School of Economics and Management

R&D Intensity and its impact on Emissions Intensity across industries

Master Thesis Finance

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Abstract

This paper examines the relationship between firm-level research and development (R&D) expenditure and carbon emissions across industries. Although technological innovation appears to reduce carbon emissions, its magnitude and effect across industries remain unclear, and most studies assume a linear relationship. Using a sample of 2,178 firm-year observations from 2015 to 2023, covering industrial, healthcare, and information technology firms in the United States and Europe, results indicate a negative relationship between R&D intensity and emissions intensity. Robustness tests suggest that U.S. firms primarily drive this effect. Furthermore, results reveal no evidence of diminishing returns or a U-shaped pattern, indicating that R&D intensity consistently reduces emissions intensity. Although the main results do not indicate differences across industries, several factors suggest the possibility of industry-specific differences. These include robustness tests, findings from prior studies, and observed differences in absolute emission intensity across industries. Overall, these findings emphasize the importance of R&D as a potential solution for reducing global emissions.

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1. Introduction

Global warming has become an important concern due to its significant impact on social and economic development. It is widely recognized that greenhouse gases, especially carbon emissions, are the major contributors to global warming. As a result, the role of businesses in addressing their environmental impacts, particularly carbon emissions, has become a central concern for both researchers and policymakers. The focus is on how to achieve economic growth without worsening environmental impact.

Technological innovation presents a promising solution to this problem, as an increasing number of studies demonstrate that innovation can significantly reduce carbon emissions. For instance, Chen and Lei (2018) demonstrate that increases in patent filings, a proxy for technological innovation, lead to lower carbon emissions. This effect is especially strong in countries with high baseline emissions. Similarly, Carrión-Flores and Innes (2009) find that innovation plays an important role in pollution reduction and call for policies to promote environmental research and development (R&D) initiatives. These findings emphasize that innovation, and especially R&D investments, can drive development in cleaner technologies and energy efficiencies. This, in turn, enables companies to grow without proportionally increasing carbon emissions. As a result, firms can play a crucial role in achieving global emission reductions by investing in environment-specific R&D. However, there is still a lack of understanding of how R&D investments translate into improved environmental performance, especially across industries. Most prior studies have examined the relationship between R&D expenditure and carbon emissions either at the country level or within one specific industry. It remains unclear whether the impact of R&D on emissions is uniform across industries or if certain industries benefit more from R&D in reducing carbon emissions.

This paper addresses that gap by examining whether and how firm-level R&D intensity is associated with emissions intensity and whether this relationship varies across industries. Most importantly, to what extent does firm-level R&D intensity translate into lower emissions intensity? To address this question, the analysis examines whether an increase in R&D intensity leads to a reduction in emissions intensity.

Building on this, two related questions are analysed. First, does the R&D emissions relationship follow a linear pattern, or do diminishing returns or a U-shaped effect occur at higher R&D levels? In other words, do initial R&D investments reduce emissions, while further spending leads to smaller benefits or potentially increases them? Identifying whether the relationship is linear or nonlinear is essential for firms and policymakers to recognize when further R&D spending may yield limited or adverse returns. Second, given the differences in baseline emissions across industries, does the relationship between R&D and emissions hold uniformly across industries, or do certain industries benefit more from R&D? Given that Chen and Lei (2018) demonstrate that the R&D emissions effect is stronger in countries with higher baseline emissions, a similar pattern may hold across industries. Addressing these sub-questions provides a comprehensive view of R&D's potential and limitations for reducing emissions.

To address these questions, a panel dataset of firm-level observations from 2015 to 2023 is compiled for public companies in the United States and Europe across three industries: industrials, health care, and information technology. These industries are selected to represent industries with varying emissions intensities. Industrial firms tend to have higher emissions intensity, while health care and information technology firms tend to have lower emissions intensity, allowing for meaningful cross-industry comparisons. Firm-year data on R&D expenditure, carbon emissions, and control variables are obtained from Refinitiv, whereas macroeconomic control variables are obtained from the World Bank database. Both databases are widely utilized and recognized in the literature as high-quality data sources (Gonenc & Poleska, 2022). This study measures R&D intensity in a given year as R&D expenditure relative to revenue. Emissions intensity is measured by scope 1 and 2 emissions in tonnes relative to revenue. These are emissions a company can directly manage through its operations and energy use, while scope 3 emissions are excluded due to their significant measurement, control, and cost challenges (Patchell, 2018; Vieira et al., 2024). Tamayao et al. (2014) similarly limit their emissions intensity to scope 1 and 2 emissions, and many firm-level studies, including Alem et al. (2019), Gonenc and Poleska (2022), and Jiang et al. (2013), scale both R&D expenditure and emissions intensity by revenue to adjust for firm size. Both R&D intensity and emissions intensity are log-transformed to reduce skewness and enable elasticity interpretation, following Capasso et al. (2015) and Yang et al. (2023), respectively.

The empirical approach is based on multivariate panel regressions estimated by ordinary least squares (OLS). The within-transformation is applied to absorb region and year fixed effects, and standard errors are clustered at the firm level. This approach, or very similar ones, is common in related research (Carrión-Flores & Innes, 2009; Gonenc & Poleska, 2022; Li et al., 2020). The models gradually introduce (i) the linear effect of R&D intensity, (ii) industry dummies to capture baseline differences across the three industries, (iii) both the linear effect of R&D and the industry dummies, (iv) a quadratic term of R&D intensity to test for non-linear effects, and (v) an interaction between R&D intensity and industry dummies to test whether the effect of R&D varies across industries. In addition, robustness tests are conducted using alternative model specifications and subsamples to test whether results remain consistent.

The empirical results provide evidence that higher R&D intensity is associated with lower emissions intensity. In the baseline model, a 1% increase in R&D intensity leads to approximately a 0.27% reduction in emissions intensity, holding all else equal. Robustness tests, however, reveal that U.S. firms primarily drive this effect. Allowing for nonlinearity by including a squared R&D term reveals no diminishing returns or a turning point in which increases in R&D will start to increase emissions intensity. Therefore, R&D intensity continues to yield emissions reductions even at high levels.

The interaction terms do not show any statistical significance, indicating that the effect of R&D intensity on emissions intensity does not differ across industries. In other words, even though absolute emissions vary by industry, R&D investments appear to reliably lower emissions intensity across all industries. Although the main regressions lack statistical significance, robustness tests suggest the possibility of heterogeneity across industries. When focusing on U.S.-only firms or scope 2-only emissions, the results suggest that R&D intensity might be associated with varying reductions in emissions intensity across industries.

Results from this study both confirm and contribute to the existing literature on innovation and environmental performance. Results indicating that higher R&D intensity leads to reduced emissions intensity are strongly consistent with prior studies in diverse contexts. For instance, using firm-level data from G6 economies, Alam et al. (2019) find that R&D investments improve environmental performance by lowering energy and carbon emissions intensities. Similarly, Cole et al. (2012) highlight that Japanese manufacturers with greater R&D expenditures report significantly lower emissions. Moreover, the magnitude and direction of the findings of Petrović and Lobanov (2019) closely align with the results of this paper.

Additionally, this study contributes to the existing literature by testing for a non-linear, U-shaped relationship, which was previously underexplored. This is important for firms and policymakers to identify whether a threshold exists at which increasing R&D intensity no longer reduces emissions intensity. Prior studies have highlighted a linear effect of R&D on environmental outcomes, which is consistent with the findings of this study. Although direct comparisons with other studies are limited, the observed findings nevertheless contribute to research on the changing impact of R&D over time. Contrary to this study's findings, Li et al. (2020) observe an inverted U-shape between R&D expenditure and carbon emissions reduction. Another relevant study by Churchill et al. (2018) observed that the effect of R&D on carbon emissions in G7 countries was not constant. R&D reduced emissions for most of the past two centuries, but the effect turned positive during a 35-year period from 1955 to 1990, largely due to high industrial expansion. This suggests the possibility that during periods of rapid growth, R&D investments may be insufficient to offset emissions or may not be specifically targeted towards environmental improvement.

Given the heterogeneity of industries, the impact of R&D on emissions was expected to vary across industries. However, the lack of statistical significance provides no evidence of systematic differences across industries. Only a few prior studies have examined cross-industry specific effects of innovation on carbon emissions. Mo (2021) demonstrated that the impact of patent counts on carbon emissions differs by semiconductor and process industries. Similarly, Erdoğan et al. (2020) find that higher levels of innovation are associated with a reduction in carbon emissions for the industrial industry, while the opposite is true for the construction industry. Since most prior studies have not examined cross-industry specific effects of R&D on emissions, this study's findings can also be compared to studies that examine cross-country differences. For instance, Petrović and Lobanov (2019) analysed 16 OECD countries and highlighted that in about 40% of those countries, R&D investments had no significant long-term effect on reducing emissions. It appeared that the effect of R&D on emissions could be positive or negative, depending on the country. Although the main model in this study lacks statistical significance for industry-specific differences, the models using scope 2-only emissions or U.S.-only firms do suggest the possibility of variation across industries. Additionally, separate regressions for each industry reveal that R&D intensity is significantly associated with lower emissions in certain industries, suggesting that R&D may be more effective in reducing emissions in some industries than in others.

The results of this study help clarify and reveal new evidence on how R&D intensity, as a proxy for innovation, impacts emissions intensity. Using a dataset across three industries and combining linear, non-linear, and interaction models, the results demonstrate that R&D investments lower emissions at the firm level. Following the approach suggested by Li et al. (2020) for industry-specific analysis reveals that, while industries differ greatly in their average emissions, it cannot be confirmed that the effectiveness of R&D in reducing emissions differs across industries. Moreover, the analysis reveals no diminishing returns or a U-shaped effect between R&D and emissions. Together, these findings contribute to the literature on innovation and firm environmental performance. By addressing a previously underexplored area and offering practical recommendations, this study contributes to the ongoing discussions on how firms can align with global climate goals.

The rest of the thesis is organized as follows. Section 2 reviews the relevant literature on R&D expenditure and carbon emissions and develops the hypotheses that follow from theory and prior findings. Section 3 describes the data and methodology, including sample selection, variable definitions, and the models employed. Section 4 presents the empirical results of the study, discussing the main findings and various robustness tests. Finally, Section 5 provides a summary of the results, a discussion of their implications for policy and practice, limitations of the study, and suggestions for future research.

2. Literature review and hypothesis development

This section reviews relevant literature on R&D intensity and emissions intensity and examines whether this relationship differs across industries. Based on these theories and prior findings, three hypotheses are proposed.

2.1 R&D expenditure and carbon emission

The resource-based view (RBV), introduced around 1990, argues that firms having resources that are valuable, rare, inimitable, and non-substitutable (VRIN) can achieve sustainable competitive advantage (Barney, 1991; Wernerfelt, 1984). However, during that period, environmental impact was not yet taken into account. Following that period, environmental regulations tightened, and consumer preferences shifted toward sustainability. The traditional view of maximizing profits expanded to also consider environmental performance. Recognizing that ignoring environmental issues can harm long-term profitability through regulatory fines, reputational damage, and resource scarcity, studies extended the resource-based framework to incorporate environmental impact. Hart (1995) was among the first to argue that, to achieve sustainable competitive advantage, firms must also consider environmental impact. His framework, called the natural resource-based view (NRBV), provided the foundation for more studies to examine how firms can achieve economic growth without worsening environmental impact.

Building on this view, researchers have increasingly focused on particular environmental issues, such as the reduction of carbon emissions. When specifically focusing on carbon emissions mitigation, a growing body of research supports the view that technological innovation plays a crucial role in reducing carbon emissions (Li et al., 2020). For instance, Chen and Lei (2018) show that patent applications, used as a proxy for technological innovation, reduce carbon emissions. This effect is particularly strong in countries with higher levels of carbon emissions. Similarly, Carrión-Flores and Innes (2009) highlight that innovation plays an important role in mitigating pollution and emphasize the importance of policies focused on promoting environmental R&D initiatives.

Turning to country-level evidence, Ganda (2019) examines the Organization of Economic Co-operation and Development (OECD) countries, which include the leading emitters of carbon emissions around the world. Findings indicate that the effectiveness of investments to reduce carbon emissions varies by their application. In particular, green energy use and R&D spending have been more effective in reducing carbon emissions than factors such as the number of researchers or the number of triadic patent families. This suggests that not all innovation inputs are equally effective and that the impact of R&D spending depends on its type and application.

At the firm level, similar patterns occur. Cole et al. (2012) demonstrate that Japanese firms with higher levels of R&D report lower emissions intensity. Similarly, Cole et al. (2004) observe that firm-level R&D spending is associated with lower air pollution intensity. These studies indicate that the relationship between innovation and emissions intensity holds across both national and firm-level contexts. Expanding on these findings, Churchill et al. (2018) demonstrate that higher R&D intensity reduces carbon emissions, except during the period 1955 to 1990. However, this was explained by a scale effect, where initial economic growth driven by R&D increased emissions, but technological progress later helped reduce them. This finding highlights that the relationship between R&D and carbon emissions may differ over time, with initial growth potentially increasing emissions, while technological progress can later help reduce them.

Building further on this literature, Gonenc & Poleska (2022) highlight that both multinational and domestic firms reduce carbon emissions through increased R&D spending, with the effect being stronger for multinational firms. This suggests that the impact of R&D expenditure on carbon emissions may differ depending on firm characteristics, such as international presence or industry type. Finally, Hailemariam et al. (2022) argue that there is significant room for reducing emissions by increasing the share of GDP that is allocated towards R&D expenditure in renewable technologies. Given the current pressure of global warming, policymakers could potentially fund and incentivize firms to accelerate the transition to a lower-carbon economy (Hailemariam et al., 2022).

Despite this consensus on a positive relationship between R&D and carbon emission reductions, the precise mechanisms remain uncertain. Much of the literature identifies a constant positive linear relationship between R&D and carbon emission reduction, suggesting that each additional input of R&D would lead to a constant reduction in carbon emissions (Cole et al., 2012; Churchill et al., 2018). However, the law of diminishing returns, also known as the law of diminishing productivity, suggests that if one factor of production is increased while others remain constant, the additional output gained from each extra input will eventually decrease (Brue, 1993). Following this theory, after a certain point, additional increases in R&D investment will result in a smaller reduction in carbon emissions. The rationale of this theory is also followed by Li et al. (2020), who suggest an inverted U-shape and diminishing returns effect. There are three phases in the marginal effect of R&D input on carbon emission reduction: a growth phase, followed by a peak phase, and lastly a decline phase. Moreover, this turning point differs between developing and developed countries. Although findings remain inconclusive, firms with higher R&D expenditure tend to be more environmentally responsible (Li et al., 2020). Note that some studies examine emissions reductions, whereas other studies, including this one, use emissions intensity. For instance, Li et al. (2020) assumed an inverted U-shape between R&D and emissions reduction, which is equivalent to a U-shape between R&D and emissions intensity.

Based on the analysis above, the following hypotheses are proposed:

H1: R&D intensity is negatively associated with emissions intensity.

H2: The relationship between R&D intensity and emissions intensity follows a U-shape.

2.2 Industry type

The relationship between R&D expenditure and carbon emissions is complex and likely varies across industries due to the significant differences in baseline emissions. Although numerous studies have explored the impact of R&D on carbon emissions at national or firm levels, direct comparisons across industries remain underexplored.

Mo (2021) examined Korean manufacturing firms that are part of the Korean Emission Trading Scheme (KETS) and demonstrated that the impact of innovation activities, such as R&D spending and patent counts, on carbon emissions differs by industry. Patents specifically contributed to the reduction of carbon emissions in the semiconductor industry, but not in the process industries. Building on this, Lee and Min (2015) demonstrate a negative relationship between green R&D and carbon emissions for manufacturing firms. However, when firms also invest in non-green R&D, gains from green R&D can be offset by R&D that aims to increase production. This suggests that not only the quantity of R&D is important, but also its focus. Notably, their findings cannot be generalized across industries, emphasizing the importance of examining this effect across industries.

Erdoğan et al. (2020) support this view by demonstrating that, across G20 economies, higher levels of innovation are associated with reduced carbon emissions in the industrial industry. By contrast, in the construction industry, innovation actually increases carbon emissions. Erdoğan et al. (2020) explain this outcome by highlighting that efficiency improvements might lower per-unit energy use but also lower the costs or enable more construction activity, which ultimately raises total emissions. The results indicate that each industry, due to diverse characteristics, differs in how R&D impacts carbon emissions. Consequently, Erdoğan et al. (2020) recommend that national policies should implement different policies for each industry rather than a uniform policy across all industries. Additionally, Amosh and Khatib (2025) examine the effect of environmental innovation on carbon emissions with a focus on the healthcare industry. Results indicate that while carbon emissions initially rise due to higher energy inputs and operational scales, they ultimately decrease when environmental monitoring is implemented. Future research should consider other industries beyond healthcare to test whether these results hold across industries (Amosh & Khatib, 2025).

In conclusion, although R&D investments are generally associated with lower carbon emissions, the magnitude and direction of this relationship depend on industry-specific characteristics. These include factors such as technological intensity, production processes, and the nature of the innovation itself. Li et al. (2020) also recognize industry-specific differences and recommend future research to examine whether the relationship between R&D and carbon emissions differs by industry.

Based on the analysis above, the following hypothesis is proposed:

H3: The effect of R&D intensity on emissions intensity differs by industry.

3. Data and methodology

This section describes the data and methodology, including the sample selection, variable definitions, and the models that are employed.

3.1 Sample selection

To examine the effect of R&D intensity on emissions intensity, data were retrieved from Refinitiv. By using the screener function, publicly listed companies in Europe and the United States within the industrial, health care, and information technology industries were selected. The dataset covers the period from 2015 to 2023 and includes only firms for which all necessary variables were available, after filtering out those with limited data or missing observations. The final dataset consists of 2,178 firm-year observations. Because the dataset contains more U.S. than European companies, and to be consistent, all data are expressed in U.S. dollars. The data cover nine years of observations, beginning in 2015. This start date aligns with the adoption of the Paris Agreement and the launch of the UN Sustainable Development Goals (SDGs), both of which increased the focus on corporate sustainability reporting. Given that environmental performance disclosure is not mandatory, the dataset primarily consists of large firms, which are generally more likely to report voluntarily. Li et al. (2020) confirm that large firms are more likely to engage in voluntary social responsibility disclosures.

Table 1. Country of incorporation

Country of incorporation	**Number of companies**	**Country of incorporation**	**Number of companies**
United States	158	Ireland	6
EU	***84***	Finland	5
Germany	13	Denmark	4
Sweden	13	Belgium	3
France	11	Spain	2
United Kingdom	9	Austria	1
Switzerland	8	Hungary	1
Netherlands	7	Italy	1

Notes: This table presents the number of companies per country.

Table 2. Industry type

Industries	Number of companies
Industrials	75
Health care	86
Information technology	81

Notes: This table presents the number of companies per industry type.

3.2 Variables

3.2.1 Dependent variable

This study utilizes scope 1 and scope 2 carbon emissions in tonnes relative to revenue as a proxy for a firm’s emissions intensity. This follows Alam et al. (2019), who note that using carbon emissions relative to revenue represents a firm’s actual carbon emissions during production processes. Emissions intensity is also log-transformed to reduce skewness and allow for elasticity interpretation (Yang et al., 2023). Scope 1 emissions refer to a firm's direct on-site carbon emissions, while scope 2 emissions are the indirect emissions resulting from the purchase of electricity and energy. Scope 3 emissions consist of indirect emissions occurring throughout a company’s supply chain, both upstream and downstream (Mahapatra et al., 2021). While scope 1 and 2 emissions are more straightforward to measure, scope 3 emissions present significant challenges. Although scope 3 often accounts for the majority of a company’s emissions, including them could significantly affect the analysis of how effective R&D is at reducing emissions. Companies struggle to fully map their supply chains, obtain high-quality data due to diverse measurement methods, and manage the costs associated with processing this data (Patchell, 2018; Vieira et al., 2024). For these reasons, scope 3 emissions are excluded, and the analysis focuses on scope 1 and 2 emissions, following a similar approach to Tamayao et al. (2014).

3.2.2 Independent variable

This study utilizes R&D expenditure relative to revenue as a proxy for a firm's R&D intensity during a given year, following the rationale used in most other studies (Alam et al., 2019; Gonenc & Poleska, 2022; Jiang et al., 2013). This approach is adopted because obtaining firm-level R&D data specifically allocated to improving environmental performance, such as carbon emissions, is often unavailable or very difficult to obtain (Li et al., 2020). Moreover, consistent with Capasso et al. (2015), R&D intensity is log-transformed to reduce skewness and allow for elasticity interpretation. One limitation of log-transforming a variable is that observations with zero values are dropped, as ln(0) is undefined. However, since the sample consists mostly of large firms that report non-zero R&D expenses, no observations are lost when log-transforming R&D intensity.

3.2.3 Moderating variable

The moderating variable, industry type, is represented by two dummy variables. Each dummy will take a value of 0 for the reference industry and a value of 1 for the respective industry being analysed. In this study, the industrial industry serves as the reference industry, while health care and information technology are included as two dummy variables. These three industries were selected based on the recognized Global Industry Classification Standard (GICS) developed by MSCI and S&P in 1999. After filtering out those with limited data or observations, only industries with sufficient data were included to ensure meaningful comparisons. Table 2 shows that the three included industries have a similar number of observations, whereas the excluded industries contain only around 25 or fewer observations.

3.2.4 Control variables

Control variables are included to ensure that the estimated relationship between R&D and emissions is not driven by other firm characteristics. Therefore, the following firm-level variables are retrieved from Refinitiv and incorporated into the regression models: firm size, leverage, capital intensity, Tobin's Q, return on assets (ROA), capital expenditure, and market-to-book (MTB) ratio. Carrión-Flores and Innes (2009) suggest that larger, more capital-intensive firms tend to emit more but also have a greater capacity to reduce emissions. According to Cheng et al. (2013) and Alam et al. (2019), larger firms tend to be more socially responsible and are associated with lower carbon emissions.

Conversely, higher leverage is generally associated with increased carbon emissions. In addition, Gonenc and Poleska (2022) suggest that higher capital expenditures and dividend payments reduce the free cash flows available for R&D investment. These findings emphasize the importance of accounting for firm characteristics when analysing the impact of R&D on emissions. Appendix A (Table A1) provides definitions of all dependent, independent, and control variables.

Not only do firm-level characteristics impact R&D levels and carbon emissions, but macroeconomic factors also have a significant influence. Because R&D investments may increase due to regulatory pressure, they are potentially subject to omitted variable bias (Alam et al., 2019). One way to avoid this bias is by including macroeconomic variables to ensure that variation in R&D does not come from broader economic impacts. Therefore, inflation, gross domestic product (GDP), exports relative to GDP, and foreign direct investment (FDI) inflows relative to GDP are included as macroeconomic control variables.

R&D investments may differ depending on the level of economic development. According to Liu et al. (2015), regions with higher GDP tend to have lower carbon emissions per unit of output, primarily due to more advanced energy-use technologies and more efficient industries. By contrast, areas with low GDP levels tend to rely more on industries that are more energy-intensive, which in turn leads to higher emissions per unit of output. Another important finding indicates that an increase in per capita GDP is often accompanied by increased per capita carbon emissions from consumption, suggesting that economic growth has not necessarily led to better sustainable outcomes (Liu et al., 2015).

Industries that are more export-oriented could also be more exposed to environmental pressures from abroad, which could influence a company's carbon emission intensity (Carrión-Flores & Innes, 2009). Additionally, empirical evidence from Gonenc and Poleska (2022) demonstrates that R&D expenditure reduces emissions intensity more effectively in countries with high levels of FDI. They argue that FDI creates knowledge and technological spillovers, enhances innovation, and increases efficiency. These macroeconomic variables are retrieved from the World Bank database.

3.3 Data description

The descriptive statistics for all the variables used in the regression analysis are presented in Table 3. This table reports the number of observations (N), mean, median, minimum, maximum, and standard deviation for each variable. The sample contains 2,178 firm-year observations for each variable. Although the main analysis covers the period 2015 to 2023, explanatory variables begin in 2014 to allow for one-year lags, resulting in a dataset that spans from 2014 to 2023. Although emissions intensity is not lagged, it similarly contains 2,178 firm-year observations since data is available from 2015 to 2023. For instance, R&D intensity in 2014 is used to assess its impact on emissions intensity in 2015.

In addition to lagging explanatory variables, some variables are also log-transformed. Besides firm size and GDP, emissions intensity and R&D intensity are also log-transformed to reduce skewness and allow for elasticity interpretation. Furthermore, all variables are winsorized at the 1^{st} and 99^{th} percentiles to reduce the influence of extreme outliers.

On average, firms exhibit a log-transformed emissions intensity of 3.22, which corresponds to approximately 25 tons of CO_2 per million dollars of revenue. Because R&D intensity is measured by R&D expenditure relative to revenue, it typically lies between 0 and 1. Taking its natural logarithm produces negative values, consistent with the approach used by Capasso et al. (2015). A positive log value will only arise when R&D exceeds revenue. The mean log R&D intensity of about -2.7 indicates that firms, on average, invest about 6.7% of their revenue in R&D. The mean and median are very close to each other for both emissions intensity and R&D intensity, showcasing that there is no extreme skewness after log-transforming.

The sample consists of three industries, with information technology and health care accounting for 35.5% and 33.5% of the observations, respectively. This implies that the omitted industry, industrials, accounts for 31% of the observations. Other firm-level statistics indicate that, on average, firms are leveraged by about 27% and invest about 3.3% of their total assets annually in capital expenditures. Macroeconomic indicators demonstrate that firms operate in diverse environments. For instance, inflation in the sample ranges from approximately -0.4% to 8.5%.

Table 3. Descriptive statistics

Variable	N	Mean	Median	Min.	Max.	St.Dev.
Emissions Intensity	2178	3.222	3.189	0.665	5.753	1.030
R&D Intensity	2178	-2.698	-2.710	-6.202	0.551	1.148
dh	2178	0.355	0.000	0.000	1	0.480
df	2178	0.335	0.000	0.000	1	0.470
Size	2178	22.690	22.500	19.490	26.120	1.540
Leverage	2178	0.274	0.255	0.000	0.897	0.160
CapInt	2178	1.936	1.659	0.571	8.487	1.150
Tobin's Q	2178	3.033	2.089	0.874	18.494	2.830
ROA	2178	0.051	0.054	-0.424	0.340	0.100
CapEx	2178	0.033	0.025	0.004	0.164	0.030
MTB	2178	7.127	3.475	0.000	108.196	13.660
GDP	2178	29.640	30.570	26.270	30.890	1.510
Export/GDP	2178	26.600	12.290	10.070	127.270	25.470
FDI	2178	2.067	1.573	-25.385	34.568	6.400
Inflation	2178	2.279	1.622	-0.435	8.548	2.250

Notes: This table presents the descriptive statistics for the variables. Firm-level controls are retrieved from Refinitiv, whereas macroeconomic-level controls are retrieved from the World Bank database for the period 2015-2023. Variable definitions can be found in Appendix A (Table A1).

3.4 Methodology

To examine the research question and test the hypotheses, multivariate panel regressions using ordinary least squares (OLS) are employed. The within-transformation is applied to absorb region and year fixed effects, and standard errors are clustered at the firm level. This approach, or very similar ones, is common in related research (Carrión-Flores & Innes, 2009; Gonenc & Poleska, 2022; Li et al., 2020). To justify the use of fixed-effects panel regression, Hausman tests are conducted to compare fixed effects (FE) and random effects (RE) estimators. The results indicate that for Models 2 to 5, RE estimators are inconsistent, likely due to correlation between explanatory variables and unobserved firm-level effects. Consequently, the fixed-effects estimator is preferred. The Hausman test for Model 1 did not reject the null hypothesis, indicating that random effects could be suitable in this case. However, to maintain consistency across models and because fixed effects still provide consistent estimates, fixed effects are also applied in Model 1. For illustration, the RE estimates for Model 1 are provided in Appendix A (Table A3). The results for the Hausman tests are found in Appendix A (Table A4).

1. $\text{Emissions Intensity}_{i,t} = \beta0 + \beta1R\&D_{i,t-1} + X_{i,t-1} + M_{c,t-1} + \text{Region FE} + \text{Year FE} + \epsilon_{i,t}$

2. $\text{Emissions Intensity}_{i,t} = \beta0 + \beta1dh_{i,t} + \beta2df_{i,t} + X_{i,t-1} + M_{c,t-1} + \text{Region FE} + \text{Year FE} + \epsilon_{i,t}$

3. $\text{Emissions Intensity}_{i,t} = \beta0 + \beta1R\&D_{i,t-1} + \beta2dh_{i,t} + \beta3df_{i,t} + X_{i,t-1} + M_{c,t-1} + \text{Region FE} + \text{Year FE} + \epsilon_{i,t}$

4. $\text{Emissions Intensity}_{i,t} = \beta0 + \beta1R\&D_{i,t-1} + \beta2dh_{i,t} + \beta3df_{i,t} + \beta4(R\&D_{i,t-1})^2 + X_{i,t-1} + M_{c,t-1} + \text{Region FE} + \text{Year FE} + \epsilon_{i,t}$

5. $\text{Emissions Intensity}_{i,t} = \beta0 + \beta1R\&D_{i,t-1} + \beta2dh_{i,t} + \beta3df_{i,t} + \beta4(R\&D_{i,t-1} \times dh_{i,t}) + \beta5(R\&D_{i,t-1} \times df_{i,t}) + X_{i,t-1} + M_{c,t-1} + \text{Region FE} + \text{Year FE} + \epsilon_{i,t}$

In these regression models, *i* refers to firms, *c* to countries, and *t* to years. To mitigate endogeneity concerns arising from omitted variables, reverse causality, and measurement error, several actions are taken. To control for time-specific effects, unobserved regional differences, and to eliminate bias from omitted variables, fixed effects (FE) for region and year are included. Standard errors are clustered at the firm level to control for within-firm correlation across observations. Furthermore, relevant firm-level and macroeconomic variables are included to control for their impact. Additionally, all independent variables, except FDI, which measures capital flows in a given year by construction, are lagged by one year. This helps address the potential for reverse causality between R&D intensity and emissions intensity.

Table 4. Subscript

Subscript	**Description**
R&D	R&D expenditure relative to revenue
Emissions Intensity	Total estimated scope 1 and 2 emissions in tonnes relative to revenue
dh	Dummy variable health care
df	Dummy variable information technology
X	Firm control variables: Size, Leverage, CapInt, Tobin's Q, ROA, CapEx, MTB
M	Macroeconomic control variables: GDP, Inflation, Export, FDI
ϵ	Error term

Notes: This table presents the description of variables incorporated into the regression models. Firm-level controls are retrieved from Refinitiv, whereas macroeconomic-level controls are retrieved from the World Bank database for the period 2015-2023. Variable definitions can be found in Appendix A (Table A1).

4. Results

The research designs employed are described in section 3.4, and the corresponding results are discussed in this section.

4.1 Time trends and pairwise correlations

Figures 1 and 2 present the time-series trends for emissions intensity and R&D intensity. To keep interpretation intuitive, both figures display the raw (untransformed) data. Figure 1 illustrates the relationship between emissions intensity and R&D intensity over time, while Figure 2 compares the same trend across the three industries.

Figure 1 shows that average emissions intensity steadily decreases over time, while the average R&D intensity remains relatively stable. Notably, during periods when R&D intensity rises, particularly in 2017-2018 and 2019-2021, emissions appear to drop even faster in the subsequent years. For instance, the increase in R&D intensity in 2017-2018 is followed by a steeper drop in emissions intensity in 2018-2019. This pattern aligns with the one-year lag of R&D used in the regression models.

Figure 2 visualises the relationship between emissions intensity and R&D intensity across industries. Information technology firms show a steep decline in emissions intensity alongside a moderate rise in R&D intensity, suggesting a negative relationship between the two. Visually, the trends suggest that industry differences may exist. However, after controlling for other variables, regression estimates show that none of these differences across industries are statistically significant. This indicates that the evidence does not support the idea that the negative relationship between R&D intensity and emissions intensity differs across industries.

To assess the risk of multicollinearity, a Pearson pairwise correlation method was conducted among the explanatory variables. Appendix A (Table A2) demonstrates that the majority of the variables correlate only weakly, indicating that multicollinearity is unlikely to bias the regression estimates. Although there are a few notable exceptions, they are largely intuitive. GDP and the export-to-GDP ratio are highly negatively correlated, since growth in GDP reduces the relative size of exports. In other words, whenever GDP increases, the export as a share of GDP decreases, and vice versa, which explains why they are so highly correlated.

Similarly, Tobin's Q and the market-to-book ratio are strongly correlated, as both reflect market valuation relative to book value. Finally, there is a 0.44 correlation between R&D intensity and capital intensity, as firms that invest more in R&D also tend to invest more in capital assets, thereby increasing total assets relative to revenue.

Figure 1. The relationship between emissions intensity and R&D intensity in the full sample

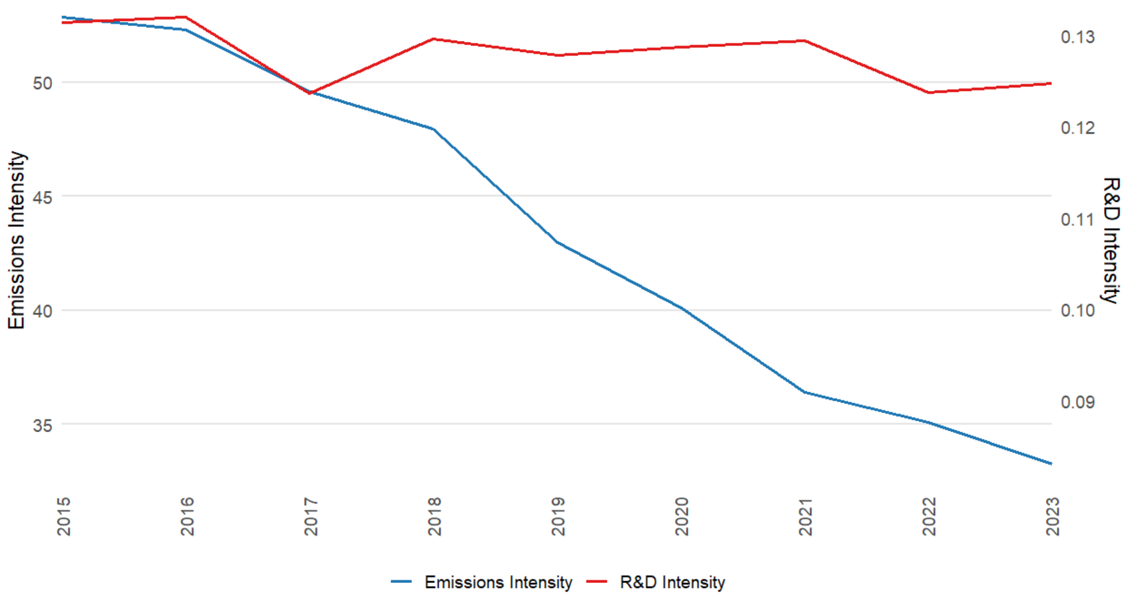
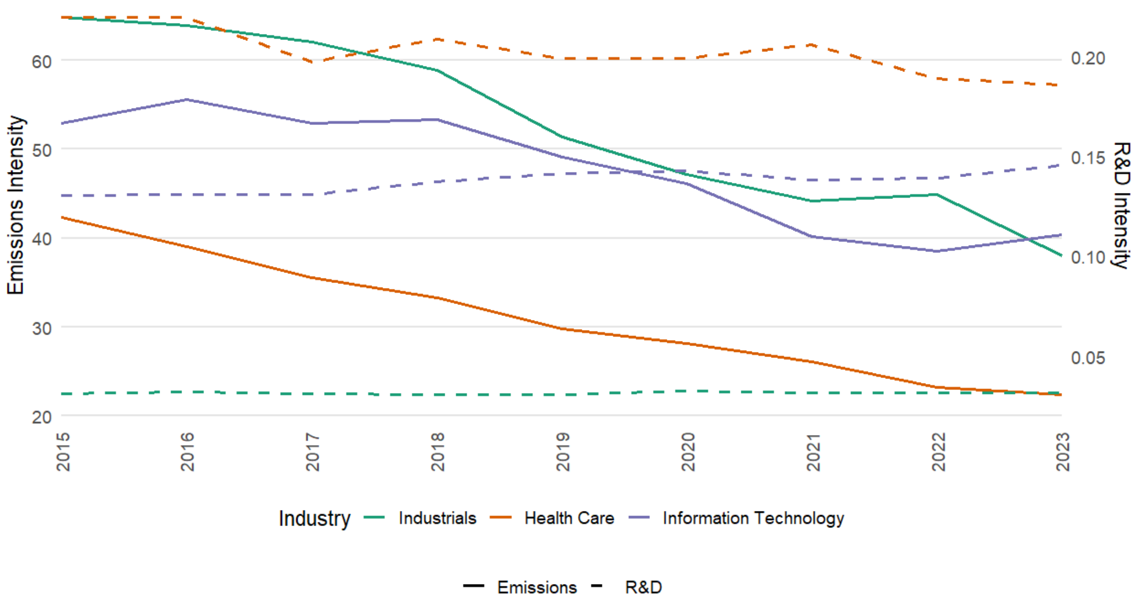


Figure 2. Comparison of the relationship between emissions intensity and R&D intensity across industries



4.2 Main results

Table 5 presents the regression results for Models 1 to 5, corresponding to the five regressions employed. Model 1 establishes the linear, baseline effect of R&D intensity on emissions intensity, testing Hypothesis 1. Model 2 identifies how emissions vary by industry, whereas Model 3 examines the persistence of R&D's effects after controlling for industry differences. To explore the possibility of diminishing returns or a U-shaped effect of R&D intensity on emissions intensity, Model 4 adds a quadratic R&D term, addressing Hypothesis 2. Finally, Model 5 incorporates interactions between R&D intensity and industry dummies, allowing the R&D emissions relationship to vary by industry. It reveals whether the relationship between R&D intensity and emissions intensity differs across industries, testing Hypothesis 3.

Across Models 1 and 3, the coefficient for R&D intensity is negative and statistically significant. Given that both emissions intensity and R&D intensity are log-transformed, a 1% increase in R&D intensity is associated with a 0.27% and 0.20% reduction in emissions intensity, respectively, holding all else equal. In other words, Model 1 implies that if a firm increases R&D spending by 1% of its revenue, its emissions intensity would fall by 0.27%. Since higher R&D intensity is associated with lower emissions intensity, Hypothesis 1 is supported.

Model 2 introduces two dummy variables, health care (dh) and information technology (df), to assess whether emissions intensity differs across industries. Since emissions intensity is log-transformed, a coefficient of -0.499 corresponds to a percentage difference by computing exp(β)-1, for instance, exp(-0.499)-1 ≈ 39%. Therefore, the coefficients in Model 2 imply that, compared to the industrial industry, health care firms are associated with 39% lower emissions intensity and information technology firms with 38% lower emissions intensity, holding all else equal. These findings are statistically significant and align with prior studies, confirming that firms in the health care and information technology industries have lower emissions intensity than industrial firms.

Model 5 is designed to test Hypothesis 3 by allowing the effect of R&D intensity to vary across industries. Therefore, both interaction terms R&D x dh and R&D x df are employed in this model. The results indicate that a 1% increase in R&D intensity for health care firms is associated with a 0.24% decrease in emissions intensity, while a 1% increase in R&D intensity for information technology firms is associated with a 0.21% decrease in emissions intensity. For the baseline industry, industrials, the corresponding effect is a 0.12% reduction. However, both interaction terms and the baseline effect are statistically insignificant, indicating no evidence that the relationship between R&D intensity and emissions intensity varies across industries. Therefore, Hypothesis 3 is not supported.

While Models 1, 3, and 5 estimate the linear relationship between R&D intensity and emissions intensity, Model 4 includes a quadratic term to test for a potential non-linear relationship. Although the coefficient on the linear term remains negative, it is no longer statistically significant. Moreover, the insignificant coefficient on the quadratic term suggests that there is no turning point at which additional R&D intensity stops reducing emissions intensity. While diminishing returns and a potential U-shaped effect were expected due to earlier findings of Li et al. (2020) and the diminishing returns concept of Brue (1993), the results indicate that R&D consistently reduces emissions intensity within this sample. In other words, with no evidence of a U-shaped effect, Hypothesis 2 is not supported.

The control variables offer additional insights into their effect on emissions intensity. Across all models, a 1% increase in size is associated with about a 0.09% reduction in emissions intensity, suggesting that larger firms tend to emit less. By contrast, firms with higher leverage tend to pollute more. The results indicate that a one percentage point increase in leverage increases emissions intensity by around 0.54%. Greater capital intensity also contributes modestly to higher emissions intensity, with a one percentage point increase in capital intensity associated with approximately a 0.13% increase in emissions intensity.

Both profitability measures, Tobin's Q and ROA, are negatively associated with emissions intensity; however, ROA is not statistically significant across the models. A one-unit increase in Tobin's Q is associated with a 5% reduction in emissions intensity. The market-to-book ratio also shows a small negative but statistically insignificant effect. Additionally, a one percentage point increase in capital expenditure is associated with a 12% increase in emissions intensity. In this sample, higher capital expenditure appears to be associated with production growth, which in turn substantially increases emissions intensity.

Macroeconomic variables also provide relevant insights. Results demonstrate that GDP is positive and statistically significant at the 5% and 1% levels across the models. The findings suggest that countries with higher GDP have higher emissions intensity. Specifically, a 1% increase in GDP is associated with approximately a 0.3% increase in a firm's emissions intensity. This finding supports the view that economic growth is accompanied by increased carbon emissions. Exports and FDI are also associated with higher emissions intensity, but their effect is smaller. Lastly, inflation has a very small but statistically insignificant effect on emissions intensity.

Table 5. The effect of R&D Intensity on Emissions Intensity

	Model 1	Model 2	Model 3	Model 4	Model 5
R&D Intensity	-0.265***		-0.203***	-0.221	-0.120
	(0.052)		(0.056)	(0.150)	(0.134)
dh		-0.499***	-0.286**	-0.286**	-0.687
		(0.125)	(0.130)	(0.130)	(0.505)
df		-0.492***	-0.243*	-0.243*	-0.571
		(0.135)	(0.144)	(0.144)	(0.531)
R&D x dh					-0.122
					(1.47)
R&D x df					-0.090
					(0.162)
R&D^2				-0.003	
				(0.025)	
Size	-0.087***	-0.097***	-0.091***	-0.091***	-0.092***
	(0.033)	(0.033)	(0.033)	(0.034)	(0.033)
Leverage	0.501**	0.682***	0.548**	0.543**	0.539**
	(0.250)	(0.254)	(0.258)	(0.259)	(0.256)
CapInt	0.134***	0.077**	0.141***	0.143***	0.146***
	(0.035)	(0.033)	(0.037)	(0.041)	(0.037)
Tobin's Q	-0.052**	-0.074***	-0.052**	-0.052**	-0.051**
	(0.022)	(0.021)	(0.021)	(0.021)	(0.021)
ROA	-0.473	-0.013	-0.311	-0.330	-0.370
	(0.365)	(0.331)	(0.359)	(0.386)	(0.370)
CapEx	11.225***	12.450***	11.830***	11.829***	11.833***
	(2.233)	(2.243)	(2.247)	(2.249)	(2.244)
MTB	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
GDP	0.282**	0.303***	0.293**	0.293**	0.286**
	(0.115)	(0.116)	(0.117)	(0.117)	(0.116)
Inflation	0.033	0.016	0.035	0.035	0.031
	(0.052)	(0.052)	(0.052)	(0.051)	(0.050)
Export/GDP	0.011***	0.011***	0.011***	0.011***	0.012***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
FDI	0.005**	0.005**	0.005**	0.005**	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Adj. R^2	0.278	0.262	0.286	0.286	0.287
N	2178	2178	2178	2178	2178
Region FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results from multivariate OLS panel regressions for the effect of R&D intensity on emissions intensity based on models 1-5. Firm-level controls are retrieved from Refinitiv, whereas macroeconomic-level controls are retrieved from the World Bank database for the period 2015-2023. Variable definitions can be found in Appendix A (Table A1). The robust standard errors are reported in parentheses and are clustered at the firm level. ***, **, and * significant at the 1%, 5%, and 10% levels, respectively.

4.3 Robustness tests

To test whether the results can be generalized and hold across regions, two subsamples are estimated. One sample estimates EU-only firms, whereas the other includes U.S.-only firms. Table 6 reports the results of models 1, 4, and 5 for the full sample and both subsamples. To maintain clarity, only these models are reported, as models 2 and 3 offer little additional insight. Coefficients for the U.S. subsample closely mirror those of the full sample in both statistical significance and economic magnitude. In contrast, the EU subsample demonstrates noticeably different and statistically less significant results. These results suggest that U.S. firms largely drive the findings of the full sample.

An additional robustness test examines whether the impact of R&D intensity differs by emissions scope. Although the main analysis uses combined scope 1 and 2 emissions intensity, the observed estimates might be driven more by one of the two scopes rather than both equally. Table 7 reports the results for Models 1, 4, and 5 for each measure: combined scope 1 and 2, scope 1-only, and scope 2-only emissions. Both scope 1 and scope 2 demonstrate similar negative coefficients and are both statistically significant at the 1% level. This suggests that the impact of R&D intensity on emissions intensity is driven fairly equally by reductions in both scope 1 and scope 2 emissions.

Notably, while the main analysis finds no statistically significant industry-specific effects, the U.S.-only and scope 2-only specifications do provide some statistical significance. In the U.S. subsample, the R&D intensity coefficient for industrials remains significant. In the scope 2-only specification, the interaction between R&D intensity and the healthcare industry becomes significant. These findings suggest that, although the main regressions reveal no industry-specific differences, the robustness tests indicate the possibility of such differences.

The third robustness test examines whether the main findings hold under an alternative measure of R&D intensity. Following Li et al. (2020), R&D intensity is scaled by total operating expenses rather than by revenue. This measure captures R&D as a share of total operating expenses instead of revenues.

The results in Table 8 indicate that the direction and significance remain similar in both R&D intensity specifications. A 1% increase in R&D relative to operating expenses reduces emissions intensity by around 0.265%, nearly identical to the 0.266% reduction when R&D is measured relative to revenue. Economically, this suggests that R&D expenditure is similarly associated with emissions reduction when R&D is scaled by operating costs rather than revenue.

Additionally, in Model 4, where R&D is scaled by operating expenses, the coefficient is both negative and statistically significant. A 1% increase in R&D intensity is associated with a 0.32% reduction in emissions intensity. However, the quadratic term is insignificant, indicating no evidence of diminishing or reversing returns. In other words, R&D intensity consistently reduces emissions at a constant rate, without any observed turning point in the sample. In general, it seems that scaling R&D by operating expenses produces similar coefficients and statistical significance. This implies that a cost-based measure captures a firm's R&D efforts very similarly to a revenue-based measure.

The final robustness test examines whether splitting the sample into the three industries reveals industry-specific effects. The U.S.-only and scope 2-only specifications already suggest potential industry-specific differences, which indicates the need for a more detailed analysis. Therefore, the sample is split into the three separate industries to examine whether the relationship between R&D and emissions differs across industries. Table 9 reports results for both the full sample and each industry separately. Although the interaction terms in the main analysis did not show statistically significant differences across industries, the industry subsample regressions reveal some variation. R&D intensity is significantly associated with lower emissions intensity for firms in the health care and information technology industries, but not for firms in industrials. This suggests the possibility that R&D is effective in reducing emissions for health care and information technology firms, whereas it may not be beneficial for industrial firms.

Overall, these robustness tests confirm the validity of the main findings. They demonstrate that the observed negative relationship between R&D intensity and emissions intensity remains consistent across alternative measurement approaches and regional subsamples.

Table 6. The role of region in the relationship between Emissions Intensity and R&D intensity

	Full sample			U.S.			EU		
	M1	M4	M5	M1	M4	M5	M1	M4	M5
R&D Intensity	-0.265***	-0.221	-0.120	-0.321***	-0.201	-0.252**	-0.154*	-0.285	0.014
	(0.052)	(0.150)	(0.134)	(0.058)	(0.145)	(0.123)	(0.092)	(0.399)	(0.207)
dh		-0.286**	-0.687		-0.334**	-0.301		-0.083	-0.914
		(0.130)	(0.505)		(0.156)	(0.470)		(0.237)	(0.800)
df		-0.243*	-0.571		-0.258	-0.294		-0.108	-0.176
		(0.144)	(0.531)		(0.178)	(0.500)		(0.260)	(0.926)
R&D × dh			-0.122			0.016			-0.253
			(1.47)			(0.139)			(0.234)
R&D × df			-0.090			-0.015			0.060
			(0.162)			(0.161)			(0.270)
R&D²		-0.003			0.009			-0.024	
		(0.025)			(0.022)			(0.063)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.278	0.286	0.287	0.334	0.343	0.342	0.210	0.210	0.222
N	2178	2178	2178	1422	1422	1422	756	756	756
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results from multivariate OLS panel regressions for the full sample, U.S.-only subsample, and the EU-only subsample, for the effect of R&D intensity on emissions intensity based on models 1, 4, and 5. Firm-level controls are retrieved from Refinitiv, whereas macroeconomic-level controls are retrieved from the World Bank database for the period 2015-2023. Variable definitions can be found in Appendix A (Table A1). The robust standard errors are reported in parentheses and are clustered at the firm level. ***, **, and * significant at the 1%, 5%, and 10% levels, respectively.

Table 7. The effect of R&D Intensity on combined (scope 1 + 2), scope 1, and scope 2 Emissions Intensity

	Scope 1 + 2			Scope 1			Scope 2		
	M1	M4	M5	M1	M4	M5	M1	M4	M5
R&D Intensity	-0.265***	-0.221	-0.120	-0.327***	-0.004	-0.221	-0.243***	-0.378**	-0.005
	(0.052)	(0.150)	(0.134)	(0.086)	(0.232)	(0.194)	(0.053)	(0.151)	(0.111)
dh		-0.286**	-0.687		-0.310*	-0.249		-0.295**	-1.375***
		(0.130)	(0.505)		(0.170)	(0.705)		(0.141)	(0.446)
df		-0.243*	-0.571		-1.204***	-0.873		0.019	-0.775*
		(0.144)	(0.531)		(0.203)	(0.800)		(0.155)	(0.466)
R&D × dh			-0.122			-0.174			-0.330**
			(1.47)			(0.207)			(0.130)
R&D × df			-0.090			0.076			-0.208
			(0.162)			(0.258)			(0.145)
R&D²		-0.003			0.018			-0.026	
		(0.025)			(0.041)			(0.024)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.278	0.286	0.287	0.169	0.264	0.265	0.259	0.277	0.287
N	2178	2178	2178	2178	2178	2178	2178	2178	2178
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results from multivariate OLS panel regressions for the effect of R&D intensity on emissions intensity based on models 1, 4, and 5, using three different measures for emissions intensity: combined scope 1 + 2, scope 1-only, and scope 2-only. Firm-level controls are retrieved from Refinitiv, whereas macroeconomic-level controls are retrieved from the World Bank database for the period 2015-2023. Variable definitions can be found in Appendix A (Table A1). The robust standard errors are reported in parentheses and are clustered at the firm level. ***, **, and * significant at the 1%, 5%, and 10% levels, respectively.

Table 8. Comparison of R&D Intensity scaled by revenue vs. operating expenses on Emissions Intensity

	R&D / Revenue			R&D / Operating expenses		
	M1	M4	M5	M1	M4	M5
R&D Intensity	-0.265***	-0.221	-0.120	-0.266***	-0.317*	-0.109
	(0.052)	(0.150)	(0.134)	(0.051)	(0.163)	(0.133)
dh		-0.286**	-0.687		-0.254*	-0.757**
		(0.130)	(0.505)		(0.132)	(0.482)
df		-0.243*	-0.571		-0.219	-0.546
		(0.144)	(0.531)		(0.147)	(0.506)
R&D × dh			-0.122			-0.163
			(1.47)			(0.147)
R&D × df			-0.090			-0.081
			(0.162)			(0.161)
R&D²		-0.003			-0.018	
		(0.025)			(0.028)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R²	0.278	0.286	0.287	0.281	0.289	0.290
N	2178	2178	2178	2178	2178	2178
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results from multivariate OLS panel regressions for the effect of R&D intensity on emissions intensity based on models 1, 4, and 5, using two different measures for R&D intensity: R&D scaled by revenue and R&D scaled by operating expenses. Firm-level controls are retrieved from Refinitiv, whereas macroeconomic-level controls are retrieved from the World Bank database for the period 2015-2023. Variable definitions can be found in Appendix A (Table A1). The robust standard errors are reported in parentheses and are clustered at the firm level. ***, **, and * significant at the 1%, 5%, and 10% levels, respectively.

Table 9. Comparison of pooled vs. industry-specific estimates

	Three industries	Industrials	Health Care	Information Technology
	M1	M1	M1	M1
R&D Intensity	-0.265***	-0.120	-0.259***	-0.183*
	(0.052)	(0.132)	(0.070)	(0.100)
Controls	Yes	Yes	Yes	Yes
Adj. R^2	0.278	0.215	0.317	0.352
N	2178	675	774	729
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: This table reports multivariate OLS panel regression results of Model 1 for the full sample and for three subsamples: industrials-only, health care-only, and information technology-only firms. Firm-level controls are retrieved from Refinitiv, whereas macroeconomic-level controls are retrieved from the World Bank database for the period 2015-2023. Variable definitions can be found in Appendix A (Table A1). The robust standard errors are reported in parentheses and are clustered at the firm level. ***, **, and * significant at the 1%, 5%, and 10% levels, respectively.

5. Conclusion

Driven by the combined pressure of stricter regulations, climate-risk disclosure requirements, and growing consumer preferences for environmental sustainability, firms are increasingly exploring strategies to reduce their carbon emissions footprint. Given that innovation and technological advancements can improve energy efficiency and substantially reduce carbon emissions, firms can play a key role in achieving global emissions reduction goals. While prior studies have examined the relationship between R&D expenditure and carbon emissions, research on how this relationship differs across industries remains underexplored. This paper addresses that gap by exploring whether the impact of R&D on emissions is uniform across industries or if certain industries benefit more than others. Furthermore, this study contributes to the existing literature by exploring diminishing returns and a U-shaped effect.

Using multivariate panel OLS regressions on a sample of 2,178 firm-year observations from 2015 to 2023, the findings indicate that higher R&D intensity significantly reduces emissions intensity. Additionally, robustness tests reveal that this effect is largely attributed to U.S. firms. Results further indicate no evidence of a non-linear effect of R&D intensity on emissions intensity. In other words, the relationship between R&D intensity and emissions intensity is linear. Following the concept of diminishing returns, it would be intuitive to expect that beyond a certain level of R&D, additional investments would no longer reduce emissions intensity. However, the findings reveal no evidence of this, and therefore, R&D intensity consistently reduces emissions. Given the mixed findings of prior studies and this study, additional research is needed to conclusively determine whether the relationship is linear or non-linear.

Since the interaction terms with industry type are not statistically significant, no definitive conclusions can be drawn about the industry-specific effects of R&D on carbon emissions. However, when the sample is restricted to U.S. firms or to scope 2-only emissions, some interaction terms become statistically significant. Additionally, separate regressions for each industry reveal that R&D intensity is significantly associated with lower emissions intensity in the health care and information technology industries. However, no statistically significant results are found for the industrial industry. This suggests that R&D effectively reduces emissions intensity for health care and information technology firms, while no evidence is found for industrial firms. This suggests that the effectiveness of R&D differs across industries.

While the main regressions do not confirm significant differences across industries, these robustness tests do suggest the possibility of industry-specific differences. Combined with the fact that industries differ substantially in their emissions intensity, this evidence suggests that the relationship between R&D intensity and emissions intensity is unlikely to be uniform across industries. Therefore, implementing industry-specific policies, like subsidizing R&D where it generates a substantial reduction in emissions and using different strategies in less responsive industries, could maximize the climate benefits of R&D. Policymakers should take this into consideration. Subsidies for R&D in health care and information technology firms could reduce emissions intensity, whereas similar incentives may not be beneficial for industrial firms.

These findings carry important economic implications. For firms, investing in R&D can reduce emissions, increasing their environmental performance. It may reduce future compliance costs and satisfy consumer demand for 'green' products, which can enhance long-term profitability and competitiveness. However, firms should recognize that the effectiveness of R&D investments in reducing emissions intensity can potentially differ across industries. Accordingly, firms should adjust their R&D strategies by industry to achieve optimal emissions reductions. For policymakers, these findings underscore the importance of encouraging and subsidizing firms to invest more in R&D, which in turn reduces emissions intensity. At the same time, industry differences in baseline emissions, together with the robustness tests, indicate that one-size-fits-all policies may not be optimal.

These insights suggest several policy recommendations. First, governments should increase support for R&D. This can be done through targeted tax credits, grants, or subsidies that incentivize investments in clean-energy innovation. Second, regulators should set stricter emissions limits, with clear targets. This approach both pushes firms to reduce emissions through stricter regulations and incentivizes them toward cleaner innovation with targeted funding. Combining stricter emissions limits with increased R&D incentives would ensure that firms are motivated to reduce their emissions, which ultimately helps mitigate climate change.

Although these findings broadly align with existing literature, several factors may explain why results differ. For instance, Churchill et al. (2018) use G7 macro data from 1870 to 2014 and report that the relationship between R&D and emissions is time-varying. By contrast, this analysis uses recent firm-level data from 2015 to 2023 in the U.S. and the EU. Moreover, this study measures R&D relative to firm revenue and only scope 1 and 2 emissions, whereas country-level studies use aggregate R&D relative to GDP and total CO_2.

In contrast to this paper, Li et al. (2020) do report a U-shaped relationship between R&D and emissions. However, they scale R&D by operating expenses and use total CO_2. Consequently, these choices affect the magnitude of the relationship between R&D and emissions. In short, methodology, data period, and the definitions used for R&D and emissions are the main reasons for different results across studies. Despite these differences, the vast majority of studies, from macro-level studies to firm-level studies, consistently report a negative relationship between R&D intensity and emissions intensity. This underscores the robustness of the negative effect of R&D on emissions.

This study has several limitations that also suggest directions for future research. First, the analysis focused on only three industries to assess whether the relationship between R&D and emissions would differ across industries. Although the industry-specific estimates lack statistical significance, the clear difference in emissions intensity across industries, combined with statistically significant results in robustness tests, highlights the need for further research. Future research could include a broader range of industries and larger samples to identify where R&D investments are most effective in reducing emissions. Second, the study measures emissions intensity using scope 1 and 2 emissions, excluding scope 3. This approach was taken because capturing accurate scope 3 emissions presents significant challenges, as outlined earlier. Once scope 3 measurements and reporting become more standardized, future studies should assess the impact of R&D on a firm's total carbon emissions, rather than only scope 1 and 2.

Third, although this study employed the same measure for R&D intensity as most studies, future research could investigate the impact of environmentally targeted R&D on emissions intensity. Although such data is not yet widely available, future studies should employ it as it becomes available to reveal the true impact of environmentally focused R&D. Alternatively, a custom metric for environmentally targeted R&D could be developed and tested on a small set of firms through detailed analysis of their sustainability and annual reports. Lastly, this study evaluates the effect of technological innovation from an input perspective. While R&D expenditure is a useful proxy, incorporating innovation outputs, such as the number of patents or green product introductions, would reinforce the findings.

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AI usage:

I acknowledge the limited use of ChatGPT, which was used exclusively for minor adjustments. These include: grammar and coherence checks where needed, help resolve coding issues in R, and initial brainstorming. Every suggestion was critically reviewed and carefully cross-checked against reliable academic sources to ensure full accuracy and academic integrity. These sources have been cited in this thesis. I take full responsibility for the accuracy of this thesis and confirm that this is my original research.

Appendix A

Table A1. Definitions of variables

Variable name	**Variable definition**	**Variable measure**
Dependent variable		
Emissions Intensity	Total estimated scope 1 and 2 emissions in tonnes relative to revenue in millions	ln(Total estimated scope 1 and 2 emissions in tonnes / revenues)
Independent variable		
R&D Intensity	Research and development expenditures (R&D) relative to revenue	ln(R&D / Revenue)
Moderating and control variables		
dh	Dummy variable for health care industry	1 for firms classified as health care; otherwise, 0
df	Dummy variable for information technology industry	1 for firms classified as information technology; otherwise, 0
Size	Firm size	Ln (Total assets)
Leverage	Firm leverage	Total debt / Total assets
CapInt	Capital intensity: amount of capital required to run the production process	Total assets / Total revenue
Tobin's Q	Firm market performance	(Total assets – Book value of equity + Market capitalization) / Total assets
ROA	Return on assets, firm accounting performance	Net income / Total assets
CapEx	Capital expenditure	Capital expenditure / Total assets
MTB	Market-to-book ratio	Market capitalization / Book value of equity
GDP	Gross domestic product	ln(GDP)

Inflation	Inflation is measured by the Consumer Price Index (CPI), which tracks the yearly percentage change in the cost of a fixed or adjusted basket of goods and services	CPI (year-on-year %)
Export	Exports of goods and services provided to the rest of the world relative to GDP	Export / GDP
FDI	Foreign net inflows in the reporting economy from foreign investors relative to GDP.	FDI inflows / GDP

Notes: This table provides the definitions of the firm- and macroeconomic-level variables. Firm-level controls are retrieved from Refinitiv, whereas macroeconomic-level controls are retrieved from the World Bank database for the period 2015-2023.

Table A2. Pairwise correlation

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	Emissions Intensity	1														
(2)	R&D Intensity	-0.23***	1													
(3)	dh	-0.10***	0.29***	1												
(4)	df	-0.06**	0.28**	-0.53***	1											
(5)	Size	-0.10***	-0.12***	0.01	-0.10***	1										
(6)	Leverage	0.08***	-0.02	0.08***	-0.05**	0.04**	1									
(7)	CapInt	0.04*	0.44***	0.29***	-0.08***	0.02	0.10***	1								
(8)	Tobin's Q	-0.20***	0.29***	0.09***	0.12***	-0.28***	0.04*	-0.10***	1							
(9)	ROA	-0.13***	-0.21***	-0.07***	0.05**	0.23***	-0.07***	-0.42***	0.18***	1						
(10)	CapEx	0.27***	-0.01	-0.00	0.14***	-0.07***	-0.08***	-0.12***	0.12***	0.05**	1					
(11)	MTB	-0.15***	0.17***	-0.07***	0.04**	-0.12***	0.13***	-0.09***	0.66***	0.06***	0.05**	1				
(12)	Inflation	-0.15***	0.05**	0.00	0.04*	0.07***	0.05**	0.06**	0.03	0.06***	-0.03	0.04	1			
(13)	GDP	0.05**	0.18***	-0.01	0.16***	-0.07***	0.20***	0.14***	0.12***	-0.05**	-0.06***	0.11***	0.24***	1		
(14)	Export	0.01	-0.11***	0.02	-0.10***	0.11***	-0.14***	-0.09***	-0.13***	0.03	-0.06***	-0.09***	-0.14***	-0.86***	1	
(15)	FDI	0.07***	-0.01	0.00	-0.02	-0.01	-0.01	-0.00	-0.02	-0.01	-0.01	-0.03	-0.21***	-0.10***	0.08***	1

Notes: This table present the Pearson pairwise correlations. Firm-level controls are retrieved from Refinitiv, whereas macroeconomic-level controls are retrieved from the World Bank database for the period 2015-2023. Variable definitions can be found in Appendix A (Table A1).

Table A3. Fixed-effects vs. Random-effects estimates for the effect of R&D Intensity on Emissions Intensity

	FE	RE
	M1	M1
R&D Intensity	-0.265***	-0.157***
	(0.052)	(0.043)
Controls	Yes	Yes
Adj. R^2	0.278	0.208
N	2178	2178
Region FE	Yes	No
Year FE	Yes	No

Notes: This table presents Fixed-effects (FE) and random-effects (RE) estimates of Model 1 from OLS panel regressions of R&D intensity on emissions intensity are shown. Firm-level controls are retrieved from Refinitiv, whereas macroeconomic-level controls are retrieved from the World Bank database for the period 2015-2023. Variable definitions can be found in Appendix A (Table A1). The robust standard errors are reported in parentheses and are clustered at the firm level. ***, **, and * significant at the 1%, 5%, and 10% levels, respectively.

Table A4. Hausman test results

Model	Chi-squared	df	P-value	Result
M1	10.714	12	0.554	Fail to reject H0: RE acceptable
M2	57.166	11	3.1e-08	Reject H0: FE preferred
M3	33.015	12	0.001	Reject H0: FE preferred
M4	55.002	13	4.0e-07	Reject H0: FE preferred
M5	41.387	14	0.00015	Reject H0: FE preferred

Notes: a P-value > 0.05 indicates no significant difference between fixed-effects (FE) and random-effects (RE) estimates, so the RE model may be used for efficiency. In contrast, a P-value < 0.05 indicates a significant difference between the estimators, meaning that the RE estimator is inconsistent, and the FE model is preferred for reliable estimation.