically insignificant. This pattern suggests that coinsurance does not uniformly reduce carbon intensity across all firms, but its effect is concentrated among firms with an Environmental or CSR Committee. This finding is particularly evident in the diversified subsample, where the interaction term is negative and statistically significant at conventional levels. Taken together, these results support the view that coinsurance primarily alleviates financial constraints on targeted decarbonization investment, rather than broadly facilitating general capital expenditures that unintentionally reduce emissions.

4.7 Carbon emission data from CDP

Next, we verify whether our findings are robust to the choice of GHG emission data. There is a concern for GHG emission data's accuracy and consistency (Busch al., 2022). We re-estimate the regression by using GHG emission data provided by CDP, which is widely used in previous studies. Table 10 presents the result. Given that the annual coverage of CDP data is smaller than that of Toyo-Keizai data and the available period is also limited, the number of observations decreases substantially. Despite this reduction in sample size, the coefficients on cfcoins are still significant in the expected sign in the first two columns, whereas the coefficients on the interaction term become insignificant in the last two columns. The analysis results here indicate that our discussion is relatively robust to the choice of emission data.

4.8 Scope 1 emission and Scope 2 emission

Finally, we consider the difference between Scope 1 and Scope 2 emissions. Whereas evaluating Scope 1&2 emissions is common practice in ESG investing and firms have incentives to reduce these emissions to improve the evaluation of their firms from investors, there exist important differences in reducing Scope 1 emissions and Scope 2 emissions. Reducing Scope 1 emissions is a challenging task because it requires firms to replace fixed assets used in the production process or other operations within the company. On the other hand, firms can reduce Scope 2 emissions relatively easily by adopting renewable energy. Thus, if cash flow coinsurance improves corporate carbon performance by mitigating financing constraints when exploiting decarbonization investment opportunities, we expect a clearer result for Scope 1 emissions than Scope 2 emissions.

The results of Table 11 are consistent with this interpretation. Whereas the coefficients on cfcoins are negative and statistically significant for the regressions in which

Scope 1 emissions is the dependent variable (the first two columns), we do not find statistically significant results for Scope 2 emissions regression. These findings further support our argument that financing constraints are particularly relevant for capital-intensive decarbonization activities.

5. Conclusion

In this paper, we empirically analyze the impact of corporate diversification on carbon intensity, focusing on the cash flow coinsurance effect. The results indicate that firms with a high cash flow coinsurance effect (i.e., those with low correlations among segment cash flows) experience a reduction in carbon intensity. Furthermore, this effect has become more pronounced after the Paris Agreement. Our findings suggest that, in an era where substantial investments are required for decarbonization, the enhanced external financing capacity and the functioning of internal capital markets facilitated by corporate diversification play a crucial role. Our findings highlight the advantage of corporate diversification in reducing carbon emissions.

Several limitations remain to be addressed in future research. First, this study does not directly analyze investments related to decarbonization, making it unclear through which specific mechanisms corporate diversification contributes to reducing carbon intensity. Due to data constraints, conducting an analysis that clearly establishes causality is challenging, highlighting the need for further investigation into the pathways involved. Additionally, it is important to examine the extent to which the coinsurance effect influences external financing, such as the issuance of green bonds. Finally, it is also important to investigate the impact of the coinsurance effect on Scope 3 emissions, which include emissions from both upstream and downstream segments of the supply chain, because reductions in Scope 1 & 2 emissions can also be achieved through carbon leakage. These issues remain as avenues for future research.

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Table 1: Definition of Variables

Variable Name	Definition/Description
ghg_ems12	A carbon intensity score defined as the total Scope 1 & 2 greenhouse gas emissions divided by total revenue. Scope 1 emissions: Direct emissions within the company, including those associated with production processes. Scope 2 emissions: Indirect emissions from purchased energy consumption, such as electricity.
diveersification	A binary variable indicating whether a firm operates multiple segments with distinct primary industries (JSIC 4-digit level).
CF-Coinsurance	A measure of inter-segment risk reduction, calculated using the standard deviation and correlation of segmental cash flows. Correlations and standard deviations are calculated from imputed cash flows of standalone firms matched to each segment. Higher values indicate a greater ability to stabilize performance through diversification.
fsales	Defined as foreign sales divided by total revenue.
Paris	A binary variable that takes the value of 1 for years after the Paris Agreement and 0 otherwise.
lev	Defined as interest-bearing debt divided by total assets.
size	The natural logarithm of total assets.
roa	Return on assets, defined as operating income divided by total assets.
bm	The ratio of the book value of equity to the market value of equity.
RD	Defined as R&D expenditures divided by total revenue.
roa_std	Standard deviation of return on assets (roa) over the past 10 years
ind_HHI	HHI (Herfindahl-Hirschman Index) based on revenue for each industry
Inst	The percentage of shareholdings owned by domestic institutional investors.

Table 2: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
diversification	5207	.763	.425	0	1
cfcoins	4938	.001	.002	0	.025
ghg ems12 (Toyo-keizai)	5113	1.304	3.666	.001	23.061
ghg ems12 (CDP)	1132	1.372	2.9	.004	18.183
ghg ems1 (CDP)	1144	.994	2.908	0	18.146
ghg ems2 (CDP)	1138	.402	.445	.002	2.275
size	5261	12.741	1.484	7.96	15.508
bm	5261	1.01	.58	.101	3.726
lev	5261	.202	.16	0	.689
roa	5261	.054	.04	-.198	.394
fsales	5261	.299	.265	0	.837
RD	5261	.024	.027	0	.235
roa std	3530	.024	.017	.001	.207
ind HHI	5261	.092	.071	.031	.912
Inst	1834	.139	.075	0	.455

This table presents the descriptive statistics of the sample. The sample comprises non-financial firm-years listed on the Tokyo Stock Exchange (TSE) for the period 2006–2019. We winsorize all variables included in our empirical analyses at the top and bottom 1% to mitigate the influence of outliers. The variable definitions are provided in Table 1.

Table 3: Diversification Dummy and Carbon Performance

	ghg_ems12	ghg_ems12	ghg_ems12	ghg_ems12	ghg_ems12	ghg_ems12
diversification	-0.362	-0.311	-0.359	-0.360	-0.377	-0.199
	[2.15]**	[1.85]*	[2.15]**	[2.14]**	[1.72]*	[1.08]
size	0.269	0.360	0.229	0.285	0.331	0.273
	[3.31]***	[3.73]***	[3.25]***	[3.43]***	[3.29]***	[3.40]***
bm	0.487	0.321	0.497	0.463	0.709	0.414
	[2.38]**	[1.71]*	[2.39]**	[2.26]**	[2.33]**	[2.19]**
lev	4.827		4.767	4.619	5.480	5.610
	[3.85]***		[3.85]***	[3.71]***	[3.72]***	[3.48]***
roa	2.185	-4.728	1.510	2.079	0.477	3.793
	[0.84]	[2.11]**	[0.64]	[0.80]	[0.15]	[1.16]
fsales	-0.786	-0.639		-0.644	-1.281	-1.231
	[1.82]*	[1.50]		[1.50]	[2.22]**	[2.58]**
RD				-7.937		
				[2.41]**		
roa_std					19.818	
					[2.84]***	
Inst						-0.805
						[0.71]
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.56	0.54	0.56	0.56	0.59	0.58
N	4,858	4,858	4,858	4,858	3,346	1,687

This table presents OLS estimation results of regressing carbon intensity on the industrial diversification dummy along with control variables. All regressions include industry and year fixed effects. The sample comprises non-financial firm-years listed on the Tokyo Stock Exchange (TSE) for the period 2006–2019. The variable definitions are provided in Table 1. We winsorize all variables included in our empirical analyses at the top and bottom 1% to mitigate the influence of outliers. Clustered t-values at the firm level are reported in brackets. Significance levels are reported at 10% (*), 5% (**), and 1% (***).

Table 4: Co-insurance and Carbon Intensity

Panel A: All firms

	ghg_ems12	ghg_ems12	ghg_ems12	ghg_ems12	ghg_ems12	ghg_ems12
cfcoins	-194.063	-167.033	-184.748	-188.102	-282.465	-272.876
	[2.37]**	[2.00]**	[2.26]**	[2.27]**	[2.53]**	[2.94]***
size	0.359	0.442	0.309	0.376	0.432	0.375
	[3.78]***	[3.99]***	[3.76]***	[3.86]***	[3.80]***	[3.91]***
bm	0.512	0.351	0.523	0.490	0.717	0.439
	[2.41]**	[1.77]*	[2.43]**	[2.31]**	[2.27]**	[2.33]**
lev	5.280		5.205	5.069	6.134	5.899
	[4.03]***		[4.03]***	[3.89]***	[3.96]***	[3.57]***
roa	2.164	-5.231	1.375	2.063	0.140	2.042
	[0.80]	[2.22]**	[0.55]	[0.76]	[0.04]	[0.61]
fsales	-0.942	-0.775		-0.789	-1.533	-1.348
	[2.08]**	[1.73]*		[1.74]*	[2.54]**	[2.68]***
RD				-7.551		
				[2.01]**		
roa_std					18.260	
					[2.70]***	
Inst						-0.111
						[0.10]
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.54	0.51	0.54	0.54	0.58	0.58
N	4,601	4,601	4,601	4,601	3,178	1,616

Panel B: Diversified firms

	ghg_ems12	ghg_ems12	ghg_ems12	ghg_ems12	ghg_ems12	ghg_ems12
cfcoins	-221.330	-193.442	-205.783	-213.985	-330.248	-318.944
	[2.56]**	[2.19]**	[2.39]**	[2.45]**	[2.88]***	[3.15]***
size	0.442	0.573	0.377	0.457	0.533	0.383
	[3.94]***	[4.27]***	[3.74]***	[3.98]***	[3.88]***	[3.25]***
bm	0.432	0.291	0.464	0.414	0.698	0.205
	[1.65]*	[1.13]	[1.73]*	[1.58]	[1.74]*	[0.84]
lev	6.490		6.443	6.257	7.493	7.825
	[4.00]***		[3.96]***	[3.90]***	[3.89]***	[3.36]***
roa	0.853	-8.007	-0.173	0.725	-1.703	0.738
	[0.24]	[2.42]**	[0.05]	[0.21]	[0.40]	[0.15]
fsales	-1.406	-1.319		-1.196	-2.374	-1.777
	[2.43]**	[2.19]**		[2.08]**	[2.98]***	[2.71]***
RD				-9.122		
				[1.67]*		
roa_std					25.776	
					[2.61]***	
Inst						-0.796
						[0.56]
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.51	0.48	0.51	0.51	0.55	0.55
N	3,453	3,453	3,453	3,453	2,383	1,179

This table presents OLS estimation results of regressing carbon intensity on cash flow co-insurance along with control variables. All regressions include industry and year fixed effects. The sample comprises non-financial firm-years listed on the Tokyo Stock Exchange (TSE) for the period 2006–2019. The variable definitions are provided in Table 1. We winsorize all variables included in our empirical analyses at the top and bottom 1% to mitigate the influence of outliers. Clustered t-values at the firm level are reported in brackets. Significance levels are reported at 10% (*), 5% (**), and 1% (***).

Table 5: Results for Remaining Diversified Firms

	ghg_ems12	ghg_ems12	ghg_ems12	ghg_ems12	ghg_ems12	ghg_ems12
cfcoins	-276.306	-246.665	-261.104	-265.773	-376.345	-371.969
	[2.94]***	[2.56]**	[2.78]***	[2.78]***	[3.29]***	[3.39]***
size	0.506	0.666	0.424	0.521	0.587	0.381
	[4.20]***	[4.39]***	[3.94]***	[4.24]***	[4.17]***	[3.13]***
bm	0.497	0.306	0.521	0.489	0.904	0.374
	[1.51]	[0.95]	[1.56]	[1.49]	[1.81]*	[1.21]
lev	7.358		7.306	7.117	8.654	9.024
	[4.12]***		[4.08]***	[4.05]***	[4.12]***	[3.45]***
roa	1.598	-8.935	-0.044	1.580	-1.471	3.948
	[0.37]	[2.26]**	[0.01]	[0.37]	[0.29]	[0.68]
fsales	-1.697	-1.604		-1.436	-2.847	-2.138
	[2.48]**	[2.21]**		[2.12]**	[3.07]***	[2.84]***
RD				-10.820		
				[1.47]		
roa_std					38.717	
					[3.30]***	
Inst						0.140
						[0.09]
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.49	0.45	0.48	0.49	0.54	0.54
N	2,897	2,897	2,897	2,897	2,010	988

This table presents OLS estimation results of regressing carbon intensity on cash flow coinsurance for firms that remained diversified throughout the sample period. All regressions include industry and year fixed effects. The sample comprises non-financial firm-years listed on the Tokyo Stock Exchange (TSE) for the period 2006–2019. The variable definitions are provided in Table 1. We winsorize all variables included in our empirical analyses at the top and bottom 1% to mitigate the influence of outliers. Clustered t-values at the firm level are reported in brackets. Significance levels are reported at 10% (*), 5% (**), and 1% (***).

Table 6: The Impact of the Paris Agreement

	All firms		Diversified firms	
	ghg_ems12	ghg_ems12	ghg_ems12	ghg_ems12
cfcoins	-155.876	-116.055	-161.986	-122.640
	[1.74]*	[1.28]	[1.70]*	[1.26]
Paris	0.037	0.096	0.270	0.265
	[0.37]	[0.95]	[1.55]	[1.55]
cfcoins × Paris	-94.955	-127.410	-148.247	-177.473
	[1.49]	[1.83]*	[1.81]*	[2.01]**
size	0.357	0.438	0.438	0.567
	[3.77]***	[3.99]***	[3.92]***	[4.28]***
bm	0.521	0.364	0.444	0.307
	[2.43]**	[1.82]*	[1.68]*	[1.18]
lev	5.242		6.443	
	[4.05]***		[4.01]***	
roa	2.204	-5.105	0.781	-8.016
	[0.81]	[2.16]**	[0.23]	[2.43]**
fsales	-0.926	-0.755	-1.358	-1.261
	[2.07]**	[1.71]*	[2.39]**	[2.14]**
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Adjusted R2	0.54	0.52	0.51	0.48
N	4,601	4,601	3,453	3,453

This table presents OLS estimation results of regressing carbon intensity on cash flow coinsurance and its interaction with the Paris Agreement dummy, which equals 1 for the post-Paris Agreement period and 0 otherwise. In addition to the covariates shown in the table, we include industry and year fixed effects. The sample comprises non-financial firm-years listed on the Tokyo Stock Exchange (TSE) for the period 2006–2019. The variable definitions are provided in Table 1. We winsorize all variables included in our empirical analyses at the top and bottom 1% to mitigate the influence of outliers. Clustered t-values at the firm level are reported in brackets. Significance levels are reported at 10% (*), 5% (**), and 1% (***).

Table 7: Carbon-Intensive Industries

Panel A: Carbon-intensive industries

	All firms		Diversified firms	
	ghg_ems12	ghg_ems12	ghg_ems12	ghg_ems12
cfcoins	-570.332	-567.653	-528.641	-582.242
	[3.01]***	[2.53]**	[2.79]***	[2.71]***
size	1.335	1.648	1.510	1.866
	[4.38]***	[4.35]***	[4.52]***	[4.50]***
bm	1.763	1.274	1.471	0.957
	[2.33]**	[1.53]	[1.83]*	[1.05]
lev	16.466		17.227	
	[4.73]***		[4.43]***	
roa	13.400	-10.449	5.245	-21.935
	[1.24]	[0.92]	[0.40]	[1.59]
fsales	-1.921	-2.225	-2.592	-3.158
	[1.29]	[1.23]	[1.61]	[1.55]
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Adjusted R2	0.56	0.47	0.54	0.44
N	1,273	1,273	1,136	1,136

Panel B: Non-carbon-intensive industries

	All firms		Diversified firms	
	ghg_ems12	ghg_ems12	ghg_ems12	ghg_ems12
cfcoins	-12.118	-10.536	-11.094	-8.487
	[1.17]	[0.99]	[1.35]	[1.04]
size	-0.020	-0.017	-0.008	-0.002
	[1.28]	[1.10]	[0.61]	[0.16]
bm	0.050	0.043	0.008	0.001
	[1.36]	[1.22]	[0.24]	[0.02]
lev	0.215		0.334	
	[0.88]		[1.57]	
roa	-0.712	-1.005	-0.084	-0.512
	[1.08]	[1.95]*	[0.20]	[1.39]
fsales	0.076	0.087	-0.065	-0.052
	[0.61]	[0.69]	[0.65]	[0.49]
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Adjusted R2	0.10	0.10	0.22	0.21
N	3,328	3,328	2,317	2,317

This table presents OLS estimation results of regressing carbon intensity on cash flow coinsurance for firms classified in carbon-intensive industries (Panel A) and those in other industries (Panel B). All regressions include industry and year fixed effects. The sample comprises non-financial firm-years listed on the Tokyo Stock Exchange (TSE) for the period 2006–2019. The variable definitions are provided in Table 1. We winsorize all variables included in our empirical analyses at the top and bottom 1% to mitigate the influence of outliers. Clustered t-values at the firm level are reported in brackets. Significance levels are reported at 10% (*), 5% (**), and 1% (***).

Table 8: Selection models and 2SLS

Panel A: Diversification dummy

VARIABLES	(1) 2SLS 1stt diversification	(2) 2SLS 2nd ghg_ems12	(3) Treatment effect 1st diversification	(4) Treatment effect 2nd ghg_ems12
avg_diversification	0.595***		4.489***	
	(4.990)		(19.949)	
ind_HHI	-0.309		-1.457***	
	(-1.209)		(-4.457)	
size	0.0618***	0.395***	0.228***	0.343***
	(13.57)	(4.340)	(12.583)	(8.434)
lev	0.119**	5.060***	0.427**	4.901***
	(2.514)	(13.699)	(2.353)	(15.081)
bm	-0.0491***	0.385***	-0.236***	0.395***
	(-3.631)	(3.273)	(-4.736)	(4.043)
roa	-1.182***	-0.223	-4.847***	0.286
	(-6.256)	(-0.106)	(-6.701)	(0.197)
fsales	-0.00943	-0.817***	-0.168*	-0.820***
	(-0.311)	(-3.820)	(-1.916)	(-4.002)
diversification		-2.403*		-1.735***
		(-1.740)		(-3.579)
lambda				0.806***
				(2.892)
Constant	-0.170	-3.459***	-4.250***	-3.489***
	(-1.417)	(-6.143)	(-14.614)	(-6.663)
Observations	4,858	4,858	4,858	4,858
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
F-stat for weak identification		12.94		
Sargan stat		0.000955		
Prob > Sargan		0.975		
Wald chi2				6445
Prob > chi2				0.000

Panel B: CF-Coinsurance

VARIABLES	(1) Heckman 1st diversification	(2) Heckman 2nd ghg_ems12
avg_diversification	4.327***	
	(19.592)	
ind_HHI	-0.917***	
	(-2.809)	
cfcoins		-225.101***
		(-8.367)
size	0.202***	0.706***
	(11.285)	(10.699)
lev	0.540***	6.970***
	(3.030)	(14.104)
bm	-0.241***	0.102
	(-4.954)	(0.691)
roa	-5.135***	-6.199***
	(-7.203)	(-2.648)
fsales	-0.253***	-1.673***
	(-2.921)	(-5.659)
lambda		3.285***
		(5.892)
Constant	-3.931***	-9.399***
	(-13.781)	(-9.039)
Industry effects	Yes	Yes
Year effects	Yes	Yes
Observations	4,685	4,685
Wald chi2		2496
Prob > chi2		0.000

This table presents the results of self-selection models and Two-Stage Least Squares (2SLS) regressions. Panel A reports the results of 2SLS regressions and the Villalonga (2004) treatment effect model for the diversification dummy. Panel B presents the results of the Heckman self-selection model (1979), where diversification is estimated in the first stage, and the second stage examines the effect of cash flow coinsurance. As excluded instruments, we use the industry-level share of diversified firms and the Herfindahl-Hirschman Index (HHI) of industry sales. In addition to the covariates shown in the table, we include industry and year fixed effects. The sample comprises non-financial firm-years listed on the Tokyo Stock Exchange (TSE) for the period 2006–2019. The variable definitions are provided in Table 1. We winsorize all variables included in our empirical analyses at the top and bottom 1% to mitigate the influence of outliers. Clustered t-values at the firm level are reported in brackets. Significance levels are reported at 10% (*), 5% (**), and 1% (***).

Table 9: Environmental committee

	All firms		Diversified firms	
	ghg_ems12	ghg_ems12	ghg_ems12	ghg_ems12
cfcoins	-50.096	-53.726	-10.444	-10.660
	[0.81]	[0.93]	[0.11]	[0.13]
committee	0.209	0.190	0.437	0.436
	[1.03]	[0.99]	[1.32]	[1.40]
cfcoins × committee	-167.965	-132.049	-244.426	-211.873
	[1.67]*	[1.31]	[1.86]*	[1.68]*
size	0.359	0.440	0.444	0.570
	[3.71]***	[3.92]***	[3.91]***	[4.23]***
bm	0.509	0.348	0.433	0.293
	[2.38]**	[1.75]*	[1.64]	[1.13]
lev	5.315		6.530	
	[4.06]***		[4.03]***	
roa	2.191	-5.247	0.759	-8.138
	[0.81]	[2.22]**	[0.22]	[2.44]**
fsales	-0.942	-0.774	-1.370	-1.286
	[2.08]**	[1.73]*	[2.37]**	[2.13]**
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Adjusted R2	0.54	0.51	0.51	0.48
N	4,601	4,601	3,453	3,453

This table presents OLS estimation results of regressing carbon intensity on cash flow coinsurance and its interaction with the committee dummy (committee) equal to 1 if a firm has either an environmental committee or a CSR committee (or both), and 0 otherwise. All regressions include industry and year fixed effects. The sample comprises non-financial firm-years listed on the Tokyo Stock Exchange (TSE) for the period 2006–2019. The variable definitions are provided in Table 1. We winsorize all variables included in our empirical analyses at the top and bottom 1% to mitigate the influence of outliers. Clustered t-values at the firm level are reported in brackets. Significance levels are reported at 10% (*), 5% (**), and 1% (***).

Table 10: CDP Emission Data

	All firms		Diversified firms	
	ghg_ems12	ghg_ems12	ghg_ems12	ghg_ems12
cfcoins	-187.603	-187.289	-270.245	-260.006
	[2.45]**	[2.30]**	[3.04]***	[2.70]***
size	0.297	0.340	0.348	0.412
	[3.29]***	[3.48]***	[3.34]***	[3.77]***
bm	1.012	0.894	0.855	0.751
	[3.11]***	[2.88]***	[2.14]**	[1.89]*
lev	4.834		6.329	
	[3.25]***		[3.18]***	
roa	5.229	-1.459	1.948	-6.956
	[1.70]*	[0.55]	[0.54]	[1.88]*
fsales	-0.711	-0.618	-0.881	-0.566
	[1.01]	[0.90]	[0.94]	[0.62]
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Adjusted R2	0.55	0.53	0.58	0.55
N	1,030	1,030	786	786

This table presents OLS estimation results of regressing carbon intensity on cash flow coinsurance for sample firms using carbon emissions data from CDP instead of Toyo Keizai data. All regressions include industry and year fixed effects. The sample comprises non-financial firm-years listed on the Tokyo Stock Exchange (TSE) for the period 2006–2019. The variable definitions are provided in Table 1. We winsorize all variables included in our empirical analyses at the top and bottom 1% to mitigate the influence of outliers. Clustered t-values at the firm level are reported in brackets. Significance levels are reported at 10% (*), 5% (**), and 1% (***).

Table 11: Scope 1 and Scope 2 Emissions

Panel A: Scope 1 emissions

	All firms		Diversified firms	
	ghg_ems1	ghg_ems1	ghg_ems1	ghg_ems1
cfcoins	-176.931	-176.750	-250.800	-240.353
	[2.31]**	[2.17]**	[2.85]***	[2.52]**
size	0.279	0.322	0.319	0.386
	[3.20]***	[3.41]***	[3.05]***	[3.63]***
bm	0.844	0.720	0.742	0.630
	[2.70]***	[2.45]**	[1.98]**	[1.71]*
lev	4.893		6.613	
	[3.33]***		[3.32]***	
roa	5.566	-1.237	2.576	-6.750
	[1.85]*	[0.47]	[0.71]	[1.78]*
fsales	-0.889	-0.793	-1.178	-0.844
	[1.30]	[1.19]	[1.30]	[0.95]
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Adjusted R2	0.57	0.55	0.60	0.57
N	1,042	1,042	796	796

Panel B: Scope 2 emissions

	All firms		Diversified firms	
	ghg_ems2	ghg_ems2	ghg_ems2	ghg_ems2
cfcoins	-15.208	-15.170	-23.156	-23.154
	[1.21]	[1.20]	[1.51]	[1.51]
size	0.016	0.017	0.029	0.029
	[0.56]	[0.63]	[0.84]	[0.88]
bm	0.160	0.156	0.092	0.092
	[2.65]***	[2.50]**	[1.15]	[1.12]
lev	0.171		0.001	
	[0.50]		[0.00]	
roa	-0.244	-0.480	-0.808	-0.810
	[0.35]	[0.73]	[0.94]	[0.92]
fsales	0.104	0.107	0.228	0.228
	[0.74]	[0.77]	[1.27]	[1.32]
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Adjusted R2	0.29	0.29	0.32	0.32
N	1,036	1,036	791	791

This table presents OLS estimation results of regressing carbon intensity on cash flow coinsurances for sample firms using carbon intensity defined as Scope 1 emissions (or Scope 2 emissions) instead of Scope 1+2 emissions. Carbon emission data is obtained from CDP. All regressions include industry and year fixed effects. The sample comprises non-financial firm-years listed on the Tokyo Stock Exchange (TSE) for the period 2006–2019. The variable definitions are provided in Table 1. We winsorize all variables included in our empirical analyses at the top and bottom 1% to mitigate the influence of outliers. Clustered t-values at the firm level are reported in brackets. Significance levels are reported at 10% (*), 5% (**), and 1% (***).