Does Greenwashing Pay?

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Abstract

This thesis tackles the tricky topic of greenwashing and how it may affect a company's financial performance. This is done by creating a greenwashing indicator (GWI), using a company's rating on environmental performance (E-score) as measured by a rating organization and its reported carbon emissions. The E-score is part of the more general ESG-scores, which are a widely used metric in environmentally sustainable investing and sustainability research. This metric does however have a lot of shortcomings and can not be interpreted at face value. This thesis provides insights into the shortcomings of the E-score.

The quantitative analysis reveals no significant relationship between E-scores and carbon emissions, suggesting other factors besides a company's quantitative environmental footprint dominate the E-score calculations. The relationship between the GWI and financial performance is complex, with varying results across different models. Overall, we find no significant relationship between the GWI and the performance in the following year. Contrary to expectation, non-heavy-polluting sectors exhibit higher greenwashing scores than heavy-polluting sectors, indicating a greater likelihood of greenwashing where regulations may be less stringent.

This thesis provides a step in the right direction of analyzing greenwashing and environmental performance with quantifiable metrics. The findings in this thesis also emphasize the importance of establishing standardized and more extensive guidelines for gathering environmental data. Data availability is one of the major shortcomings of environmental analysis, and stricter guidelines will help to develop better metrics of greenwashing, and lead to a better, more comprehensive way to answer this important research question in the future.

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Does Greenwashing Pay?

1. Introduction

Governments, businesses, and individuals are increasingly worried about the consequences of climate change. Governments stepped up their efforts to counter the impact by negotiating agreements under the guise of the United Nations. The Paris Climate Accord (2015) was an important milestone, in which these governments agreed to limit the production and use of fossil fuels and take a number of other measures to keep our planet livable.

Companies around the world are encouraged to abide by new standards such as SFDR[1], but they may also view the awareness regarding climate as an opportunity. Many companies adjust their strategies accordingly. Some companies genuinely prioritize efforts to significantly reduce their CO2 emissions in response to consumer demands. On the other hand, there are concerns about certain companies possibly leveraging consumer wishes merely as a marketing strategy, potentially obscuring their actual environmental impact to the uninformed consumer. This is a practice also known as **greenwashing** (De Freitas Netto et al., 2022).

Greenwashing is problematic for several reasons. First, it can lead to consumer confusion and mistrust, as people may be misled about the true environmental impact of the products they buy. Second, it can discourage people from taking genuine action to reduce their environmental impact, as they may feel that their efforts are futile if companies are not being honest about their own practices. And third, greenwashing can have negative consequences for the environment, as it may allow companies to continue harmful practices while appearing to be eco-friendly (Lyon & Montgomery, 2015).

An example of greenwashing can be found in the **net-zero** campaign. Producers of products as well as governments use terms like net-zero to label their policies. When for example an organization achieves net-zero emissions, it means they are balancing their carbon emissions with an equivalent amount of carbon removal or offset. This would result in no net contribution of greenhouse gases into the atmosphere. There is a danger in using these terms when you don't have a clear definition and you don't back it up with concrete action. Over the last few years the term 'net-zero' has become the main term for companies and governments when they talk about what they are going to do to halt climate change. A study on the largest corporate greenhouse gasses emitters revealed that out of the 160 biggest polluters, "only six companies explicitly commit to aligning their future capital

[1] Sustainable Finance Disclosure Regulation

expenditures with their long-term emissions reduction targets, and none of these companies has committed to aligning future capital expenditure with the goal of limiting temperature rise to 1.5 degrees Celsius" (Climate Action 100+, 2021). They view the way we currently use and report on companies' net-zero pledges as nothing more than greenwashing.

Net-zero suggests that you are helping to mitigate the impact of climate change when, for example, buying a product with that label, in reality is not a sustainable solution at all. Net-zero is a way for certain polluting companies to continue their polluting practices and pay other parties to 'offset' their emissions. This is a major obstacle to the change in behavior that is needed to create the sustainable world governments are aiming for, and it hinders awareness among consumers as well. People think that by buying products with certain labels, they are contributing to the fight against climate change, while in reality these products may hinder the necessary progress. Polluting companies continue their harmful practices, while on paper they reach certain climate goals.

International organizations are struggling to fight greenwashing. A good example is the European Commission, which in 2023 did an extensive survey[2] among national governments, to provide input on (1) definitions, cases and risks of greenwashing, (2) the ways greenwashing and relevant sustainable finance requirements can and should be supervised, and (3) proposals to improve the regulatory framework. The UN is starting similar initiatives, slamming companies that mislead their customers with weak net-zero pledges.[3]

Young generations are determined to keep the planet livable and realize that real action is needed. Greenwashing is an important obstacle to real action and it should be eradicated. The problem is that greenwashing is a relatively qualitative and under-researched topic.

This thesis explores whether it is possible to create a quantitative metric to detect possible greenwashing and make a more comprehensive use of the sustainability-related data. This thesis aims to shed light on greenwashing with the use of ESG-scores in the practice of environmentally sustainable investing and how sustainability-related metrics are used.

There is a lot of research linking high ESG-scores to financial performance. A wrong conclusion people often draw from this, is that the score can also be widely used to promote environmentally friendly investing (Ehlers et al., 2022): a high ESG-score doesn't necessarily mean a company is environmentally friendly, because the ESG-score contains not only an environmental pillar, but also a social and governance pillar. Another issue is that the environmental pillar score can be easily

[2] https://www.eba.europa.eu/esas-launch-joint-call-evidence-greenwashing

[3] United Nations' High-Level Expert Group on the Net Zero Emissions Commitments of Non-State Entities, 2022, *Integrity Matters: Net Zero Commitments by Businesses, Financial Institutions, Cities and Regions*, pp.42.

manipulated and is therefore prone to greenwashing. Both the companies themselves and the ESG rating agencies have difficulty finding a way on how to report and interpret ESG- and sustainability-related data (Christensen et al., 2019). In short, there are a number of struggles regarding the use and interpretation of sustainability metrics that are widely used. The main suggestion these papers and others make is that instead of creating new metrics, it might be better to try and better understand what is wrong with how we currently use ESG data for environmentally sustainable investing and how we could tackle those problems.

Ehlers et al. (2022) suggest that it is better to focus solely on the environmental pillar when discussing environmental sustainability. In et al. (2021) propose to use carbon emission related data to quantitatively analyze greenwashing. This thesis aims to combine carbon emission data and the Environmental score (E-score) to quantitatively analyze this subject.

To tackle the above mentioned problems, we will take a number of steps. First, an overview is provided of carbon emission data and E-scores at the company level. This allows us to see trends over time and better understand the dynamic of these metrics. Second, we will try to relate the actual action of companies as measured by their emission data, to their E-score. This will allow us to distinguish companies that truly make a difference from those that do not. If a company's E-score is significantly higher (suggesting better environmental performance) than its peers, but its carbon intensity is also much higher (suggesting more emissions per unit of production), this discrepancy could indicate greenwashing. A truly environmentally-conscious company should strive for both a high and rising E-score and low and falling carbon intensity. I will use the results from this analysis to explain differences in performance. With these performance results, I will try to answer the main research question: ‘Does greenwashing lead to better financial performance’.

This thesis investigates the relation between greenwashing and financial performance. The Greenwashing Indicator (GWI) is developed to assess discrepancies between companies' reported environmental performance (E-score) and their actual carbon emissions. The quantitative analysis reveals no significant relationship between E-scores and emissions, suggesting other factors dominate the quantitative environmental impacts in E-score calculations.

The relationship between greenwashing and financial performance is complex, with varying results across different models. Overall, we find no significant relationship between the greenwashing indicator and the performance in the following year. Contrary to the expectation, non-heavy-polluting sectors exhibit higher greenwashing scores than heavy-polluting sectors, indicating a greater likelihood of greenwashing where regulations may be less stringent.

This thesis provides a step in the right direction of analyzing greenwashing and environmental performance with quantifiable metrics. However, the findings in this thesis also emphasize the importance of establishing standardized and more extensive guidelines for gathering environmental data. This hopefully helps to develop better metrics of greenwashing, and lead to a better, more comprehensive way to answer this important research question in the future.

The structure of this thesis is as follows. Chapter 2 reviews the literature on the measurement of greenwashing and the way these measures are used in practice. Chapter 3 provides an overview of the data and the methodology. Chapter 4 presents the empirical results and finally, Chapter 5 concludes.

2. Literature Review

This chapter reviews the literature needed to develop testable hypotheses on greenwashing. First, the ways sustainability is measured is presented. Second, the link between ESG-data and company performance is explored. Third, the concept of greenwashing is explained. Fourth, the research questions and hypotheses are presented.

2.1 Measuring sustainability

One specific classification used in responsible investing that has become increasingly popular over the last two decades is the ESG-score of a company. The ESG-score is a measure used to evaluate the performance of a company in three important areas: Environment, Social responsibility, and Governance. The ESG-score represents how well a business is doing in terms of sustainability, treating people fairly, and running its operations in an ethical and transparent manner. Higher scores indicate better performance in these areas. High scores signal to investors and other stakeholders that the company is committed to sustainable and responsible practices (Li et al. 2021).

However, there are a number of problems that have to be taken into account when using ESG-scores.

The first problem is that there is limited consensus among rating agencies on the ESG-performance of companies. ESG-scores are determined by specialized agencies that evaluate the environmental, social, and governance performance of companies. These agencies use a large variety of data sources to assess a company's ESG performance. They then assign a score to each company based on their assessment, which is intended to provide investors and stakeholders with a standardized measure of a company's ESG practices.

These ESG-scores differ quite extensively among agencies, which make the general applicability of these scores problematic. Berg et al. (2022) explore and explain the large divergence of ESG-scores between 6 prominent ESG rating agencies: MSCI, Sustainalytics, RobecoSAM, Vigeo-Eiris, ISS ESG, and S&P Global. These agencies are widely used by investors and researchers.

Each agency developed its own methodology for evaluating ESG performance, which leads to significant differences in scores across agencies. One agency may place greater emphasis on environmental factors, while another may focus more on social or governance factors. Additionally, agencies may use different data sources or weighting schemes, which can also contribute to rating divergence. This is a counterintuitive finding, as these ESG-scores are supposed to measure the same characteristics of a company. Berg et al. (2022) find that the metrics used to evaluate the same attributes are responsible for most of this difference between rating agencies, and that weighting differences can explain only 6% of the differences. This indicates that there isn't one universal measurement standard for ESG rating agencies across the board, which also undermines the representability of ESG-scores. Even consistently using one rating agency to evaluate a company doesn't solve these problems. This divergence of ratings brings into question the representability of ratings as a whole. The divergence in ratings, combined with other flaws in ESG-scores, implies that it may not be sufficient for investors and other stakeholders who try to make environmentally responsible decisions to solely consider ESG-scores.

Christensen et al. (2019) further confirm these issues around the interpretation ESG rating agencies have. They find that with more ESG related data disclosure of a firm, the larger the variability across these rating agencies becomes. According to the authors, these disagreements across agencies are driven primarily by the environmental and social pillar data. Even though they highlight that there is a lot of disagreement on how to interpret and handle ESG related data, they say that there is still a lot to explore about the potential consequences of such disagreements and how to tackle those problems.

Despite these challenges, ESG-scores remain an important tool for investors and researchers who want to evaluate companies' sustainability practices (Berg et al., 2022). By providing a measure of ESG performance, these scores can help investors make informed decisions about which companies to invest in and can encourage companies to improve their sustainability practices. However, as Berg et al. (2022) state, the divergence of ESG-scores across agencies can create confusion and misinterpretation of ESG performance, which highlights the need for standardization in the ESG rating industry.

The second problem is that there has been a consistent upward drift over time across the board in ESG-scores. According to Larcker et al. (2022), this is not due to actual improvements in ESG performance. These changes appear to be mainly caused by changes in the way ESG rating companies assign ESG-scores. The two contributing factors are (1) changes in the weighting assigned to certain components, and (2) more disclosure about private data by companies. According to the paper, a company appears to be significantly more likely to receive an increase in its ESG-score, when it starts *disclosing* more emission data, without there actually being a change in emission behavior.

New regulation

Regulators recognize the problems with data and aim to sharpen the reporting requirements. Financial regulators in Europe are front-runners on this topic and introduced the Sustainable Finance Disclosure Regulation (SFDR) in 2021. The SFDR builds on the United Nations' Sustainable Development Goals and the Paris Agreement, which aim to significantly reduce the risks and effects of climate change.[4] SFDR seeks to improve the disclosure of information regarding the impact on sustainability by the investment policies and investment decisions made by financial market participants. Investors increasingly require the SFDR label, but actions underlying the products seem to be limited (Fillippi, 2022). SFDR distinguishes different types of labels for investment funds, where truly green funds can label themselves Article 8 or Article 9 funds, while all the others are labeled Article 6 funds. Investment funds with and without an Article 8 or 9 label are expected to be viewed and priced differently by the market.

Fillippi (2022) explains that there is both intentional and unintentional greenwashing, leading investors to choose a product on the wrong grounds. Unintentional greenwashing can arise from genuine misunderstandings or misinterpretations of what sustainability entails or what the SFDR requires. Given that SFDR is relatively new and the field of sustainability reporting is evolving, companies might inadvertently report or highlight aspects that do not genuinely reflect their environmental or sustainable impact. They might believe they are in compliance with the SFDR and genuinely strive for sustainability, even if they fall short in certain respects. This not only applies to SFDR, but sustainability reporting in general has its problems. Unlike financial metrics, which are predominantly quantitative and precise, many sustainability metrics involve qualitative assessments or are based on assumptions that can be interpreted differently across companies. Both the companies themselves and the ESG rating agencies struggle with finding a consensus on how to report and interpret ESG and sustainability-related data (Christensen et al., 2019). SFDR is just another example of how across the board there are problems with interpreting environmental sustainability data and this isn't exclusive to ESG. Therefore instead of creating new metrics, it might be better to try and better understand what is wrong with how we currently use ESG data for environmentally sustainable investing and how we could tackle those problems. In this case, my contribution to the literature would be running an analysis that combines E-scores and financial performance. It will include Carbon Intensity to measure the relationship of environmental performance with the E-score.

[4] https://www.robeco.com/nl-nl/begrippenlijst/duurzaam-beleggen/sustainable-finance-disclosure-regulation

2.2 ESG and Performance

Over the last few decades a lot of research has been conducted on the relationship between ESG-scores and financial performance. Past research suggests that a high ESG-score tends to be positively correlated with financial performance (Friede et al., 2015). Based on their analysis of more than 2,000 papers on the subject, the authors conclude that "roughly 90% of studies find a nonnegative relation between ESG-scores and corporate financial performance. More importantly, the large majority of studies report positive findings".

The positive correlation between ESG-scores and financial performance is relevant in the context of greenwashing because it suggests that companies that manipulate their ESG-score may see financial benefits from doing so. In other words: companies that are not actually focused on material ESG issues may still see the same financial benefits as companies that are truly committed to sustainability (Friede et al. 2015).

However, a problem with most of this research is that it uses the general ESG-scores when running performance analysis (Ehlers et al., 2022). This is not complete evidence that running an environmentally green operation leads to a higher performance, as a company's ESG-score is not only determined by environmental sustainability, but also Social and Governance component of ESG. The main critique of Ehlers et al. (2022) is that just looking at the ESG-score as a whole is not enough to claim you're an environmentally responsible investor. Past research has mostly focused on this broader ESG-score for environmentally responsible investing. The way this thesis aims to contribute to the literature is exploring to what extent greenwashing, as represented Greenwashing Indicator developed in this thesis, is associated with company performance.

When looking at the performance based on just the Environmental Pillar Score (the E-score), there has been some previous research on the subject. For example, Ehlers et al. (2022) explore the separate pillars that comprise the ESG-score. Their main idea is the fact that high scores in one pillar can offset the low scores in another. In the pursuit of creating a sustainable portfolio, this phenomenon can lead sustainable investors to make choices that are inconsistent with their original intentions, without realizing it. Ehlers et al., (2022) state that investments based only on the E-score prevent potential confusion around the interpretation of ESG-scores, improves an investor's ability to better track the environmental sustainability performance of their portfolio, and leads to just a small impact on performance compared to a general stock market benchmark.

2.3 Greenwashing

The discussion on ESG-scores, the separate environmental pillar, and E(SG) based performance is directly linked with the subject of greenwashing. It poses challenges to both investors and to the integrity of ESG-metrics in general. Companies that engage in greenwashing may take advantage of the variability in ESG-scores across agencies (Berg et al.,2022). The divergence of these ratings creates an incentive for companies to focus on specific metrics that are emphasized by certain agencies. Companies potentially neglect important aspects of their actual sustainability practices and this can prevent an accurate representation of a company's true sustainability efforts. By exploiting the complexity of rating methodologies, greenwashing not only misleads investors but it also undermines the aim to be truly impactful. Companies create a façade of environmental responsibility. All this underscores the urgency of comprehensive transparency, standardized evaluation metrics, and vigilant due diligence in sustainable investment practices.

The implications of greenwashing go beyond misleading investors; they also cast a shadow over the overarching goals of responsible investing. The rising interest in ESG-scores as key indicators of a company's sustainability performance highlights the need for cohesive and reliable evaluation mechanisms (Larcker et al., 2022). The prevalence of greenwashing not only erodes investor trust, but also obscures the genuine efforts of companies that strive for environmentally responsible practices. Consequently, the broader goal to drive positive environmental and social impact through investment is jeopardized by the divergence of ESG-scores and the lack of standardization (Larcker et al., 2022). This highlights the need for consistent industry-wide standards, increased regulatory oversight, and improved disclosure practices.

The problems found around ESG-scores and potential greenwashing are further highlighted by In et al. (2021), who focus on the E-score. They introduce the term “carbonwashing” as a form of greenwashing and propose a quantitative approach to research the subject. The authors explore how companies may be able to take advantage of the inconsistency between rating agencies and how environmental data is examined (see above). They state that the way the sustainability of a company is measured, reported and tracked has always lagged behind. Corporations therefore have conflicting interests to intentionally convey information that may not accurately reflect their genuine environmental impact or to offer unsupported commitments regarding future sustainability goals. The divide between corporate pledges of reducing carbon emissions and actual concrete steps has grown wider. According to In et al. (2021), a significant portion of financial markets continues to primarily depend on unverified, self-reported data as of 2021. With the lack of proper validation procedures, the motivation to pursue strategies involving deliberate misinformation has not significantly diminished. This leads to drawing possibly biased conclusions when analyzing carbon data and it requires a lot of caution. However, even with this problem in mind, combining carbon emission data and E-score may provide a suitable approach to run a quantitative analysis on a more qualitative subject. It is still data that is widely available for a large number of public companies.

A concrete and really important example of greenwashing is the gap between corporate pledges and actual concrete steps in their 'net-zero' aim. Over the last few years 'net-zero' has become an important term used by companies and governments when they talk about what they are going to do to halt climate change. When for example an organization achieves net-zero emissions, it means they are balancing their carbon emissions with an equivalent amount of carbon removal or offset, resulting in no net contribution of greenhouse gases to the atmosphere. Climate Action 100+ (2021) conducted a study on the largest corporate greenhouse gasses emitters. It revealed that out of the 160 biggest polluters, "only six companies explicitly commit to aligning their future capital expenditures with their long-term emissions reduction target(s), and none of these companies has committed to aligning future capital expenditure with the goal of limiting temperature rise to 1.5 degrees Celsius". They view the way we currently use and report on companies' net-zero pledges can be seen as nothing more than greenwashing.[5]

2.4 Research questions and hypotheses

As indicated in the introduction, the main goal of this research is to see if greenwashing is associated with better financial performance of a company. To answer this question, an overview is presented of trends in carbon emission data and E-scores at the company level. Next, actual actions by companies as measured by their emission data will be related to their published E-score.

Hypothesis 1

The E-score and the carbon intensity of a company should be closely related: a higher carbon intensity should be associated with a lower Environmental Pillar score, as emissions are the main determinant of the E-score of a company.[6] The E-score ranges between 0 to 100, with a score of 0 as being the worst and a score of 100 as the best a company can do. For the carbon intensity a similar 0-100 scale is created for each industry. We create a greenwashing indicator by combining these scores. This indicator should help us to distinguish companies that truly make a difference from those that do not. The issue of manipulability of ESG-scores to enable greenwashing is a concern emphasized in

[5] https://www.climateaction100.org/news/climate-action-100-issues-its-first-ever-net-zero-company-benchmark-of-the-worlds-largest-corporate-emitters
[6] https://www.refinitiv.com/en/sustainable-finance/esg-scores

multiple studies. The literature review discussed the important discrepancies found in rating methodologies among different agencies, as highlighted by authors like Berg et al. (2022). Not only variation across agencies, but also the way carbon emission data is collected and interpreted is an important contributor to possible greenwashing. Such variations provide companies with opportunities to improve their scores without necessarily making impactful sustainable changes. Another problem is that most research looked at general ESG-scores. High scores in one pillar can offset low scores in another, which may lead the investor or researcher to make ill-informed decisions.

Based on the literature review, the following hypothesis is formulated:

> **H1: "There is a negative association between the carbon emissions of a company and its E-Score."**

Hypothesis 2

Previous studies highlighted both the potential and the challenges of ESG-scores, especially concerning their consistency, transparency, and reliability. Combining the E-scores with emission data creates an opportunity to determine how well companies' self-reported or agency-graded environmental profiles align with their actual carbon footprints. By assessing the degree of alignment between these two metrics, we can potentially identify greenwashing. The Greenwashing Indicator (GWI) is designed to quantify the discrepancy between a company's environmental performance (E-score) and its actual carbon emissions. This indicator helps to identify instances where a company's environmental claims don't align with its carbon emission reality, which could indicate potential 'greenwashing'.

The companies with a positive value for the Greenwashing Indicator we classify as greenwashing companies, companies with a negative value for the GWI can be seen as non-greenwashing companies. The way this variable is constructed and used will be explained more in depth in the data & methodology chapter. This greenwashing indicator will be used to answer the overarching research question on the subject of greenwashing: "Is greenwashing associated with better financial performance of a company." As stated in the literature review, E-scores and rankings are increasingly important to investors and other stakeholders. Companies with higher E-scores are often seen as less risky and more attractive investment opportunities. By artificially inflating their E-scores, companies may attract more clients and investors and potentially see an increase in their stock price. But do they actually see a financial benefit from potential greenwashing? And to what extent does this

Greenwashing Indicator give us the opportunity to explore this topic in a quantitative way? This will be done with the following hypothesis:

> **H2: “There is a positive relation between the greenwashing indicator and company performance.”**

Hypothesis 3

The final section focuses on differences between more polluting and less polluting industries. Cao et al. (2022) explore the relationship between the quality of carbon information disclosure and enterprise value for heavy-polluting industries versus non-heavy-polluting industries. The quality of carbon information disclosure is also an important part of the methodology used to construct the E-score.[7] Cao et al. (2022) find that carbon information disclosure has a small, non-significant impact for heavy polluting firms. For non-heavy-polluting firms carbon information disclosure and enterprise value are positively and significantly correlated.

Heavy-polluting companies and non-heavy-polluting companies may adopt different approaches to environmental reporting. High-polluting companies may engage in greenwashing to maintain their image and manage regulatory and public pressure, while low-polluting companies might focus on actual improvements and transparent reporting. Cao et al. (2022) mention that the need to account for future environmental liabilities may incentivize these highly polluting companies to engage in greenwashing, presenting themselves as more environmentally friendly than they are to mitigate potential backlash or regulatory penalties. Another argument they mention is that non-heavy-pollution enterprises face less environmental pressure and may therefore be more responsive and sensitive to government ecological regulations. Their operations inherently carry lower environmental risks, making it easier and more beneficial for them to comply with regulations and improve their carbon intensity disclosure (CID) quality.

They only mention possible reasons for a higher prevalence of greenwashing in highly-polluting industry. This hypothesis then aims to further explore this topic using the greenwashing index created in this thesis to see to what extent greenwashing is more prevalent in highly polluting sectors, compared to less polluting sectors, splitting the dataset in the same way Cao et al. (2022) did. The hypothesis to be tested is the following:

> **H3: Greenwashing is more prevalent in heavy-polluting sectors compared to non-heavy-polluting sectors**

[7] https://www.lseg.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf

3. Data and methodology

This chapter presents the dataset used in the quantitative analysis. The methodology is presented next.

3.1 Data

Data sources

The data used was made available through the Refinitiv Eikon database. Refinitiv Eikon is a widely used tool in the world of financial analysis. It offers its extensive database to professionals across finance, banking, and various corporate sectors. Refinitiv Eikon is known for its comprehensive insights into markets, companies, and global economies, as it integrates a wealth of information including real-time data, news, analytics, and trading capabilities.

A feature of Refinitiv Eikon that makes it of value for this specific research is its Environmental, Social, and Governance (ESG) data, particularly the environmental pillar. This aspect of Eikon's database offers detailed insights into the environmental practices and impacts of companies. Their Environmental pillar score, which Refinitiv Eikon created based on self-reported company data and public records, is considered one of the top ESG databases available[8]. The database's analytical tools ensure that the data are standardized and comparable across different companies and industries.

The Refinitiv Eikon database also contains detailed carbon emissions data, focusing on Scope 1 and Scope 2 emissions of companies. Scope 1 emissions are those that come directly from sources that a company owns or controls, which are a direct consequence of the company's actions and operational decisions. These emissions are a key indicator of a company's carbon footprint and operational efficiency. Scope 2 emissions are indirect and arise from the company's energy consumption, specifically from the generation of purchased electricity. These emissions reflect the company's choices in sourcing its energy and can be influenced by the mix of energy sources used by the utility providers. Together, Scope 1 and Scope 2 emissions provide a comprehensive metric of a company's environmental impact.[9]

The carbon and ESG related data is at the basis of this thesis. The database used for the empirical study therefore contains companies for which E-scores as well as carbon intensity data are available. The reasons to use these metrics are: (i) their large coverage of publicly traded companies, (ii) their

[8] https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf
[9] https://www.epa.gov/climateleadership/scope-1-and-scope-2-inventory-guidance

ease of understanding, and (iii) the availability of a wide range of research papers on similar topics, allowing us to compare the outcome of this analysis with the results of a wide range of other papers.

Table 1 presents data from Refinitiv Eikon. It shows average data for several important sectors from around the world. The original dataset contained around 1,500 companies in the period 2016-2022. Companies without an E-score were dropped. Although essential for performing this analysis, it is important to consider that this will lead to a significant bias in the dataset, as it is not random if a company has an E-score or not. It might for example over-represent companies that are more environmentally conscious or proactive in disclosing environmental data. This doesn't necessarily mean they perform better environmentally. It might just be the case that these companies are more open or obliged to report such information. Companies that don't report enough data to have an E-score might do so for various reasons, such as lack of resources or strategic choice to not disclose. This could skew results towards companies with better environmental practices or higher awareness. On the other hand, greenwashing typically involves companies actively portraying themselves as more environmentally friendly than they really are, which often happens through ESG reporting. Companies without an E-score might not engage in ESG reporting at all, and hence, are less likely to be involved in greenwashing practices.

Before 2016, carbon emission data was very limited, so even though E-score data are available for previous years, the focus is on the period 2016-2022. For 2022 there were no missing values. We had to drop 58 observations because the E-score was missing in 2021. Every subsequent year dropped removed on average around 150 companies per year due to lack of E-related data. By selecting the period 2016-2022, the number of observations appeared to be sufficiently large and recent to perform the analysis. Subsequently, companies were selected for which sufficient emission data were available. These steps led to a panel dataset of 283 unique companies in a wide range of sectors, with almost 2,000 observations in total. Because of the available E-scores and scope 1 and 2 emission scores, I was also able to calculate the carbon intensity of all the companies over the years. Table 1 shows the number of companies per sector, and sector averages for the year 2021, indicating the range of data for the analysis. These data are available for the period 2016-2022. This table clearly shows which industries have the highest carbon intensity. These are also the sectors for which I have the most observations available. As can be seen in the table, the energy sector is the biggest polluter. And has the worst carbon intensity score. The Chemicals and basic resources sectors are also big emitters and have a high carbon intensity, indicating bad environmental performance.

Table 1: Descriptive statistics on sectors (2016-2022)

Industries	#	**Revenue**	**E-Score**	**Scope 1+2**	**Carbon Intensity**
		Avg (mln Euro)	**Avg**	**Avg emissions (tonnes CO2)**	**Scope1+2 / revenue (mln Euro)**
Automobiles and Parts	12	37803	71.7	1318450	51.08
Basic Resources	36	6154	66.4	7278421	636.89
Chemicals	26	10608	68.0	8548453	864.11
Construction and Materials	7	9615	78.8	2370020	169.56
Consumer products and services	12	8879	64.5	116922	14.10
Energy	36	38953	61.2	16293127	1164.80
Food, Beverage and Tobacco	13	18226	68.1	1575129	197.22
Health Care	45	14833	68.8	447745	35.76
Industrial Goods and Services	56	13449	71.1	1302261	86.72
Technology	42	26631	65.3	878880	72.41

Source: Refinitiv Eikon Database

Non-heavy-Polluting: Consumer Products and Services, Health Care, Technology, Industrial Goods and Services, Automobiles and Parts

Heavy-Polluting: Basic Resources, Chemicals, Food Beverage & tobacco, Construction and Materials, Energy

3.2 Variables

Table 2 lists the variables used in the quantitative analysis. Each variable will be explained further below.

Table 2: Variables and their role in the regressions

Variable	**Definition**	**Unit of Measurement**	**Regression Role**
Country of Headquarters	Country where the company headquarters are located	N/A	Control Variable
Carbon Intensity	Amount of emissions generated for each EUR of revenue	Tons CO2e/EUR Revenue	Independent Variable
Firm Size	Size of each company	LN of Assets	Control Variable
R&D Intensity	Amount spent on Research and Development per Euro of Revenue	R&D in EUR/Revenue in EUR	Independent Variable
Total Emissions	Total GHG emission (Scope 1 + Scope 2)	Tons CO2e	Independent Variable
Revenue	Yearly revenue generated by company	EUR	Dependent Variable H2
Environmental Pillar Score	Metric that evaluates a company's environmental performance and impact	0-100 Scale	Dependent in 1st
Greenwashing Indicator	Unit to measure discrepancy between E-Score and Carbon intensity rank	-100-100 scale	Independent Variable H2

Dependent variables

Environmental Pillar Scores (score between 0 and 100): E-scores, from Refinitiv Eikon, give a view on how companies perform regarding the environment. These scores are created by not only looking at carbon emissions, but also other important environmental aspects like, how much water is used, waste, research and innovation and how open the company is about its environmental practices. The main point of the Environmental Pillar score is to show how well a company deals with environmental risks and takes advantage of opportunities to be more sustainable. These scores cover different areas and show how committed a company is to being environmentally responsible. They check how a business manages big environmental issues through new ideas, using resources well, and reducing emissions. The way these scores are calculated makes sure they show what a company is doing now for the environment and also how it plans to keep improving. There are three main topics that Refinitiv uses to create the Environmental pillar score variable. These are the emissions, innovation, and resource use. [10]

When assessing companies, certain environmental criteria are evaluated in a yes/no format. For example, whether a company has an explicit policy to reduce carbon emissions is one of the data points: true if the policy exists, false if not. The sum of these scores is then ranked for each separate industry using the percentile rank scoring methodology. This methodology ranks a company's position, relative to the other companies in the same industry.[11]

The E-score is central in our analysis. For hypothesis 1, we use it as the main dependent variable we are looking at, to see if there is a negative association between the carbon emissions of a company and its E-Score. For hypothesis 2, it is used to create the Greenwashing Indicator.

Revenue: Revenue, measured as the annual income generated by a company in EUR, is a crucial variable that spans the entire sample period on a yearly basis. To normalize this data and address skewness, the natural logarithm (LN) of revenue will be employed. This transformation stabilizes the variance but it also helps in handling outliers, making the data more suitable for statistical analysis.

One key aspect to note is that revenue is instrumental in calculating Carbon Intensity, and thus also the greenwashing indicator for which carbon intensity is used. This interdependence raises a concern about potential reverse causality: the idea that Carbon Intensity might influence Revenue, rather than the other way around. To mitigate this issue, the study will incorporate a one-year lagged version of

[10] https://www.lseg.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf

[11] https://www.lseg.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf

Revenue in the regression analysis. By using the revenue figures from the next year, the likelihood of reverse causality impacting the results is substantially reduced, as it aligns the timing of cause and effect more appropriately.

Furthermore, the one-year lagged revenue figure will serve as the main dependent variable in the second regression model. This approach allows for a more accurate assessment of the relationship between a company's financial performance and other variables in the study, such as environmental scores and carbon emissions.

In academic literature, revenue is a widely accepted proxy for financial performance due to its direct reflection of a company's market activities and ability to generate sales (Huang et al., 2023). It offers a uniform and comparable measure across various industries, unlike profit margins or return on equity, which can vary significantly. Revenue is also less susceptible to manipulation through accounting policies, making it a more reliable indicator of a company's market performance.

Independent Variables

Total Carbon Emissions (tons of CO_2 equivalent emissions): Carbon emissions is a key metric that reflects how much carbon emissions a company produces, as measured by the sum of their scope 1 and scope 2 emissions. These two metrics are essential when trying to understand a company's environmental impact.

Scope 1 CO_2 equivalent emissions are the direct emissions in tons from sources owned or controlled by the company, indicating the immediate impact of its operational choices and efficiency. Scope 2 CO_2 equivalent emissions represent indirect emissions in tons generated from the purchase of utilities, thus reflecting the company's energy procurement practices. The importance of including both Scope 1 and Scope 2 emissions in environmental research is emphasized for a complete assessment of a company's carbon footprint, as indicated in previous studies like Long et al. (2015) and Cheng et al. (2018). Scope 1 emissions address the direct consequences of a company's activities, while Scope 2 emissions broaden the scope to include the indirect effects related to energy use.

Scope 3 emissions, which are indirect emissions linked to a company's value chain, would provide a more comprehensive view, but reporting is lacking in this area (Mercereau et al., 2020). Therefore, this research focuses on just Scope 1 and 2 emissions.

These carbon emissions data have been collected following the so-called GHG Protocol, a global standard for measuring greenhouse gas emissions. A lower carbon intensity suggests greater efficiency and a smaller environmental impact. This data will be used to assess the real environmental impact of a company and to compare it with its Environmental Pillar score. In our analysis, Carbon Emissions will be used as an explanatory variable in hypothesis 1 and will be used to create carbon intensity and the Greenwashing Indicator used in hypothesis 2.

Greenwashing Index: Previous studies have highlighted both the potential and challenges of ESG-scores, especially concerning their consistency, transparency, and reliability. Combining the E-scores with emission data creates an opportunity to determine how well companies' agency-graded environmental profiles align with their actual carbon footprints. By assessing the degree of alignment between these two metrics, we can potentially identify greenwashing, whereby companies overstate or falsely represent their environmental responsibility. The Greenwashing Indicator (GWI) is designed to quantify the discrepancy between a company's environmental performance (E-score) and its actual carbon emissions. This indicator helps to identify instances where a company's environmental claims might not align with its carbon emission reality, which could indicate potential 'greenwashing'.

First, the carbon intensity was calculated. Carbon Intensity is a metric that reflects how much carbon emissions (both Scope 1 and Scope 2) a company produces per unit of output. In this study, the variable revenue is used to proxy the economic output of the company. This metric is widely used in previous literature to help understand how efficiently a company produces goods or services in terms of carbon emissions.

To be able to compare the E-score with the carbon intensity, I then created a rank for carbon intensity. I used the same percentile rank scoring methodology that Refinitiv used to create the E-score. This rank is also on a scale from 0-100 and like Refinitiv did for the E-score will be done for each separate industry.

The steps to be followed to create the Greenwashing Indicator are the following:

a. Carbon Intensity Rank Calculation:
   Convert the Carbon Intensity data for each company per industry into a percentile rank, like Refinitiv has done with the E-score.
b. Inversion of Carbon Intensity Rank:
   Invert the Carbon Intensity rank so that higher values represent better (lower) carbon intensity, aligning with the positive interpretation of higher E-scores.
c. Annual GWI Calculation:
   For each year and each company, subtract the inverted Carbon Intensity rank from the company's Environmental Pillar score.
d. Interpreting GWI:

A positive GWI value indicates a potential greenwashing scenario, where the company's E-score is disproportionately higher than its carbon emission performance would suggest.

This indicator will be a crucial tool in analyzing whether companies with higher discrepancies in their environmental reporting and actual emissions also demonstrate better financial performance, thus providing insights into the impact of greenwashing on company success. The greenwashing indicator is a continuous variable that can take values between -100 and 100.

The E-score was benchmarked by Refinitiv against a larger database of companies, and the carbon intensity ranked was benchmarked against each industry's companies that were available in this dataset. A small degree of misalignment between the E-score and carbon intensity rank is therefore to be expected, without necessarily indicating greenwashing. This also leads to the choice of not including the Greenwashing variable as a binary variable, but to include the degree of alignment between carbon intensity and the environmental pillar score. The nuances captured in this Greenwashing index give us a more comprehensive understanding when assessing the environmental performance of a company and potential greenwashing

In the methodology section the way this Greenwashing Indicator is applied will be explained further.

Heavy-polluting vs. Non-heavy polluting industries: As an additional analysis for hypothesis 2, the dataset is split into two groups: heavy-polluting industries, and non-heavy-polluting industries. Using the approach employed by Cao et al. (2022) the dataset is split based on average total emissions per industry to test if there is a difference in the degree of greenwashing as measured by the GWI between highly-polluting industries and non-highly-polluting industries. Heavy-Polluting industries are basic resources, chemicals, Energy, Food beverage & tobacco, construction and materials, while non-heavy-Polluting industries are consumer products and services, health care, technology, industrial goods and services, automobiles and parts.

Control Variables

R&D intensity (EUR): R&D intensity refers to the funds a company allocates to research and development activities over total revenue.[12] This financial metric is significant in understanding a company's environmental performance. As identified in the study by Alam et al. (2019), R&D investments are directly linked to how a company performs environmentally. This connection is vital because R&D activities often involve developing new, more efficient technologies or processes that can lead to improved sustainability and reduced environmental impacts.

In some industries companies are larger, and will therefore spend more on R&D. This does not mean that the companies are inherently more innovative. R&D intensity provides a relative measure of a firm's commitment to research and development. A small firm may spend less in absolute terms but could be dedicating a higher proportion of its resources to R&D compared to a larger firm. To control for this, just like for carbon emissions, total R&D expenditure will be divided by revenue. Using revenue for R&D intensity is also common practice on other research like Savrul en İncekara (2015).

Given its crucial role in influencing environmental outcomes, R&D intensity is an important control variable in the performance analysis of a company. Including R&D spending in the analysis helps in more accurately isolating the effects of other variables on a company's environmental performance, thus offering clearer insights. Incorporating this variable acknowledges the significance of innovation in driving environmental improvements. Companies with higher investments in R&D tend to pioneer in developing eco-friendly technologies and practices, potentially leading to better E-scores and reduced Carbon Intensity. Controlling for R&D intensity in the analysis allows for a more precise evaluation of a company's environmental strategies and their effectiveness. It is used as a control variable in both regressions.

Industry: In the quantitative analysis of this study, the industry variable plays a pivotal role. Sourced from the Industry Classification Benchmark (ICB), this variable categorizes companies into 10 industries (also see Table 1). The ICB is a globally recognized system developed by Dow Jones and FTSE.[13] It is integral in providing a structured approach for this classification and is utilized extensively in the Refinitiv Eikon database. For the purposes of this analysis, companies are grouped according to the broadest tier of the ICB's four-tier sector/industry classification. This categorization is crucial as it

[12] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:R_%26_D_intensity#:~:text=For%20an%20enterprise%2C%20R%26D%20intensity,to%20science%20and%20technology%20worldwide.

[13] https://www.investopedia.com/terms/i/industry-classification-benchmark.asp#:~:text=The%20Industry%20Classification%20Benchmark%20(ICB)%20is%20a%20system%20for%20assigning,FTSE)%20and%20is%20recognized%20globally

forms the basis for controlling for industry-specific factors in the study. Industry is also used to split the dataset into two groups for hypothesis 3, based on the total emissions of each industry.

Table 3 shows the 10 industries in the dataset: Automobiles and Parts, Basic Resources, Chemicals, Construction and Materials, Consumer products and services, Energy, Food, Beverage and Tobacco, Health Care, Industrial Goods and Services, and Technology. These industries can be split into heavy-polluting and non-heavy polluting industries, following Cao et al. (2022). Heavy-Polluting are basic resources, chemicals, Energy, Food beverage & tobacco, and construction & materials, while non-heavy-Polluting industries are Consumer products & services, Health care, Technology, Industrial goods & services, and Automobiles & parts.

Table 3: Industries

Industries	**Heavy/non-heavy**	**# Companies**	**%**
Automobiles and Parts	N	12	4.24%
Basic Resources	H	36	12.72%
Chemicals	H	26	9.19%
Construction and Materials	H	7	2.47%
Consumer Products and Services	N	12	4.24%
Energy	H	35	12.37%
Food, Beverage and Tobacco	H	13	4.59%
Health Care	N	45	15.90%
Industrial Goods and Services	N	55	19.43%
Technology	N	42	14.84%

The primary function of the industry variable in this research is as a control variable. Its inclusion is essential to account for the inherent differences in environmental practices and revenue, and impacts that are typical of different industries. These variations can significantly influence the E-scores and, by extension, the assessment of greenwashing. It's important to clarify that using industry as a control variable does not imply any unreliability in the greenwashing measure. Rather, it is a necessary step to ensure that the analysis accurately reflects the unique environmental challenges and practices of each industry.

Size: Size, as a control variable in this analysis, is utilized to control for differences in firm size. To effectively measure firm size, the study adopts the natural logarithm (LN) of total assets. This approach, endorsed by e.g. Dang et al. (2013), suggests that the LN of total assets is an effective measure for controlling firm size, especially in the context of a company's capacity for generating revenue and growth.

The size variable, represented by the LN of total assets, is incorporated as a control variable in both regression models used in this study. This inclusion is critical to account for the potential influence of firm size on environmental practices and greenwashing behavior. Larger firms often have more resources and greater public visibility, which might influence their approach to environmental reporting and practices. Smaller firms may have different constraints and motivations. By controlling for size, the analysis aims to isolate the effect of other variables on greenwashing, ensuring a more nuanced and accurate understanding of the factors at play.

Country of headquarters: The Country of Headquarters variable captures the nation where a company's main office is based. It is included as a control variable in both regression models to account for country fixed effects, allowing the analysis to control for unobserved heterogeneity and systematic differences between countries that could influence the dependent variable.

Table 4 presents the number of companies in each geographical area, showing that the United States of America hosts the majority of company headquarters. Other well-represented countries include the United Kingdom, Canada, Germany, and France.

Table 4: Country of headquarters

Region	# Companies	%
European Union	114	40.28%
United States	107	37.81%
Canada	25	8.83%
Other	26	9.19%
BRICS	11	3.89%

The percentages reflect the proportion of unique companies, providing a clearer picture of the geographic distribution of the corporations in the dataset. This revised table ensures a more precise analysis by considering each company once rather than the number of times it appears in the dataset.

Descriptive statistics

Table 5 on the following page presents a number of key statistics for the variables used in the regressions.

Table 5: Descriptive Statistics

This table presents the descriptive statistics for key variables in the dataset, each with a count of 1981 observations, except for Scope 2 emissions which are short of five data points due to missing values from 1 company in the earlier years. However, considering that EQT Corp's subsequent data shows Scope 2 emissions as a minor portion of their total emissions, this gap is unlikely to significantly influence the overall analysis. For increased readability, the carbon intensity in this table was calculated by multiplying total emissions by one million, and dividing by revenue in Eur. For the main analysis this was not done, and total emissions/revenue is used.

variable	definition	# obs	average	median	minimum	maximum	st. dev.	skewness	kurtosis
Carbon Intensity	total emissions (1000000 tonnes) / revenue (EUR)	1981	289.6	59.50	0.656	6679.8	562.7	4.70	35.55
E-score	Refinitiv Eikon E-score	1981	67.60	69.91	0	99.14	18.20	-0.618	0.11
Total emissions	Sum of Scope 1 + Scope 2 emissions	1981	4430341	472867	1492	194800000	15231838	7.11	63.67
Greenwashing indicator	See methodology	1981	17.72	17.79	-94.2	96.85	32.55	-0.104	-0.26
Firm Size	Natural logarithm of firm assets	1981	22.03	21.92	16.94	25.85	1.48	0.021	0.08
Revenue	Annual revenue (mln EUR)	1981	18635.42	6063.97	109	406942.55	37415.33	4.834	30.06
R&D Intensity	R&D spending / revenue (EUR)	1981	0.0558	0.0317	0.0000265	0.5191	0.0667	44.52	1984.15

The dataset reveals notable variations in the standard deviations of different variables. The carbon intensity rank score displays a much higher standard deviation compared to the environmental pillar score.

This Carbon Intensity Score rank is the combined with the Environmental Pillar score to create the Greenwashing Indicator (GWI), as explained earlier in the data section. For the Greenwashing indicator we observe an average of 17.72, which indicates that on average a company in this dataset has a misalignment of carbon intensity rank and E-score, and thus shows a presence of greenwashing.

The GWI has a minimum of -94.2 and a maximum of 96.85. The standard deviation is 32.55. These extreme values might be attributable to the fact that the e-score was benchmarked by Refinitiv against a large dataset, while the carbon intensity was benchmarked against each industry's companies that were available in this dataset. Due to the fact this dataset only contained companies for which I had emission and R&D data available, this could lead to some of these extreme values. In the future research section I will delve deeper into this.

When looking at sector averages of the greenwashing score, we observe that Energy sector has the lowest greenwashing score (11.24), indicating the least amount of greenwashing. This could suggest that companies in the Energy sector are more accurately reporting or are more aligned with their environmental impact, compared to other sectors. This might be due to higher regulatory scrutiny or public pressure that these companies face, which in turn could lead to more transparent environmental reporting.

The Construction and Materials sector has the highest greenwashing score (28.79). This suggests a significant misalignment between reported environmental performance and actual carbon emissions. It could point to a higher prevalence of greenwashing practices in this sector, possibly due to less stringent regulations or a larger gap between industry practices and sustainability goals. Table 6 presents the Greenwashing index for the 10 industries.

Table 6: Greenwashing Indicator (GWI) per industry

Industries	Heavy/non-heavy	GWI
Automobiles and Parts	N	21.7
Basic Resources	H	16.5
Chemicals	H	18.0
Construction and Materials	H	28.8
Consumer Products and Services	N	14.5
Energy	H	11.2
Food, Beverage and Tobacco	H	18.2
Health Care	N	18.8
Industrial Goods and Services	N	21.1
Technology	N	15.3

Further, the analysis of the descriptive statistics shows extreme values in skewness and kurtosis for several variables, including carbon intensity, total emissions, and R&D expenditure. These metrics indicate highly skewed distributions with long tails, hinting at a few companies with exceptionally high values in these areas, while most others have much lower figures. Such disparities in the data highlight the presence of outliers and underline the diversity in corporate environmental behavior and financial metrics.

Correlation matrix

	Revenue	GWI	Firmsize	R&D Intensity	E-Score	Carbon Intensity	Total Emissions
Revenue	1						
GWI	0.0628	1					
Firmsize	0.6459	0.1947	1				
R&D Intensity	0.0064	-0.0525	0.1698	1			
E-Score	0.2917	0.4152	0.4991	0.0475	1		
Carbon Intensity	-0.0468	0.3145	-0.1529	-0.23	-0.1474	1	
Total Emissions	0.488	0.2218	0.2984	-0.1672	0.141	0.4492	1

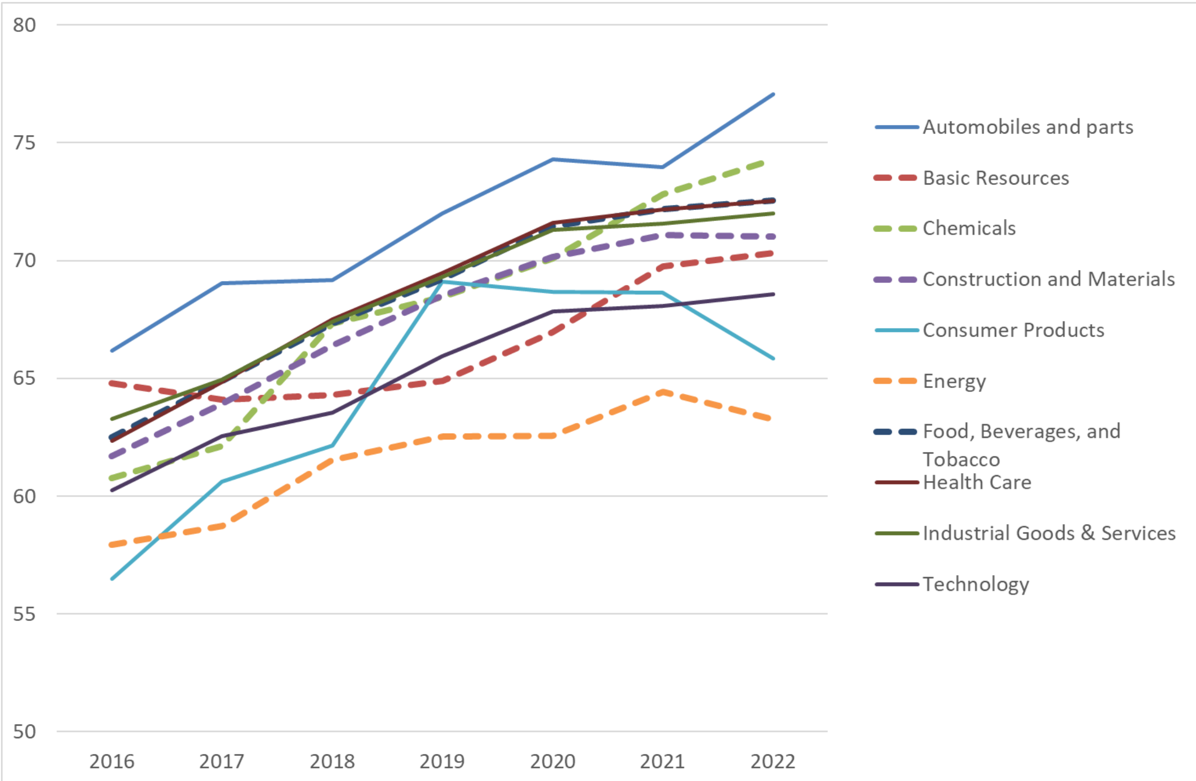
When looking at the whole dataset, we observe a weak, positive correlation between the greenwashing score and revenue. For firm size and revenue we observe a strong positive correlation, which is to be expected as larger firms tend to generate more revenue. For R&D intensity, which is a proxy for innovativeness, we observe a very small, positive correlation with revenue. We observe a weak, negative correlation between R&D intensity and the greenwashing score, indicating that being a more innovative company is correlated with a lower greenwashing score. The E-score and revenue are also positively correlated.

Carbon intensity has a weak, negative correlation with revenue. Carbon intensity has a moderate correlation with the greenwashing score. Carbon intensity is also has a weak negative correlation with firmsize, indicating that increased carbon intensity is associated with smaller firms. There is also a moderate, negative correlation between carbon intensity and R&D intensity, indicating that innovativeness of a company is negatively associated with carbon intensity. There is also a weak, negative correlation between the E-score and carbon intensity.

Total Emissions is strongly positively correlated with revenue. Total emissions and the greenwashing score also show a moderate, positive correlation, indicating that having more emissions is associated with a higher degree of greenwashing.

Graph 1 presents the development in E-scores over the sample period.

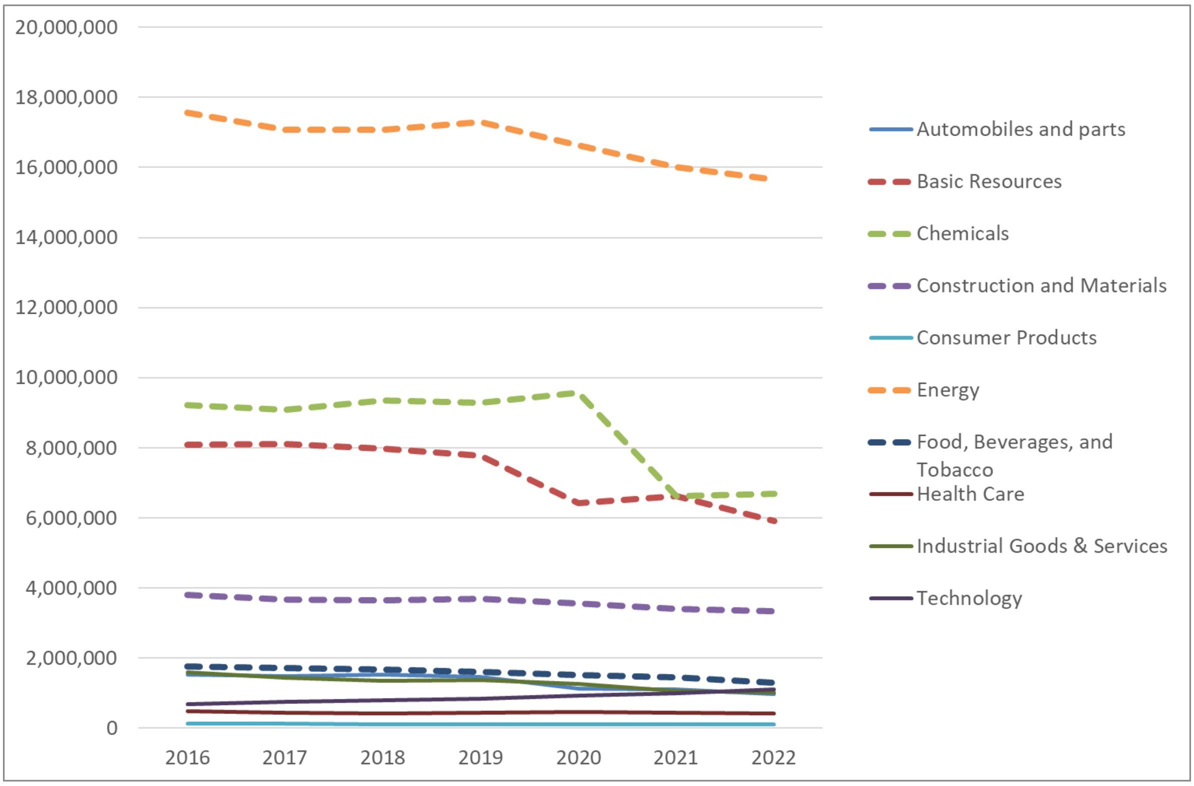
Graph 1 E-score Refinitiv Eikon: all sectors



Graph 1 shows an encouraging overall upward trend in Environmental Pillar Scores from 2016 to 2022 across industries. This reflects a broad improvement in environmental performance with the score for all sectors combined rising from 62 to 71 on average. The dotted lines represent the heavy-polluting industries (as defined by Cao et al., 2022). Notably, the Automobiles and Parts sector shows the most significant jump, indicating a strong shift towards greener practices, probably influenced by technological innovations and market demand. While sectors like Health Care and Food, Beverages, and Tobacco demonstrate steady progress, the Energy sector trails behind, showing marginal gains and suggesting ongoing challenges in environmental adaptation. The Consumer Products sector reveals some fluctuations, with a peak in 2019 followed by a slight decline, hinting at dynamic changes within the industry. Chemicals and Basic Resources sectors have seen a gradual improvement, particularly in recent years, while the Technology sector shows a consistent, but moderate, improvement. By 2022, the scores in some sectors seem to have stabilized, which may suggest a plateau in environmental efforts.

Graph 2 shows the development of total emissions (scope 1 plus scope 2) in the various sectors.

Graph 2: Total Emissions for all industries (tons CO2)



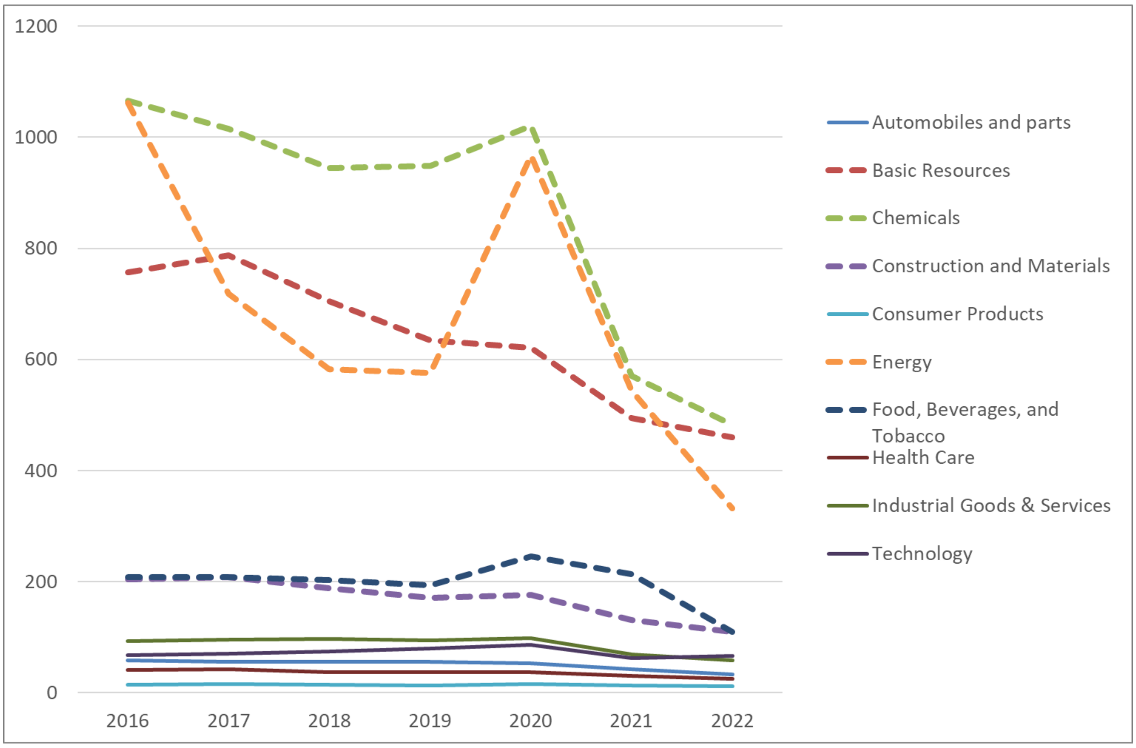
Graph 2 shows the development of total carbon emissions across various sectors from 2016 to 2022. A downward trend is notable in the Construction and Materials sector, with emissions peaking in 2018 and then decreasing significantly. This may reflect the impact of innovation and stricter regulations in the industry. The Basic Resources sector exhibits a general decline over the years, suggesting improvements or operational changes aimed at reducing emissions. The Chemicals sector's emissions fluctuate but show a sharp decline in the last two years, indicating possible recent interventions or shifts in industry practices.

The Consumer Products and Services sector presents a relatively stable trend, with a slight decrease towards the end of the period. Consumer Products and Services, while starting with the lowest emissions, show a notable drop, hinting at significant strides in sustainability within the sector. Energy remains the highest emitter throughout the period, though it also shows a decreasing trend in emissions, especially in the last reported year. This could be caused by many factors including the adoption of cleaner energy sources.

Food, Beverage, and Tobacco; Health Care; Industrial Goods and Services all show a general *upward* trend until a drop in 2022. The Technology sector is the only one that displays a consistent increase in emissions year after year, reflecting challenges or growth in this industry that may have led to increased emissions. Overall, while some sectors show progress in reducing emissions, others, especially Technology, highlight ongoing challenges or growth that has environmental impacts.

In order to make a fair comparison, we need to relate the emissions to revenue in a sector or a company, i.e. carbon intensity. If a sector's emission rises by 50%, but its revenue rises by 100%, the sector is still improving significantly. The following graph relates total emissions to revenue.

Graph 3: Carbon Intensity: Total Emissions / Total revenue



Graph 3 shows the ratios of total emissions to revenue for different industries from 2016 to 2022 (total emissions/total revenue in mln. Euro). This ratio is an indicator of carbon efficiency, with lower numbers suggesting better performance in terms of emissions per unit of revenue generated. The dotted lines represent the heavy-polluting industries (as defined by Cao et al., 2022). Across the board, there is a trend toward improved carbon efficiency, especially in the 3 most heavy polluting industries. The Basic Resources sector stands out with a consistent decrease in the ratio year over year, likely reflecting the automotive industry's efforts towards cleaner technologies and more efficient manufacturing processes. The Basic Resources sector has higher ratios than others, but a trend of improvement is evident over the years, albeit with some fluctuation.

The Chemicals sector starts with a relatively high ratio but shows an improvement in the latter years. This could indicate that the sector is beginning to address its emissions more effectively relative to its economic output. Energy, despite a spike in the Covid-year 2020, generally trends downward, indicating a slow but positive shift towards better carbon efficiency. This sector's ratios are relatively high (it is the only sector shown on the right-hand scale), which is expected given its nature, but the overall downward trend is encouraging. The dataset shows that this spike in carbon intensity during 2020 is mostly driven by sharp decreases in revenue for the companies in the energy sector. Due to the demand shock of covid 19, oil prices fell and this led to revenue decreases in the year 2020[14]. In the year after 2020 revenue stabilized to the pre-covid levels. This spike may however shift the results, but with the fixed effects model will control for this as part of the sector-specific unobserved effect as this spike is a sector wide phenomenon.

Sectors such as Construction and Materials, Food, Beverages, and Tobacco, Health Care, Industrial Goods & Services, and Technology all show a decrease in the ratio, which can be interpreted as an improvement in carbon efficiency. However, the Technology sector also had a very peculiar year in 2020.

In summary, these ratios reflect a movement towards greater carbon efficiency across most sectors. The decreasing trend is a promising indication that companies are generating more revenue for each ton of emissions, which is a positive sign in the context of global efforts to reduce carbon footprints and combat climate change.

[14] https://www.aon.com/unitedkingdom/insights/energy-sector-hit-by-covid-19-demand-shock.jsp

3.3 Methodology

This section presents the approach to testing the hypotheses.

Approach Hypothesis 1

To quantitatively analyze the potential for greenwashing, we will adopt a multi-step approach. First, we will establish baseline discrepancies by comparing the E-scores with the total carbon emissions, including R&D intensity as an independent variable, and controlling for the size, country fixed effects, and industry fixed effects.

To check for heteroskedasticity we will then carry out the Breusch-Pagan test. If heterogeneity is present, indicated by rejecting the null hypothesis, we will proceed using robust standard errors to ensure the reliability of subsequent analyses. In this case, we reject the null hypothesis and use robust standard errors going forward.

Following this, the Hausman test will be applied to determine the suitability of a fixed effects model over a random effects model. The difference between random effects and fixed effects models lies in how they treat the variation across firms.

Fixed effects only uses within variation, and discards between variation to account for all unobserved heterogeneity. A shortcoming of the fixed effects model is that it therefore can't estimate the coefficients of time invariant characteristics. They are controlled for implicitly by the fixed effects.

The random effects model is similar to the fixed effects model in that it transforms the data by quasi-demeaning it. This helps model the structure of serial correlation over time. The benefit of random effects model over the fixed effects model is that it uses both within and between variation, which makes it possible to estimate coefficients of the time invariant characteristics. If appropriate, a random effects model is therefore preferred over a fixed effects model.[15]

To check whether this is the case, the Hausman test has to be performed. This test compares the coefficients of a fixed effects with those of a random effects model. If they are systematically different this means that accounting for unobserved heterogeneity influences the results. The fixed effects model is then preferred, as this accounts for all unobserved heterogeneity.

[15] Riumallo Herl, C. (2023/2024). Applied Microeconometrics. Erasmus School of Economics

In this case the Hausman test shows us a p-value of 0.00 leading us to reject the null hypothesis, a fixed effects model will be deemed more appropriate for our panel data.

Afterwards, he Variance Inflation Factor (VIF) test is performed to detect multicollinearity issues in the dataset. Most research papers use 10 as a threshold of the VIF test. If the value is higher than 10, there is multicollinearity in the dataset. When performing the VIF test on the first regression, there are no values that reach this threshold. This would indicate that the independent variables do not show a degree of multicollinearity that would significantly impact the results. The exact values of the VIF test can be found in appendix B.

Lastly, the Ramsey reset test is performed to check for omitted variables. This test gives us a P-value of 0.0031. we therefore reject the null hypothesis of no omitted variables. This indicates that there might be specification errors in the model.

After establishing the foundational statistical parameters, we will develop a greenwashing indicator (GWI), as described in the datasection. This quantitative measure will gauge the discrepancy between changes in E-scores and changes in carbon intensity, pinpointing whether increases in E-scores are substantiated by reductions in carbon emissions.

Subsequently, we will test Hypothesis 1 by analyzing the correlation between the carbon emissions and the E-score. This will reveal whether companies with improved E-scores are genuinely reducing their carbon footprint.

> **H1: "There is a negative association between the carbon emissions of a company and its E-Score."**

Finally, we will employ a fixed effects regression to control for time-invariant characteristics of the companies, isolating the impact of the greenwashing indicator on company performance.

By integrating these steps, we aim to uncover whether the upward trends in E-scores reflect true environmental progress or if they are merely indicative of greenwashing practices. This comprehensive analysis will not only test our hypothesis but also provide investors and stakeholders with crucial insights into the authenticity of companies' environmental performance claims.

The regression equation to be tested is the following:

$$E\text{-}Score = \alpha + \beta 1(\text{Total Emissions})i,t + \beta 2(\text{firmsize})i,t + \beta 3(\text{R\&D expenditure}) + \text{Year FEt} + \text{Industry FEi} + \text{Country FEi} + A\_i + u,it$$

The regression equation is designed to analyze the relationship between a company's Environmental Pillar Score and its carbon emissions, with R&D intensity as another independent variable, alongside other control variables such as firm size and fixed effects for year, industry, and country. To test Hypothesis 1, which states that there is no correlation between the carbon emissions of a company and its E-score, the regression analysis focuses on the statistical significance and sign of the coefficient β1.

The approach to the regression analysis is as follows:

Dependent Variable: The dependent variable in the regression would be the E-Score.

Key Independent Variable: The primary independent variable of interest is the Total Emissions, which is expected to have a significant impact on the Environmental Pillar Score if the hypothesis is incorrect.

Control Variables: Firm size and R&D expenditure are included as control variables, because they can also influence a company's environmental score.

Fixed Effects:

> **Year Fixed Effects** (Year FE): Control for any time-specific effects that could influence all companies similarly, such as changes in environmental regulations or economic conditions.
>
> **Industry Fixed Effects** (Industry FE): Control for unobserved industry-specific characteristics that might affect environmental scores, such as industry norms or pressures.
>
> **Country Fixed Effects** (Country FE): Control for country-specific factors that might influence environmental scores, such as national environmental policies or cultural attitudes towards sustainability.

Error Term ($\varepsilon_{i,t}$): The error term captures the unexplained variation in the E-Score after accounting for all the variables in the model.

The regression model is run as a panel data regression to make use of the data structure where the same companies are observed across multiple time periods. The choice between a fixed effects or random effects model is guided by the **Hausman test**.

To test Hypothesis 1, we examine coefficient β1 for Total Emissions:

> If β1 is not statistically significant, this does not support the hypothesis that there is a negative correlation between carbon emissions and the E-score.

If β1 is statistically significant and the sign is negative, this would suggest that higher carbon emissions are associated with lower environmental scores, which supports the hypothesis.

If β1 is statistically significant and the sign is positive, it indicates a positive association between carbon emissions and environmental scores, which would be counterintuitive and could suggest greenwashing or other factors at play.

The statistical significance of β1 will be critical in confirming or rejecting Hypothesis 1.

Approach Hypothesis 2

To test Hypothesis 2, the approach involves two main steps:

Step 1 Development of the Greenwashing Indicator (GWI),

After establishing the foundational statistical parameters, we will develop a greenwashing indicator (GWI), as described in the data section. This quantitative measure will gauge the alignment between changes in E-scores and changes in carbon intensity rank, pinpointing whether increases in E-scores are substantiated by reductions in carbon emissions.

Step 2 Relationship between the GWI and Company Performance

The next step is to test hypothesis 2, which states:

H2: "There is a positive relation between Greenwashing indicator and company performance"

First, the variable with the one-year ahead value of revenue is used This leaves us with observations for the years 2016-2021. In this regression the Greenwashing Indicator is the key independent variable. In the analysis, we focus on the coefficient of the GWI; a positive and significant coefficient suggests that greenwashing is positively correlated with financial performance.

We carried out the Breusch-Pagan test to check for heteroskedasticity within the dataset. If heterogeneity is present, indicated by rejecting the null hypothesis, we will proceed using robust standard errors to ensure the reliability of subsequent analyses. In this case, the test gives us a p- value of 0.00. We therefore also reject the null hypothesis and use robust standard errors going forward.

Following this, the Hausman test was applied to determine the suitability of a fixed effects model over a random effects model. With a p-value of 0.00 leading us to reject the null hypothesis, a fixed effects model will be deemed more appropriate for our panel data.

Next, the Variance Inflation Factor (VIF) test was performed to detect multicollinearity issues in the dataset. Most research papers use 10 as a threshold of the VIF test. If the value is higher than 10, there is multicollinearity in the dataset. When performing the VIF test on the regression for the second hypothesis, there are no values that reach this threshold. This would indicate that the independent variables do not show a degree of multicollinearity that would significantly impact the results. The exact values of the VIF test can be found in appendix C.

Lastly, the Ramsey reset test was performed to check for omitted variables. This test gives us a P-value of 0.00. We therefore reject the null hypothesis of no omitted variables. This indicates that there might be specification errors in the model.

The following regression equation will be used to test hypothesis 2:

Ln Revenue t+1

= α + β1(Greenwashing Indicator)i,t + β2(Firm Size)i,t + β3(R&D expenditure)i,t

+ Year Fixed Effects + Industry Fixed Effects + Country Fixed Effects + A_i + u, it

The dependent Variable is the natural logarithm of Revenue in the following year, representing the financial performance of the company. The independent Variables are the Greenwashing indicator, R&D intensity, and other relevant control variables such as firm size. We control for external factors by including fixed effects for year, industry, and country.

Robustness Checks Hypothesis 2

Including i.year controls for unobserved year-specific factors leads to more precise estimation by isolating the effect of the independent variables on future revenue from these time-related influences. If the greenwashing indicator itself is influenced by year-specific factors, then controlling for year fixed effects might absorb some of the variation in greenwashing that we are actually interested in. This could potentially lead to underestimating the true effect of the greenwashing indicator.

Including year fixed effects in the model controls for these year-specific effects of for example the COVID-19 crisis. This might however also absorb some of the variation in greenwashing that is directly related to the unique conditions of the pandemic years. If greenwashing practices were particularly influenced by the pandemic, controlling for year fixed effects could mask this specific impact. This could in turn potentially lead to an underestimation of the true effect of the greenwashing indicator on future revenue. As a robustness check, the same regression will be performed without the inclusion of year fixed effects. The model provides a generalized understanding of the relationship between greenwashing and future revenue over the study period. It offers insights into the average effect of greenwashing on revenue, inclusive of all the variations and changes that happened year by year within the period of the study. It doesn't differentiate between the specific impacts of each individual year, but might still give us valuable insights.

$$\text{Ln Revenue}_{t+1} = \alpha + \beta 1(\text{Greenwashing Indicator})_{i,t} + \beta 2(\text{Firm Size})_{i,t} + \beta 3(\text{R\&D expenditure})_{i,t} + \text{Industry Fixed Effects} + \text{Country Fixed Effects} + A_i + u_{it}$$

Approach second robustness check hypothesis 2

To gain more insight into the effects of greenwashing on revenue, the polluting dummy variable is used to split the dataset into two. The main sample is too small to run meaningful separate sector analysis. This approach allows for a more comprehensive analysis on how the relationship between greenwashing and firm performance varies across sectors with different environmental impacts. It allows us to see the difference in effect of greenwashing on performance for heavy-polluting sectors compared to non-heavy-polluting sectors.

After splitting the dataset into two, the same regression as performed for hypothesis two is performed.

$$\text{Ln Revenue}_{t+1} = \alpha + \beta 1(\text{Greenwashing Indicator})_{i,t} + \beta 2(\text{Firm Size})_{i,t} + \beta 3(\text{R\&D expenditure})_{i,t} + \text{Year Fixed Effects} + \text{Industry Fixed Effects} + \text{Country Fixed Effects} + A_i + u_{it}$$

Approach hypothesis 3

First the dataset was split into two parts using a dummy variable, as explained in the variables section. Just like in Cao et al. (2022) I will be splitting the dataset in two based on total emissions per industry to test if there is a difference in the degree of greenwashing as measured by the greenwashing index between highly-polluting industries and non-highly-polluting industries.

> H3: Greenwashing is more prevalent in heavy-polluting sectors compared to non-heavy-polluting sectors

This hypothesis is first explored with a t-test. The t-test is a statistical analysis technique designed to determine if there is a statistically significant difference between the means of two groups. It does this by comparing the means of the two groups and assessing whether any observed differences are substantial enough to be unlikely due to chance alone.

4. Empirical results

This chapter presents the empirical results.

4.1 Hypothesis 1

Hypothesis 1 suggests a negative correlation between a company's carbon emissions and its E-score. This hypothesis is set against concerns about the manipulability of E-scores: discrepancies in rating methodologies and the interpretation of carbon emission data can allow companies to inflate their scores without making genuine sustainable changes. The hypothesis aims to create a greenwashing indicator by linking the E-score with industry-specific carbon intensity measures. This would help to distinguish between companies making genuine sustainable changes and those that do not. The following regression model is used to test the first hypothesis:

E-Score = α + β1(Total Emissions)i,t + β2(firmsize)i,t + R&D expenditure + Year FEt + Industry FEi + Country FEi + εi,t

Table Y1 shows the results.

The main coefficient to look at in this table, is the one showing the relationship between the E-score and the emissions. The main independent variable of interest is total emissions, measured in 10,000 tonnes. The coefficient for this variable is 0.0014. This suggests that for every additional 10,000 tonnes of emissions, the e-score *increases* by 0.0014 units, holding all other variables constant. However, the p-value for this coefficient is 0.104, which is just above the threshold for statistical significance of 0.10. This means that the relationship between total emissions and e-score is not statistically significant at 10% level. **As β1 is not statistically significant, this does not support the hypothesis that there is a negative correlation between carbon emissions and the E-score. Hypothesis 1 can therefore be rejected.**

The coefficient for R&D intensity is 26.95. This implies an increase in the e-score of 26.95 for each one unit increase of R&D intensity. With a p-value of 0.267 relationship is statistically insignificant at the 5% level, suggesting that the data does not provide evidence that R&D intensity, and thus innovation, is not significantly associated with the e-score.

The coefficient for firm size is 1.54, indicating that larger firms tend to have a higher e-score by 1.41 units for each unit increase in the firm size variable. With a p-value of 0.253 this relationship is however not statistically significant and we can therefore not conclude that larger firms have higher e-scores.

The coefficient for each year is significant at the 1% level. What we also observe is that the coefficient of year increases each consecutive year compared to the reference year 2016, indicating an positive and increasing trend over time for the e-score. We already saw this in the graphs and in previous research.

The within R-squared of the model is 0.2143, indicating that approximately 21.43% of the within variation in e-score is accounted for by the model. The explanatory power of the model can be considered moderate, suggesting other factors will also be influencing the e-score. Nevertheless, these results provide some insight into the relationship between emissions and environmental performance.

The constant is 26.23, with a p value of 0.377. The constant is therefore not statistically significant. The constant represents the expected value of the E-score of a company in 2016, with 0 emissions, 0 R&D spending, and a firm size of 0. This is therefore not a realistic starting point for interpretation.

Table R1 Regression results H1: The effect of Total Emissions On The E-Score

Dependent Variable: E-Score Variables	Value	Robust Standard Errors
Emissions in 10000	0.00136 (0.104)	0.0008
R&D Intensity	26.95 (0.267)	24.25
Firm Size	1.54 (0.253)	1.35
Year Fixed Effects	Yes	-
Sector Fixed Effects	Yes	-
Country Fixed Effects	Yes	-
Robust Standard Errors	Yes	-
Constant	26.23 (0.377)	29.62
Within R2	0.2143	-
Observations	1981	-
N Firms	283	-

4.2 Hypothesis 2

Hypothesis 2 explores the relationship between the Greenwashing Indicator (GWI) and company performance. The GWI is measures the discrepancy between the e-score and carbon intensity rank, while performance is measure by future revenue of the company. This hypothesis examines whether companies that engage in greenwashing have stronger financial results. The regression model aims to quantitatively assess the financial impact of greenwashing on company performance. The following regression equation will be used to test hypothesis 2:

Ln Revenue t+1

= α + β1(Greenwashing Indicator)i,t + β2(Firm Size)i,t + β3(R&D expenditure)i,t

+ Year Fixed Effects + Industry Fixed Effects + Country Fixed Effects + A_i + u, it

Model 1 in table R2 presents the results.

The greenwashing score has a coefficient of 0.0005488 and a p-value of 0.572. This suggests that a one point increase in Greenwashing score is associated with an increase in future revenue of 0.055 percentage points, holding other variables constant. However, this association is not statistically significant at the 5% level, which implies that the data does not provide evidence of a positive impact of Greenwashing on future revenue. However, this analysis takes the full sample into account.

The coefficient for firm size is 0.265, significant at the 1%-level. This results is not surprising: larger firms tend to have a larger revenue. A 1% increase in firm size, leads to a 0.24% increase in revenue, ceteris paribus.

R&D Intensity appears to be negatively associated with future revenue, with a coefficient of -2.34. With a p-value of 0.00, this effect is significant at the 1% level. This entails that a 1 point increase in R&D intensity, leads to a decrease in future revenue of 234 percentage points. This effect has to be interpreted in the context of how the R&D intensity variable is distributed, as the average company in the dataset takes has a value of 0.056 for R&D intensity.

Each year's coefficient compares that year's future revenue to the reference year of 2016. The coefficients for 2017, 2018, 2020, and 2021 are all positive and statistically significant, indicating higher future revenue compared to 2016. The negative coefficient for 2019 reflects an increase in future revenue. With a p-value of 0.602 this effect is however insignificant at the 5% level and can likely be attributed to the COVID-19 pandemic's impact on the revenue of 2020, as 2019's revenue figure includes one year ahead revenue.

The constant has a coefficient of 16.809 and is significant at the 1% level. The constant represents the expected value of future revenue for a company in 2016, with all other control variables with a value of 0, which is not a realistic scenario for interpretation in this context.

The within R-squared of the model is 0.4506, indicating that 45.06% of the within variation in E-score is accounted for by the model. In such a complex and normally mostly qualitative field, this is a fairly high R-squared. Even though there is still a 54.94% of the variation of the dependent variable that is not explained by the independent variables included in the model, these results provide some insight into the relationship between greenwashing and financial performance.

As the coefficient for greenwashing is not statistically significant, the empirical results do not support the hypothesis that there is a positive relation between Greenwashing indicator and company performance. Hypothesis 2 should therefore be rejected.

Table R2: Effect of Greenwashing on Revenue t+1

This table represents the fixed-effects regressions performed for hypothesis 2. Model 1 represents the main regression to test the effect of greenwashing on revenue. Model 2 shows the effect of greenwashing on revenue without the inclusion of year fixed effects. Model 3a shows the effect of greenwashing on revenue for heavy-polluting sectors. Model 3b shows the effect of greenwashing on revenue for non-heavy-polluting sectors. The p-value is presented in parentheses. The 1%, 5% and 10% significance value are represented by *, **, *** respectively.

Dependent Variable: LN Revenue t+1	Model 1	Model 2	Model 3a	Model 3b
Greenwashing Indicator	0.000549	0.0023***	-0.00076	0.00136
	(0.572)	(0.005)	(0.425)	(0.335)
Firm Size	0.265***	0.426***	0.129**	0.356***
	(0.000)	(0.000)	(0.029)	(0.000)
R&D Intensity	-2.34***	-2.82***	-2.16**	-2.23***
	(0.000)	(0.000)	(0.027)	(0.000)
Year Fixed Effects	Yes	No	Yes	Yes
Sector Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Robust Standard Errors	Yes	Yes	Yes	Yes
Constant	16.81***	13.4***	19.52***	14.93***
	(0.000)	(0.000)	(0.000)	(0.000)
Within R2	0.4506	0.2264	0.4658	0.4893
Observations	1698	1698	702	996
N Firms	283	283	117	166

Robustness check Hypothesis 2

Regression without year fixed effects

When running the regression without year fixed effects, we observe different results. These results are presented in table R2 by model 2. We observe a coefficient of 0.0023 for the greenwashing indicator. This effect is significant at the 1% level. A one unit increase in the greenwashing indicator leads to an increase in future revenue of 0.23 percentage points, ceteris paribus.

Firm size has a coefficient of 0.43 and is significant at the 1% level. A 1% increase in firm size, is associated with a 0.43% higher future revenue.

R&D intensity has a negative coefficient of -2.82. This effect is significant at the 1% level. A 1 point increase in R&D intensity, leads to a 282 percentage point decrease of future revenue, ceteris paribus. This negative correlation might be attributable to the fact that R&D intensity has a negative impact on short term firm performance, but has a positive effect in the long run (Vithessonthi & Racela, 2016).

The constant in this case is 13.40, and is significant at the 1% level. The constant represents the ln future revenue when all independent variables are 0. So a company with a firm size of 0, an R&D intensity of 0, and a greenwashing indicator value of 0. Just like with the previous regression, this constant is not a realistic scenario for interpretation in this context.

The within R-squared of the model is 0.2264, indicating that 22.64% of the within variation in E-score is accounted for by the model. Even though this is a moderate R-squared, suggesting other factors also influence future revenue, these results provide some insight into the relationship between greenwashing and financial performance. This is another argument for the inclusion of year-fixed effects, as including these leads to a strong increase of the within R-squared.

Additional analysis heavy-polluting vs non-heavy-polluting Hypothesis 2

To get a more comprehensive understanding of the effect on greenwashing, I conducted a separate analysis that compared the effect of greenwashing on revenue for both heavy-polluting sectors and non-heavy polluting sector. The dataset was split into two datasets based on the polluting dummy that was created earlier. The same regression as done for hypothesis 2 was then performed on both these datasets.

Table R2, model 3a shows us the results for companies that are in a heavy-polluting sector, while model 3b shows us the results for companies that are in a non-heavy-polluting sector.

For heavy-polluting sectors, the greenwashing score has a coefficient of -0.0007584 and a p-value of 0.425. This suggests that a one point increase in Greenwashing score is associated with a decrease in future revenue of 0.07584 percentage points, holding other variables constant. However, this association is not statistically significant at the 5% level, which implies that the data does not provide evidence of a negative impact of Greenwashing on future revenue for heavy polluting sectors. For non-heavy polluting sectors, the greenwashing score has a coefficient of 0.0013611 and a p-value of 0.335. this suggests that a one point increase in Greenwashing score is associated with an increase in future revenue of 0.13611 percentage points, holding other variables constant. This association is however not statistically significant at the 5% level, which implies that the data does not provide evidence of a positive impact of greenwashing on future revenue for non-heavy polluting sectors.

For heavy-polluting sector, the coefficient for firm size is 0.1287, significant at the 5%-level. A 1% increase in firm size, leads to a 0.13% increase in revenue, ceteris paribus. For non-heavy-polluting sectors, the coefficient for firm size is 0.3562, significant at the 1% level. A 1% increase in firm size leads to a 0.36% increase in revenue, ceteris paribus.

For heavy-polluting sectors, R&D Intensity appears to be negatively associated with future revenue, with a coefficient of -2.158. With a p-value of 0.00, this effect is significant at the 1% level. This entails that a 1 point increase in R&D intensity, leads to a decrease in future revenue of 216 percentage points. For non-heavy-polluting sectors, R&D intensity is also negatively associated with future revenue, with a coefficient of -2.23. With a p-value of 0.00, this effect is significant at the 1% level. A 1 point increase in R&D intensity, leads to a decrease in future revenue of 223 percentage points. The effect of R&D intensity has to be interpreted in the context of how the R&D intensity variable is distributed, as the average company in the dataset takes has a value of 0.059 for R&D intensity.

Each year's coefficient compares that year's future revenue to the reference year of 2016. For both heavy-polluting and non-heavy polluting sectors the coefficients for 2017, 2018, 2020, and 2021 are all positive and statistically significant, indicating higher future revenue compared to 2016. Only 2019 has a different coefficient. For heavy-polluting sectors, 2019 has a negative coefficient of -0.013. With a p-value of 0.663 this effect is however insignificant at the 5% level. For non-heavy-polluting sectors, the coefficient for 2019 is 0.016 and has a p-value of 0.517. This effect is insignificant at the 5% level.

For heavy-polluting sectors, the constant has a coefficient of 19.52 and significant at the 1% level. The constant represents the expected value of future revenue for a company in 2016, with all other control variables with a value of 0, which is not a realistic scenario for interpretation in this context.

For non-heavy-polluting sectors, the constant has a coefficient of 14.93 and is significant at the 1% level as well.

The within R-squared of the model for heavy-polluting sectors is 0.4658, indicating that 45.68% of the within variation in E-score is accounted for by the model. In such a complex and normally mostly qualitative field, this is a fairly high R-squared. These results provide some insight into the relationship between greenwashing and financial performance for heavy-polluting sectors.

The within R-squared of the model for non-heavy-polluting sectors is 0.4893, indicating that 48.93% of the within variation in E-score is accounted for by the model. In such a complex and normally mostly qualitative field, this is a fairly high R-squared. These results provide some insight into the relationship between greenwashing and financial performance for heavy-polluting sectors.

We find that greenwashing, as measured by the greenwashing indicator, has no significant effect on revenue for both heavy-polluting and non-heavy-polluting sectors.

4.3 **Hypothesis 3**

Hypothesis 3 aims to determine if greenwashing is more common in heavily polluting industries compared to less polluting ones. This hypothesis extends the work of Cao et al. (2022), who found differing impacts of carbon information disclosure on enterprise value in heavy versus non-heavy polluting industries. It explores the idea that heavily polluting companies may use greenwashing to improve their public image and comply with regulations, while less polluting companies may focus on genuine environmental improvements. The hypothesis will use the greenwashing index (GWI) to quantitatively assess the prevalence of greenwashing across different industry sectors.

The results are presented in Table R3. There are 1162 observations in the Non-heavy polluting group (Group 0), with a mean greenwashing score of 18.60 and a standard deviation of 0.97. There are 819 observations in the heavy polluting group (Group 1), with a mean greenwashing score of 16.48 and a standard deviation of 1.10.

Pr(T > t) = 0.0759 (Ha: diff > 0): This p-value tests the hypothesis that the mean greenwashing score is higher in non-heavy polluting sectors. The p-value of 0.0759 is above the typical threshold for significance (0.05). The results suggest that, across the entire sample from 2016 to 2022, there is a trend toward higher greenwashing scores in non-heavy polluting sectors compared to heavy polluting sectors. These results are significant at the 10% level. These results therefore do not support the hypothesis.

Based on these results we reject H3, which states that greenwashing is higher for more polluting compared to less polluting sectors in the dataset. We find, albeit weak, evidence of the opposite. That greenwashing, as measured by the greenwashing indicator, is higher in non-heavy-polluting sectors compared to heavy-polluting sectors.

As an additional analysis the same t-test was performed on just the observations from the year 2016, and a separate analysis on 2022. This was done to compare the differences of the degree greenwashing between non-heavy polluting-sectors vs heavy-polluting sectors over the years. Due to the small sample size however these results were insignificant. The only interesting observation that can be derived from both t-tests is that the average greenwashing score for non-heavy polluting sectors increased from 12.23 in 2016 to 22.43 in 2022. For heavy-polluting sectors the average greenwashing score increased from 11.95 in 2016 to 20.10 in 2022. Both heavy-polluting and non-heavy polluting have seen a drastic increase in greenwashing, as measured by this metric. And the difference between the two has also increased. The results are presented in appendix D.

Table R3: T-Test Hypothesis 3

Comparison of Greenwashing between Heavy-Polluting and Non-Heavy-Polluting Sectors

Description	Non-Heavy Polluting Sectors (Group 0)	Heavy Polluting Sectors (Group 1)	Combined	Difference (Group 0 - Group 1)
Number of Observations	1162	819	1981	-
Mean Greenwashing Score	18.60	16.48	17.72	2.12
Standard Deviation	33.02	31.57	32.43	-
95% Confidence Interval	[16.70, 20.50]	[14.31, 18.64]	[16.29, 19.15]	[-0.78, 5.02]
T-Statistic	-	-	-	1.4337
Degrees of Freedom	-	-	1979	-
P-Value (Ha: diff < 0)	-	-	-	0.9241
P-Value (Ha: diff 6= 0)	-	-	-	0.1518
P-Value (Ha: diff > 0)	-	-	-	0.0759

5. Summary and conclusions

Summary

In this thesis, we explored the phenomenon of greenwashing by companies and the impact on financial performance. We developed a new Greenwashing Indicator (GWI) to quantitatively assess the disparity between companies' environmental performance as measured by the Environmental pillar score on the one hand, and their actual carbon emissions on the other. Through empirical analysis, we examined the relationship between greenwashing and company performance across various industries. The analysis sheds light on the strategies companies adopt in their environmental reporting and the financial impact of these practices. This study contributes to a deeper understanding of greenwashing and its impact, offering valuable insights for companies, investors, and policymakers.

The main conclusions are as follows:

The regression performed for hypothesis one, found no significant relationship between the E-score and total emissions. As Total Emissions is not statistically significant, the hypothesis is not supported that there is a negative correlation between carbon emissions and the E-score. Hypothesis 1 can therefore be rejected. The other independent variables, R&D intensity and Firm Size, had insignificant coefficients as well. Even though emissions and innovation, of which R&D intensity is a proxy, are two of the three main pillars used by Refinitiv to determine the E-score, in this dataset they don't show to be significant determinants of the E-score. This might indicate that the qualitative metrics Refinitiv incorporates in the E-score with the help of Boolean questions are more important determinants of the E-score compared to these quantitative metrics Refinitiv uses. On the one hand, this broadens the factors that are looked at when determining the environmental performance of a company as measured by the E-score. On the other hand, this could also underestimate the environmental impact of a company. Using Boolean questions the way Refinitiv uses them could undermine the representability of the E-score.

Refinitiv uses questions like for example if a company has an emissions reduction strategy as a Boolean question, while this does not say anything about the actual quality of the company's environmental reduction strategy and if they are on course to achieve their goals. Making E-scores more dependent on actual quantifiable metrics might help with the quality of E-score as a marker for environmental performance.

These results indicate the potential dominance of qualitative over quantitative metrics in the E-score formulation. This observation suggests that the E-score might not fully reflect the actual environmental impact of companies, which is a critical consideration for users of this score.

The primary regression model for hypothesis 2, which includes year, industry, and country fixed effects, suggests a very weak and statistically insignificant association between greenwashing and revenue. This indicates that the data does not support the hypothesis of a positive impact of greenwashing on financial performance. We therefore reject hypothesis 2 which states that there is a There is a positive relation between Greenwashing indicator and company performance

The results from the second regression for hypothesis two that excluded year fixed-effects showed a significant positive coefficient for the greenwashing indicator, suggesting that an increase in the greenwashing indicator is associated with an increase in future revenue. By focusing on cross-sectional variation and not accounting for temporal (yearly) changes, the analysis provides a different perspective on the relationship between greenwashing and revenue in the following year. It helps to understand how greenwashing practices might be associated with company performance across the entire sample, irrespective of specific annual events or trends. This method reveals underlying trends that might be obscured when year-specific variations are taken into account. It does however have its limitations, as it doesn't take important temporal effects into account. This difference in results highlight the importance of temporal effects. The model also has a within R-squared that is less than half of that of the full model. This again highlights the importance of including year fixed-effects

The relationship between R&D intensity and future revenue was found to be negative and highly significant in the regression for hypothesis 2. This is possibly due to the short-term negative impact of R&D investments, which could yield benefits in the long run (Vithessonthi & Racela, 2016).

To gain more insight into the effects of greenwashing on revenue, a second additional analysis was performed that split the dataset into two based on heavy-polluting vs non-heavy-polluting sectors. The main sample was too small to run meaningful separate sector analysis. This approach allowed for a more comprehensive analysis on how the relationship between greenwashing and firm performance varies across sectors with different environmental impacts. This analysis found that greenwashing, as measured by the greenwashing indicator, has no significant effect on revenue for both heavy-polluting and non-heavy-polluting sectors.

The t-test performed for hypothesis 3 found that non-heavy-polluting sectors tend to have higher greenwashing scores compared to heavy-polluting sectors. This is contrary to the initial hypothesis, which suggested that heavy-polluting sectors would have a *larger* discrepancy between reported E-Scores and actual environmental performance. The results suggest that non-heavy polluting sectors, perhaps due to less stringent regulations, might be more prone to greenwashing. Cao et al. (2022) also mentions the fact that non-heavy-polluting industries face limited environmental pressure during production compared to heavy polluting industries. This could be a contributing factor to the fact that we found a smaller degree of greenwashing, as measured by the greenwashing index, for heavy-polluting industries compared to non-heavy-polluting industries. Hypothesis 3, which states that greenwashing is more prevalent in more polluting compared to less polluting sectors in the dataset can therefore be rejected.

These conclusions highlight crucial aspects of greenwashing, its prevalence across sectors, and its impact on financial and environmental performance metrics. The findings suggest a lack of significant correlation between the E-score and total emissions, indicating that qualitative aspects might outweigh quantitative environmental impacts in E-score evaluations, as discussed in the previous section of this conclusion. They also reveal a nuanced relationship between greenwashing and financial performance, with one model showing no significant effect and another suggesting a slight positive influence, albeit without year fixed-effects.

Implications for stakeholders

There are a number of implications of these results for policymakers, companies, and investors.

For **Regulators**, the findings suggest a need for stricter regulation and oversight, especially in non-heavy polluting sectors where greenwashing appears to be more prevalent. The higher incidence of greenwashing in non-heavy-polluting sectors suggests that regulatory attention should not be limited to traditionally polluting industries. Policymakers should consider implementing more rigorous standards for environmental reporting and disclosures. Policies could be designed to standardize reporting practices, making it easier to compare and assess companies' true environmental performance. Regulators could also develop incentives for companies that demonstrate real and substantial efforts towards reducing their environmental impact, as opposed to merely focusing on their ESG scores. Recent efforts in Europe are a step in the right direction. It is very clear that this cannot be done at the national level, as these companies operate globally.

Companies, particularly in non-heavy polluting sectors, should reevaluate their environmental strategies to ensure they are not engaging in greenwashing. This greenwashing may be unintentional, a term developed in the context of the new SFDR-regulation. The findings also underscore the importance of genuine, long-term investments in sustainable practices rather than short-term image management. This could involve more substantial investments in R&D for sustainable technologies or processes. While R&D intensity shows a negative impact on short-term revenue, innovating helps a company stay competitive in the long run.

The call for sustainability does not disappear any time soon and companies can benefit being frontrunners. Finally, maintaining a good reputation in the market requires authentic and transparent environmental reporting. Companies should recognize that genuine environmental responsibility can be a significant factor in long-term success and brand loyalty. International standards for environmental reporting could in turn also help companies in objectively showing this.

Investors should critically analyze Environmental pillar scores and not take them at face value. Understanding the potential for greenwashing is crucial in making informed investment decisions. Enhanced due diligence is needed when assessing a company's environmental claims. This includes a deeper examination of how a company's reported environmental efforts, as measured by the E-score, efforts align with its actual environmental impact. Investors may need to adjust their investment strategies, focusing more on companies that demonstrate a true commitment to sustainability, which could yield better long-term financial performance.

The main research question was if greenwashing leads to increased financial performance. Our analysis does not provide strong support to answer this question affirmatively.

The findings in this thesis also emphasize the importance of establishing standardized and more extensive guidelines for gathering environmental data and the need for robust international regulatory frameworks to limit greenwashing practices. This hopefully leads to more sustainable business practices and investment strategies in the long term. Increasing our understanding of quantifiable metrics of greenwashing might also lead to a better, more comprehensive way to answer this important research question in the future.

Limitations of this study

The study on greenwashing presents several limitations that should be recognized.

Regarding the **data**, the ESG scores used may vary in their accuracy. Different rating agencies have different methodologies for calculating these scores, which often lead to significant inconsistencies. The accuracy and completeness of carbon emission data can also significantly impact the findings. There might be variations in how companies report their emissions, and some may not disclose full information, which would lead to potential biases in the analysis. The **methodology** for constructing the Greenwashing Indicator (GWI) has its own limitations. The assumptions and criteria used to develop this indicator could influence the results and their interpretation. The e-score and carbon intensity rank were both created using the percentile rank scoring methodology to be able to compare them and create the greenwashing indicator. However, the E-score was benchmarked by Refinitiv against a larger database of companies, and the carbon intensity rank was benchmarked against each industry's companies that were available in this dataset. The carbon intensity rank therefore has a much wider range of scores from 0-100. Some degree of misalignment is therefore to be expected in the greenwashing indicator. This also leads to the choice of not including the Greenwashing variable as a binary variable, but to include the degree of alignment between carbon intensity and the environmental pillar score. To be able to create a more robust greenwashing metric, more and higher quality carbon emission and R&D data should become available. This cannot be done at the national level: the EU's Sustainable Finance Disclosure Regulation (SFDR) is a good example of an attempt to standardize environmental data reporting, but there still is much work to be done.

The **statistical methods** used to analyze the data are robust, but they have inherent limitations. They may not capture all nuances or underlying factors that influence greenwashing and financial performance. Also, the study focuses on a relatively short **time period**, which may not capture long-term trends and effects of greenwashing practices. The findings may not apply to all industries or geographic regions. Different sectors and regions have different dynamics in terms of greenwashing and its financial implications. We were unable to delve deep into different sectors, mainly due to lack data. An important issue that is widely recognized in the literature, is the **lack of standardized ESG reporting**. Consequently, assessments can be subjective, depending on the agency. This variability will probably impact the conclusions about the relationship between E-scores, greenwashing, and financial performance. Finally, even though year and sector fixed effects were included to account for shocks, this may not fully account for all external **market and economic developments**, which could influence both greenwashing practices and financial performance. In particular, the COVID-pandemic took place in the middle of the sample period and could have had an effect on both greenwashing and financial performance. It was however not an option to only study the period before the covid-pandemic, as this would have resulted in an even smaller dataset due to lack of E-score availability. This would have made the results of this thesis less relevant.

Suggestions for future research

Future research on greenwashing could take many different angles. Studies over a **longer time** can show how greenwashing affects performance in the long run and the passing of time will automatically help to create larger databases. Looking at **more types of businesses** and **different geographies** can make the findings more widely applicable. Detailed **case studies** of certain companies and improving the way we measure greenwashing could give a clearer picture of greenwashing, and why and how it is done. It would also be useful to see how **new regulation** impacts greenwashing, and how investors react to it, by doing event studies. An important area is the comparison of **different rating agencies**, as a lack of standardization is mentioned in many studies as an important problem. More transparency in the exact way they evaluate companies on environmental issues could also lead to improved analysis on the subject. These different research paths maybe a nice starting point for future thesis researchers.

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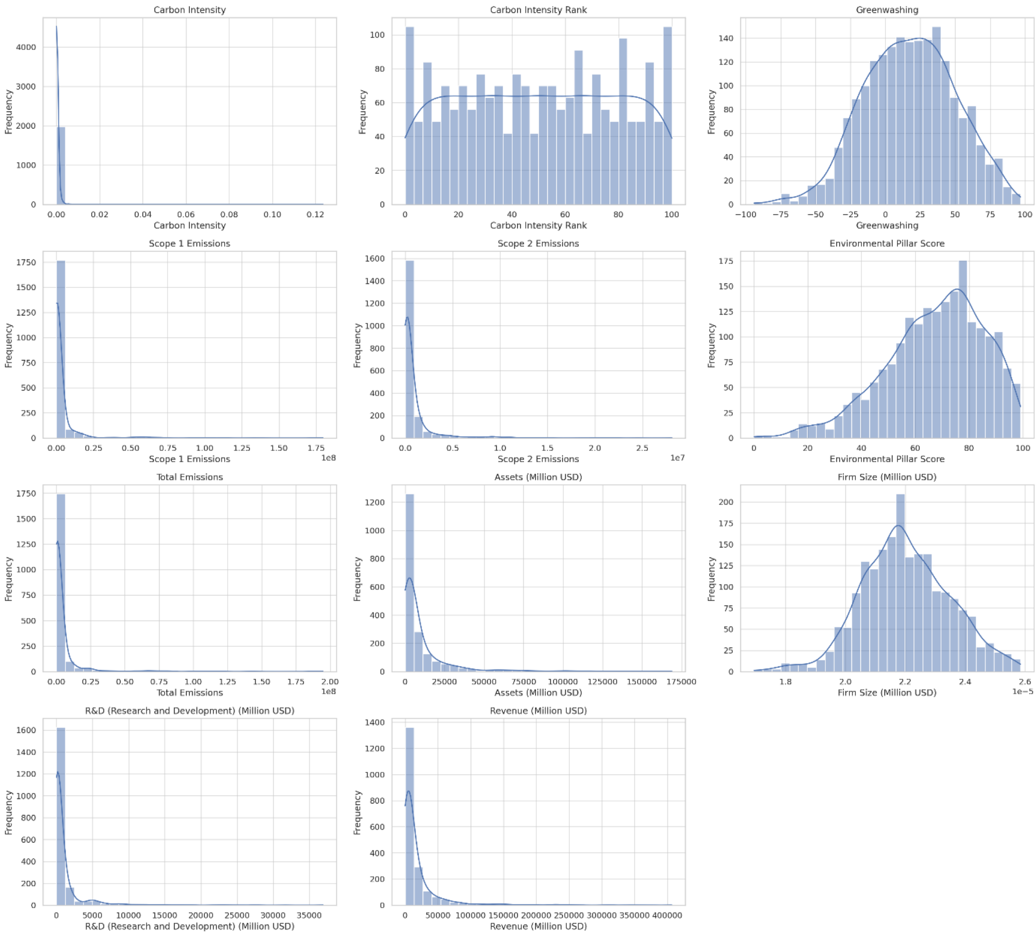
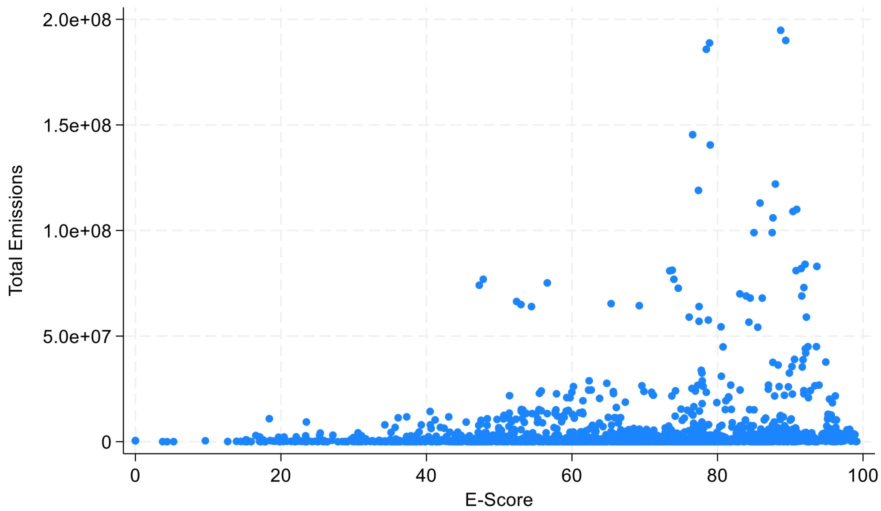
Appendices

Appendix A: Visualization of data

Frequency distributions



E-score vs. Total Emissions



Appendix B

Breusch-Pagan Test H1

Breush-Pagan Test
H0: Constant Variance

Chi^2	86.78
Prob > Chi^2	0.000

Hausman Test H1

Hausman Test
H0: Difference in coefficients is not systematic

Chi^2	42.33
Prob > Chi^2	0.000

VIF H1

Variable	**VIF**
Emissions in 10000	1.39
R&D intensity	1.78
Firm size	1.41
Year	
2017	1.71
2018	1.71
2019	1.71
2020	1.72
2021	1.72
2022	1.73
Sector	
2	4.36
3	3.07
4	1.60
5	1.99
6	3.98
7	2.12
8	4.30
9	4.60
10	4.34
Countrygroups	
2	3.23
3	7.42
4	3.27
5	7.42
Mean VIF	**3.03**

Ramsey Test H1

Ramsey Test
H0: Model has no omitted variables

F(3, 1962)	4.65
Prob > F	0.0031

Appendix C

Breusch-Pagan test H2

Breush-Pagan Test
H0: Constant Variance

Chi^2	2794.31
Prob > Chi^2	0.000

Hausman Test H2

Hausman Test
H0: Difference in coefficients is not systematic

Chi^2	70.10
Prob > Chi^2	0.000

VIF H2

Variable	VIF
Greenwashing Indicator	1.08
R&D intensity	1.01
Firm size	1.28
Year	
2017	1.67
2018	1.67
2019	1.67
2020	1.67
2021	1.68
2022	1.68
Sector	
2	4.17
3	2.98
4	1.59
5	1.99
6	3.74
7	2.08
8	4.11
9	4.63
10	4.14
Countrygroups	
2	3.18
3	7.42
4	3.22
5	7.30
Mean VIF	2.97

Ramsey Test H2

Ramsey Test
H0: Model has no omitted variables

F(3, 1962)	1042.99
Prob > F	0.000

Appendix D

T-Test Hypothesis 3 for 2016 and 2022 as a separate analysis

2016 t-test

Description	Non-Heavy Polluting Sectors (Group 0)	Heavy Polluting Sectors (Group 1)	Combined	Difference (Group 0 - Group 1)
Number of Observations	166	118	284	-
Mean Greenwashing Score	12.24	11.95	12.12	0.28
Standard Deviation	35.16	35.40	35.20	-
95% Confidence Interval	[6.85, 17.62]	[5.50, 18.41]	[8.01, 16.23]	[-8.08, 8.63]
T-Statistic	-	-	-	0.0654
Degrees of Freedom	-	-	282	-
P-Value (Ha: diff < 0)	-	-	-	0.5261
P-Value (Ha: diff 6= 0)	-	-	-	0.9479
P-Value (Ha: diff > 0)	-	-	-	0.4739

Results: there is no statistically significant difference between the greenwashing indicator in the heavy-polluting industries vs the non-heavy-polluting industries for 2016.

2022 t-test

Description	Non-Heavy Polluting Sectors (Group 0)	Heavy Polluting Sectors (Group 1)	Combined	Difference (Group 0 - Group 1)
Number of Observations	166	118	284	-
Mean Greenwashing Score	22.43	20.10	21.46	2.33
Standard Deviation	31.00	30.13	30.61	-
95% Confidence Interval	[17.67, 27.18]	[14.60, 25.59]	[17.89, 25.04]	[-4.90, 9.56]
T-Statistic	-	-	-	0.6351
Degrees of Freedom	-	-	282	-
P-Value (Ha: diff < 0)	-	-	-	0.7370
P-Value (Ha: diff 6= 0)	-	-	-	0.5259
P-Value (Ha: diff > 0)	-	-	-	0.2630

Results: there is no statistically significant difference between the greenwashing indicator in the heavy-polluting industries vs the non-heavy-polluting industries for 2022