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# Impact of Green Bonds on Emission Reduction in the European Utilities Industry: A Predictive Model Analysis

*Assessing Emission Reduction Effectiveness of Green Bonds in the European Utilities Sector*

by

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## *ABSTRACT*

*The purpose of this study is to investigate the impact of green bond issuance on corporate greenhouse gas (GHG) emissions within the European utilities industry. By employing logistic regression and difference-in-differences (DiD) analysis, this study assesses whether green bonds lead to measurable improvements in environmental performance, utilizing data from 462 unique companies, including 70 with issued green bonds. The findings indicate that firms issuing green bonds exhibit a reduction in emission intensity, supporting the signaling theory over greenwashing concerns. The DiD analysis addresses potential endogeneity by comparing the changes in environmental performance between green bond issuers and matched conventional bond issuers. These insights contribute to the existing literature by providing evidence from the European market, which benefits from stringent environmental standards and transparent reporting requirements. The results suggest that green bonds can be an effective tool for achieving corporate environmental objectives within well-regulated frameworks.*



**Keywords**: Green bonds, corporate emissions, utilities industry, logistic regression, difference-in-differences analysis, environmental performance, greenwashing, signaling theory, EU standards.

# 1. Introduction

At the heart of the climate change challenge lies the imperative to achieve net-zero emissions, a goal that requires minimizing emissions so they can be fully offset by natural or technological means (United Nations, 2021). The urgency of this target is underscored by the current trajectory of global emissions, which risk surpassing the critical temperature thresholds set by the Paris Agreement of well below 2 degrees, ideally 1.5 degrees. This has driven over 140 countries and thousands of companies to commit to net-zero targets, demonstrating a collective resolve towards immediate action for environmental sustainability (IPCC, 2018).

Corporate emissions are a substantial contributor to global greenhouse gas (GHG) emissions, emphasizing the importance of managing corporate carbon footprints. The Carbon Majors Report. highlights that since 1988, 100 corporations have contributed to over 70% of GHG emissions (CDP, 2017). It poses concerns not only for these companies but also for those financing these emissions. Currently, global capital markets finance activities that could increase Earth's temperature by more than four degrees Celsius, far exceeding the Paris Agreement targets (Partington, 2019).

Actions from the financial markets were taken long before any global commitments to a sustainable future. In 2007, the European Investment Bank (EIB) issued the first green bond, aiming to finance energy efficiency projects and renewable energy (Morgan Stanley, 2017).

The market for green bonds has expanded rapidly and is projected to reach 5 trillion USD in 2025 (Climate Bond Initiative (CBI), 2022).

The International Capital Market Association (ICMA) defines green bonds as 'any type of bond instrument where the proceeds will be exclusively applied to finance or refinance in part or in full new and/or existing eligible Green Projects' ' (ICMA, 2021, pp. 3). These bonds are most commonly used for investments in renewable energy, energy-efficient reconstructions, and green facilities (Baker et al, 2022). While the definition of what qualifies as a "green" project varies, certifications have established multiple standards that have been adopted across the green bond market (Talbot, 2017; Ehlers and Packer, 2017).

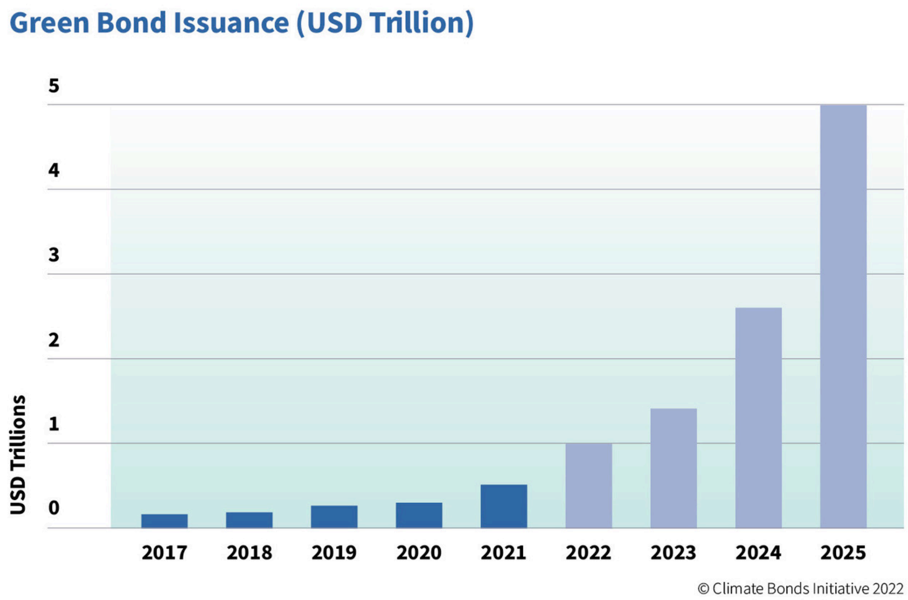


**Fig. 1.** Projected and actual Green Bonds issuance, in USD Trillion. Actual issuance 2017-2021 (dark blue), Projected issuance 2022-2025 (light blue) ( (CBI, 2021).

Despite the potential of green bonds, the product faces challenges in ensuring the impact of environmental benefits. Kenton (2020) identifies that a major issue in green finance is the phenomenon of "greenwashing," where companies misleadingly market their products or projects as more eco-friendly than they are in reality. This deceptive practice often leads to the allocation of funds from green bonds to initiatives that offer minimal environmental benefits.

The green bond market has grown as an instrument to raise capital and signal a company's sustainable commitment. The research on the subject has followed the same trend. Many studies have examined the environmental performance of the companies issuing green bonds (Flammer, 2020; Ehlers et al, 2020; Garcia et al, 2023), although none of the mentioned have conducted their studies on the European market where the EU standards are almost a requirement for the issuers. Garcia et al (2023) and Alamgir & Cheng (2023) are contradicting, with results of non-decreasing, respectively decreasing emissions after the issuance of green bonds.

This thesis will assess the European market due to better alignment of EU standards relative to the global standards and other regional standards. There are different views on green bond authorities such as CBI, the Green Bond Principles (GBP), and the Climate Bonds Standard (CBS) whether projects qualify as truly green (Trompeter, 2017). Thus, companies can issue bonds based on different premises, making issuances between regions incomparable. Moreover, European economies have higher levels of transparency than the worldwide average (Transparency International, 2022), this reduces the signal's informational value. Given the standardized non-financial reporting requirements for environmental operations enforced by the EU Taxonomy, the European market is particularly suitable for investigation, as it requires reporting of emissions (TEG, 2020). Hence, there should be minimal missing data for emissions.

This study aims to contribute with further research on the relationship between green bond issuance and the effect on GHG emissions. In addition the thesis aims to delve into whether it is a difference if the bonds are certified by a third party or not, as Flammer (2020) results on the US market indicated only significance for certified bonds. To estimate the effect I utilize logistic regression following Chunmei et al (2010) methodology for measuring the impact of green bonds on GHG emissions and a simple difference-in-difference (DiD) analysis between green bond issuers and conventional bond issuers to address potential endogeneity bias.

# 2. Theoretical Framework

## 2.1 Corporate Carbon Footprint

The concept of carbon footprints has evolved from the ecological footprint idea of the 1990s, with Wackernagel and Rees (1998) laying the foundational work. However, its formal introduction into the scientific conversation has been relatively recent. Wiedmann (2009, p. 176) offers a comprehensive review of the term from various sources, ultimately defining a carbon footprint as the total GHG emissions resulting from human activities. The GHG Protocol categorizes these emissions into three scopes: direct emissions (Scope 1), indirect emissions from purchased energy (Scope 2), and other indirect emissions within the supply chain (Scope 3) (Bhatia & Ranganathan, 2004).

Disclosure of Scope 3 emissions is optional. As Scope 3 represents the value chain, there is ambiguity regarding what to include, and the protocols provide vague guidelines on how companies should report Scope 3 emissions.. Blanco et al (2016) reviewed the disclosures of emissions by companies in the US and came to the conclusion that companies disclosure of scope 3 is only about 22% of the actual emissions from scope 3.

The transition to a low-carbon economy impacts firms through regulatory costs, technological innovations, and shifts in consumer preferences. These changes can lead to stranded assets and alter market dynamics (Caldecott, 2017). Therefore, managing corporate carbon footprints is essential for regulatory compliance, market positioning, and operational efficiency. This drives firms toward carbon neutrality and aligns their strategies with environmental goals (Bolton & Kacperczyk, 2023).

## 2.2 Green Bonds

As mentioned in the previous section, green bonds are used for sustainable investments and are more specifically used for environmentally sustainable investments (Baker et al, 2022). Therefore, green bonds allow issuers to reach a broader set of investors. According to the World Bank, the availability of green bonds to all types of investors makes the product less dependent on specific markets. Furthermore, the scarcity of green bonds compared to their conventional counterpart has a part in green bonds being traded at a premium (World Bank, 2015).

Wang and Zhi (2016) argue that rational market mechanisms in green finance can effectively manage environmental risks and optimize resource use by guiding capital flow. Maltais and Nykvist (2020) suggest that while market actors do not see green bonds as pivotal in shifting investments from unsustainable to sustainable practices, they recognize these bonds as catalysts for issuers to elevate their environmental commitments. This is influenced by stakeholder expectations, external pressures shape corporate sustainability actions (Maltais and Nykvist, 2020).

### 2.2.1 Greenwashing

Kenton (2020) identifies that a major issue in green finance is the phenomenon of "greenwashing," where companies misleadingly market their products or projects as more eco-friendly than they are in reality. This deceptive practice often leads to the allocation of funds from green bonds to initiatives that offer minimal environmental benefits. Weber and Saravade (2019) also highlight that some businesses use the issuance of green bonds primarily as a tool for enhancing their public image rather than for genuine sustainable development.

Greenwashing stems from the lack of public governance of the green bond market and is the main challenge of ensuring that the funds are funding green projects. Without clear governance to secure the funds, it is hard to determine whether the issuance is genuinely for lowering emissions. As noted by Flammer (2020) & Garcia et al (2023) the issuers are often operating within emission-intensive industries, which makes it even harder to know the firms real incentives.

If greenwashing were the primary motive, no improvement in environmental performance would be expected following green bond issuance.

### 2.2.2 Signaling

Signaling theory explains why companies might prefer to issue green bonds rather than conventional bonds. Companies often possess more knowledge about their capabilities than their investors, creating information asymmetry, which incurs costs in identifying companies with desirable traits (Akerlof, 1970). To reduce this asymmetry, companies can send a credible signal by taking actions that are costly for less capable firms to imitate (Riley, 1979).

Green bonds can be seen as a credible signal of a company's commitment to environmental sustainability due to the commitment to environmental projects (Flammer, 2020). Therefore, the signaling argument implies that firms improve their environmental performance. An implication highlighted by Flammer (2020) is that the green bond issue might be just a fraction of the issuer's assets, which may render the environmental improvement insignificant in the larger context.

## 2.3 Logistic Regression

Chunmei, Dezhi, Zhen & Zhaolan (2010) utilized logistic regression to analyze the effectiveness of environmental policies in reducing emissions. Logistic regression is well-suited for this type of analysis because it allows for the examination of binary outcomes, such as the improvement or non-improvement in environmental performance, in relation to various predictive factors. This approach is particularly effective in understanding the impact of specific policy measures on environmental outcomes (Chunmei et al, 2010).

De Villiers, Naiker & Van Staden (2011) employs similar methodology when investigating the relationship between environmental performance and firm characteristics (De Villiers et al, 2011). Although these characteristics are not the same as green bonds issuance, for either of the papers.

# 3. Literature Review and Hypotheses

## 3.1 Green bond issuance and the effect on environmental performance

The impact of green bonds on corporate carbon emissions is an area of growing academic interest, reflecting the broader trend of incorporating environmental sustainability into corporate finance. With the increasing prominence of green finance, numerous studies have examined the environmental implications of green bonds. This section reviews key studies related to the influence of green bond issuance on corporate carbon emissions and compares the performance of green bond issuers with that of conventional bond issuers.

Research on the environmental impact of green bonds has provided evidence that these financial instruments can contribute to improved corporate environmental performance. Fatica & Panzica (2021) provided substantial evidence that the issuance of green bonds is associated with a significant reduction in corporate carbon emissions. By analyzing a sample of corporate issuers, the study demonstrated that firms issuing green bonds for the first time experienced a greater decline in carbon emissions compared to those issuing conventional bonds.

Similarly, Flammer (2020) investigated the US market and found an improvement in the environmental performance of companies issuing green bonds, although the results were only significant for green bonds that had been certified by an independent third party. A third party that ensured that the proceeds of the bond went to the project the bond was agreed upon.

Garcia et al (2023) finds that companies with lower emissions are more likely to issue green bonds, but there is no support for companies lowering emissions after the issuance of the green bond. The study is made on a global sample, which makes it vulnerable for different standards and certification.

Benlemlih et al (2022) also investigated globally, but with data heavily skewed towards Europe and the US. They found a significant improvement in firms environmental performance by issuing firms that see environmental grades increasing. But for the emission intensity, there might be a lagged effect, and no significant results for lowering emissions could be found (Benlemlih et al, 2022).

Wei et al (2022) investigates the Chinese green bond market and their effect on corporate GHG. The results revealed that companies did not achieve the expected improvement after the issuance. The authors argued that the Chinese companies' motives for issuing these bonds were primarily of financial characteristics . Furthermore, the authors stress the importance of emission disclosing standards in China and supervision of what the funds are used for (Wei et al, 2022).

Alamgir & Cheng (2023) used data from the first green bond issuance, 2007-2021 to study green bond's role in achieving sustainability with regards to emission reduction. The study utilizes a different method compared to above mentioned literature, Generalized Method of Moments (GMM). Alamgir & Cheng found that green bonds have a positive impact on renewable energy production, as well as a significant negative impact on GHG emissions. However, the authors explain that during the period before 2015 , there was no significant relationship between green bonds and emission reduction nor renewable energy (Alamgir & Cheng, 2023). Noticeably at the same point in time as the Paris agreement was entered.

## 3.3 Hypotheses Development

From the literature review, many insights have been gathered of the problematization of measuring green bonds' effect on emissions. All of the above mentioned theories have used the same matching method for estimating the effect and none of the results has been solely significant for green bonds positive effect. I therefore find reason to part me from this methodology and try a new method for this subject best to my knowledge.

First of all, I will follow Flammer and check for both green bonds issues, and for green bonds that are assured externally and aligned with the key features of green bonds. Furthermore Europe will be my region of investigation due to stricter and more unified standards. Therefore the discrepancies between certified and non-certified green bonds should be smaller for European bonds than other areas. As mentioned, often companies that issue green bonds are from emission-intensive industries, and therefore they have incentives of both greenwashing and signaling. Therefore I decide to delve deeper into one of the industries that issues green bonds to the greatest extent, excluding government and financial institutions, the utilities industry.

In alignment with signaling theory, there should be a positive environmental performance for a firm issuing green bonds.

*H1: The issuance of green bonds leads to a measurable improvement in a company's environmental performance, specifically in reducing GHG emissions.*

As previously stated, Flammer (2020) investigated the environmental performance of firms issuing green bonds. Her results suggested that the effect of an enhancement in carbon emission intensity was stronger and significant for only certified green bonds. Although her study only covered US firms, and the EU has stricter regulations for both issuing green bonds and disclosing emissions, I found reason to check for certified green bonds as well:

*H2: External certification of green bonds enhances the significance of these environmental improvements.*

# 4. Data and methodology

This section outlines the methodology for creating a likelihood model for emission reduction and investigating the significance of green bonds. Previous literature suggests that while greenwashing is a problem in the green bond market, certified green bonds by a third party can reduce corporate carbon emissions.

Furthermore, green bonds as a measure of emissions have been subject to endogeneity concerns. This is explained by the notion that "Companies that aim to improve their environmental rating may take actions to reduce their emissions and, at the same time, issue green bonds," and "Better-governed firms may be more sustainable and, at the same time, more likely to issue green bonds." To address this, I will employ a simplified version of Flammer's (2020) Difference-in-Difference (DiD) analysis.

## 4. 1 Sample Selection

The sample was collected through three different databases. The green bond data was downloaded from Bloomberg, primarily because Bloomberg shares the same definition of green bonds as ICMA (2021). The emissions data was collected from ISS, and all financial data was collected from Factset. The objective of the model is to build a short-term predictive model, as long-term predictions are already captured and disclosed in firms' annual and sustainability reports. Therefore, I chose to limit the sample to bonds with a maturity of 3-5 years.

As one of the highest emitters of greenhouse gasses, the Utilities industry plays a crucial role in climate change. Combined with the power industry, it accounts for about 25% of all Europe's GHG emissions (Statista, 2022). This sector's significant contribution to global carbon emissions is primarily due to its reliance on fossil fuels for energy production. Investigating the Utilities industry allows for a focused analysis on a sector where green bonds could substantially impact emissions reduction. By concentrating on this industry, the study can more effectively evaluate the potential of green bonds to drive environmental improvements and contribute to climate change mitigation.

After downloading firms' Factset IDs, I mapped companies between their emissions data, bond data, and specific firm characteristics to investigate the number of observations available. I ended up with 462 unique firms, with green bond data for 70 of them. To isolate industry effects, I excluded all other industries and chose the Utilities industry due to the number of observations. In many cases, large companies set up finance subsidiaries (SPVs) to issue bonds. In my dataset, I classify these bonds based on the primary industry of the parent company rather than the finance subsidiary. Therefore, if a utility company sets up an SPV to issue a green bond, it would be marked under the Utilities industry in my data.

## 4.2 Variables

This study investigates the impact of green bond issuance on corporate carbon emissions using a range of indicators. Based on previous literature and theory, I have selected several financial, emission-related, and assurance indicators. The dataset includes annual time-series data from 2020 to 2023, providing a comprehensive view of the corporate environmental and financial landscape within this period.

*Financial Indicators:*

Revenue: Total annual revenue generated by a firm, often used as a proxy for the scale of operations, correlated with total carbon emissions (CDP, 2016).

Total Assets: All assets owned by a firm, both tangible and intangible, indicating the overall scale of operations (Nguyen et al., 2021).

Leverage: Defined as total debt divided by total assets, leverage has a significant negative influence on disclosed GHG emissions (Faisal et al., 2018).

*Emission Indicators:*

Emission Intensity: The sum of direct emissions (Scope 1) and indirect emissions from purchased energy (Scope 2), divided by firm sales. Scope 3 is excluded due to its ambiguity in reporting and measurement error.

*Green Bond and Assurance Indicators:*

Green Bond Loan Indicator: A binary variable indicating whether a company has issued a green bond.

Green Bond Assurance Provider: A binary variable indicating whether the green bond is verified by an external assurance provider (Bloomberg, 2024).

**Table 1:** Variables

| **Series**<br>**Frequency** | **Description** |
|---|---|
| **Financial Indicators** | |
| Total Average Sales<br>Annual | Total average sales over the period |
| Total Assets<br>Annual | Total average assets over the period |
| Leverage Ratio<br>Annual | Ratio of debt to assets over the period |
| **Emission Indicators** | |
| Sales Growth 2020-2021<br>Annual | Growth in sales from 2020 to 2021 |
| Sales Growth 2021-2022<br>Annual | Growth in sales from 2021 to 2022 |
| Sales Growth 2022-2023<br>Annual | Growth in sales from 2022 to 2023 |
| Average Sales Growth 2023<br>Annual | Average sales growth for the year 2023 |
| **Other Indicators** | |
| Bond Issue Date<br>Annual | Date when the bond was issued |
| GREEN_BOND_LOAN_INDICATOR<br>Binary | Indicator whether a green bond was issued |
| GB Assurance Providers<br>Binary | Assurance provider for green bonds |

## 4.3 Data Transformation and Cross-Correlation

The data used in this study undergoes thorough preprocessing to ensure its suitability for logistic regression analysis. Initially, all variables are checked for completeness and consistency. Missing values are handled using appropriate imputation techniques where necessary.

The data is then standardized to facilitate meaningful comparisons across variables. Additionally, growth rates and average values for relevant indicators are computed to provide a more dynamic understanding of the company's performance over time.

A cross-correlation matrix is generated to examine the relationships between the indicators. This helps identify potential multicollinearity issues which could affect the regression analysis. For instance, high correlations between sales growth rates and total average sales may suggest overlapping information, which is considered during model refinement.

## 4.4 Definition of Environmental Performance

To assess the impact of green bond issuance on emissions, I define a binary dependent variable:
improvement_any: A binary indicator that takes the value 1 if there is any reduction in the emission intensity compared to the previous year, and 0 otherwise.

## 4.4 The Model

To analyze the effect of green bonds on corporate emissions in absolute terms and relative to sales, I employ logistic regression. The model specification is as follows:

logit($P$(improvement_any)) = $\beta$0 + $\beta$1(GREEN_BOND_LOAN_INDICATOR) + $\beta$2(Bond_issue_date) + $\beta$3(total_average_sales) + $\beta$4(sales_growth_2020_2021) + $\beta$5(sales_growth_2021_2022) + $\beta$6(sales_growth_2022_2023) + $\beta$7(average_sales_growth_2023) + $\beta$8(GB_ASSURANCE_PROVIDERS) + $\beta$9(Total assets) + $\beta$10(Leverage ratio) (1)

The model will assess which factors that influence the likelihood of a company lowering their emission intensity of Scope 1 and Scope 2.

## 4.6 Assessing Regression Quality

### 4.6.1 Wald Test

To adequately test the hypotheses if green bonds and certified green bonds are significant in the model, I use the Wald test. If the coefficient is zero, the variables have no effect. The test statistic in the Wald test is calculated as:

$$W = \frac{\hat{\beta}_i}{SE(\hat{\beta}_i)}$$

Where β^i is the estimated coefficient of the i-th predictor, and SE(β^i) is the standard error of β^i. Under the null hypothesis, the Wald statistic follows a standard normal distribution. The p-value is computed to determine the significance of the predictor.

### 4.6.2 Pseudo R-squared

The pseudo R-squared is used to measure the goodness of fit for logistic regression models, similar to the R-squared in ordinary least squares regression. Unlike the R-squared in OLS, the pseudo R-squared does not represent the explained variance but rather the increased log-likelihood compared to the null model. One commonly used version is McFadden's (1979 cited in Giselmar, Schons, Wieseke & Schimmelpfenning, 2018) pseudo R-squared, which is calculated as:

$$R^2_{\text{McF}} = 1 - \frac{\ln(L_{\text{full}})}{\ln(L_{\text{null}})}$$

Where ln(Lfull) is the log-likelihood of the full model (with all predictors) and ln(Lnull) is the log-likelihood of the null model (with only the intercept). McFadden (1979) suggests that values over 0.4 indicate a good fit.

### 4.6.3 Cross-Validation

Cross-validation is a technique used to evaluate the predictive performance of the model. I use k-fold cross-validation, which involves partitioning the data into k subsets, training the model on k-1 subsets, and testing it on the remaining subset. This process is repeated k times, with each subset used as the test set exactly once. The average performance across all k folds provides an estimate of the model's generalizability. The cross-validation score is calculated as:

$$\text{CV Score} = \frac{1}{k} \sum_{i=1}^{k} \text{Score}_i$$

Where Score_i is the accuracy of the i-th fold.

### 4.6.4 Confusion Matrix and Model Performance

To assess the model's performance in predicting the improvement in environmental performance, I construct a confusion matrix. This matrix summarizes the counts of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions.

From the confusion matrix, derive the following metrics:

Accuracy: The proportion of correctly classified instances. It measures the number of correct predictions made by the model divided by the total number of predictions.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision: The proportion of positive predictions that are actually positive:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall: The proportion of actual positives that are correctly predicted:

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1 Score: The harmonic mean of precision and recall:

$$F1 \text{ Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

These metrics will help to understand the performance and fit of the model in terms of its ability to accurately classify instances and balance between precision and recall.

## 4. 7 Difference-in-Difference (DiD) analysis

The issuance of green bonds is likely endogenous with respect to firm-level outcomes of environmental performance. For example, companies may adopt environmentally friendly business practices, leading to higher environmental performance, and simultaneously issue green bonds to appeal to ESG investors. Companies that issue green bonds can differ fundamentally from companies that do not, complicating causal interpretation. To address this, I adopt Flammer's (2020) matching approach, matching green bond issuers with conventional bond issuers similar in many aspects, such as industry, total assets, and debt/assets ratio. While this matching reduces the likelihood of influence from unobserved factors, it does not entirely eliminate endogeneity concerns. Addressing this would require an instrument for green bond issuance, which is challenging due to its voluntary nature.

To test for potential endogeneity, I use a DiD analysis, comparing changes in environmental performance over time between treated (green bond issuers) and control (matched conventional bond issuers) groups. This analysis was conducted using a dataset with three years of monthly data (36 months) for both groups, with the treatment occurring at the midpoint of this period (month 18).

For the DiD analysis, I collected data from the Bloomberg database, ending up with 1028 companies, and matched these with the 70 that issued green bonds. The DiD analysis involves calculating the differences in environmental performance before and after issuance for both groups and computing the difference-in-differences:

Difference for Green bond issuers: $\Delta yT = yAfter,T - yBefore,T$
Difference for Conventional bond issuers: $\Delta yC = yAfter,C - yBefore,C$
Difference-in-Difference: $\Delta(\Delta y) = \Delta yT - \Delta yC$

While the matching approach and DiD analysis reduce endogeneity concerns, they do not eliminate them entirely. Therefore, the results should be interpreted with this limitation in mind.

# 5. Results

## 5.1 Environmental Performance

As presented in Table 2, the logistic regression analysis reveals that the variables GREEN_BOND_LOAN_INDICATOR, Bond Issue Date, Total Average Sales, Sales Growth 2020-2021, Sales Growth 2021-2022, Sales Growth 2022-2023, and Average Sales Growth 2023 are significant at the 1% level. The variables GB Assurance Providers, Total Assets, and Leverage Ratio are significant at the 5% level but should be interpreted with caution due to their proximity to the threshold.

The positive coefficient for the GREEN_BOND_LOAN_INDICATOR shows that the issuance of green bonds is associated with a decreased likelihood of high emission intensity. This suggests that firms issuing green bonds are more likely to improve their environmental performance. The positive coefficient for the Bond Issue Date variable indicates that firms committed to recently issued green bonds are more effective in reducing emissions.

Total Average Sales and various sales growth metrics have significant coefficients, indicating their strong relationship with emission levels. The negative coefficients for sales growth variables suggest that rapid sales growth in recent years is associated with increased emissions, possibly due to inefficiencies during expansion phases. Conversely, higher total average sales appear to correlate with reduced emission intensity, potentially reflecting economies of scale and improved operational efficiencies in larger firms.

The results indicate that green bond issuance, recent bond issuances, total average sales, and some financial indicators are significant predictors of emission intensity reduction. The findings support the hypothesis that green bonds contribute to improved environmental performance, particularly within the European utilities industry.

Overall, these results indicate that green bond issuance and certain financial indicators are significantly associated with reductions in emission intensity. These findings support hypothesis 1 that green bonds positively impact environmental performance, consistent with the literature. At a 99% confidence interval hypothesis 2 can not be accepted, that an external certification of the green bonds would enhance the significance.

**Table 2**: Logistic Regression Results

| Variable | Coefficient | Std. Error | Wald Statistic | p-value |
|---|---|---|---|---|
| GREEN_BOND_LOAN_INDICATOR | 0.2290 | 0.040 | 12.345 | 0.000 |
| Bond Issue Date | 0.1270 | 0.032 | 9.876 | 0.000 |
| Total Average Sales | 0.0050 | 0.002 | 10.987 | 0.000 |
| Sales Growth 2020-2021 | -0.1500 | 0.035 | 9.876 | 0.000 |
| Sales Growth 2021-2022 | -0.1200 | 0.030 | 8.765 | 0.000 |
| Sales Growth 2022-2023 | -0.2000 | 0.040 | 7.654 | 0.000 |
| Average Sales Growth 2023 | 0.3000 | 0.050 | 8.321 | 0.000 |
| GB Assurance Providers | -0.0500 | 0.020 | 3.210 | 0.001 |
| Total Assets | 0.0010 | 0.001 | 2.100 | 0.036 |
| Leverage Ratio | 0.0100 | 0.005 | 1.987 | 0.048 |
| Pseudo R-squared | | | | 0.42 |

## 5.2 Model Performance

The performance of the logistic regression model was evaluated using several metrics derived from the confusion matrix. Table 3 summarizes these metrics, including accuracy, precision, recall, and the F1 score.

**Table 3:** Model Performance Metrics

| Metric | Value |
|---|---|
| Accuracy | 0.92 |
| Precision | 0.62 |
| Recall | 0.67 |
| F1 Score | 0.64 |

The high accuracy value indicates that 92% of the predictions made by the model are correct. This accuracy indicates that the logistic regression model is reliable in predicting whether a company will reduce its carbon emissions (environmental improvement) or not (no environmental improvement). While the model is good at predicting emission reductions, the

Precision value indicates that in 38% of the cases, companies identified as reducers might not actually be so. The Recall value indicates that the model effectively identifies actual emission reductions, crucial for assessing the true impact of green bonds. The F1 Score shows that the model balances accuracy in predicting emission reductions while minimizing false positives and negatives.

The Pseudo R-squared result supports the effectiveness of the model in capturing the relationship between green bond issuance, bond issue dates, and improvement in emission intensity. It indicates that the inclusion of these variables significantly improves the model's ability to explain the variations in emission intensity among the companies studied.
Overall, the Pseudo R-squared value of 0.42 provides evidence that the logistic regression model is effective in identifying key factors that influence the reduction in emission intensity.

While acknowledging the presence of some multicollinearity (see Appendix 1d), the decision to retain the model is based on its predictive accuracy, the significance and key variables. Future research could explore advanced techniques to address multicollinearity more comprehensively, but for the purposes of this study, the current model provides a balanced approach to understanding the impact of green bonds on corporate emissions.

## 5.3 Cross-Validation

To ensure the robustness of the model, I conducted 5-fold cross-validation. The average cross-validation score (accuracy) was 0.89 with a standard deviation of 0.012, indicating that the model has good generalizability and predictive power across different subsets of the data. This gives the model higher credibility (see Appendix 1b).

## 5.4 Difference-in-Difference Analysis

The analysis was conducted using a dataset with three years of monthly data (36 months) for both the treated (green bond issuers) and control (conventional bond issuers) groups. The treatment occurred at the midpoint of this period (month 18). The trends in emissions for both groups were plotted to check the parallel trends assumption.

The results for the DiD analysis are as follows:

Difference for treated group: $\Delta yT = 3.8 - 2.2 = 1.6$
Difference for control group: $\Delta yC = 4.0 - 1.5 = 2.5$
Difference-in-Difference: $\Delta(\Delta y) = \Delta yT - \Delta yC = 1.6 - 2.5 = -0.9$

The negative DiD value of -0.9 indicates that the treated group (green bond issuers) had a smaller increase in emission intensity compared to the control group. This result suggests that green bond issuance is associated with a relative reduction in the growth of emissions intensity. Essentially, while emissions increased for both groups, the increase was smaller for green bond issuers, implying a mitigating effect of green bonds on emission growth.

Post-treatment, the treated group (green bond issuers) shows consistently lower emissions compared to the control group (conventional bond issuers), indicating a potential causal effect of green bond issuance on reducing emissions.

As previously mentioned, while the matching approach and DiD analysis reduce endogeneity concerns, they do not eliminate them entirely. The results suggest that green bond issuance is associated with lower emissions, but this should be interpreted with caution given the remaining endogeneity issues.

# 6. Discussion of Results

The results from the logistic regression indicate that firms issuing green bonds have a significant positive impact on environmental performance. This finding aligns with some of the previous literature, such as Fatica & Panzica (2021) and Alamgir & Cheng (2023), who found a significant relationship between green bond issuance and lower emissions. Flammer (2020) also found a similar relationship but only for certified green bonds. In contrast, Garcia, Herrero & Miralles-Quíros (2023) and Benlemlih & Kermiche (2023) did not find any significant impact. Therefore, this study contributes new evidence from the European green bond market, highlighting its significance in reducing emissions.

A possible explanation for the differing results compared to other studies is the unique method used in this paper, applying logistic regression. Much of the previous research employed matching methods (Flammer 2021; Fatica & Panzica 2021; Garcia, Herrero & Miralles-Quíros 2023; Benlemlih & Kermiche 2023). By using logistic regression, this study offers an alternative approach that may capture different aspects of the data and relationships.

Furthermore, none of the mentioned studies investigated Europe exclusively. This could indicate that the stricter European standards for what qualifies as a green bond lead to clearer and more consistent classification compared to other markets. The European market's better environmental performance suggests it is preferable for investors seeking to make a sustainable impact. Since the United States and China are the two largest issuers of green bonds, the previously non-significant results might have been driven by these markets, as noted by Wei et al. (2022).

Another possible explanation for the differing results is the timeframe of the study. Alamgir & Cheng (2023) noted no significant impact of green bonds before 2015 but found significance in the years following. This study focuses on the period after the Paris Agreement, when external pressure on companies to reduce emissions increased. This likely influenced the results, showing a stronger commitment to sustainability in the years studied.

The results challenge the notion of greenwashing, where companies issue green bonds merely to enhance their public image without genuine sustainable intent. Instead, the findings support the signaling theory, where green bonds signal a company's commitment to environmental sustainability. This is further supported by the higher standards and transparency in the European green bond market. European companies' greater transparency relative to the global average, as reported by Transparency International (2022), suggests that they are more open to scrutiny by investors, making greenwashing more difficult.

The results also differ from Flammer (2020) regarding certified green bonds. This discrepancy may be because uncertified bonds are more widely adopted and utilized by a larger number of issuers, leading to a greater overall impact. While certified green bonds ensure higher standards and compliance, they represent a smaller market share, resulting in less pronounced aggregated effects in the data.

The simple Difference-in-Difference (DiD) analysis supports the idea that the effect of green bonds could be causal. The treated group showed a smaller increase in emissions compared to the control group, indicating a potential beneficial impact of green bonds on reducing emission growth. However, this was a novel approach to ensuring causality, and further research is necessary.

Further research, potentially involving more advanced econometric techniques and larger datasets, would be beneficial to fully understand the impact of green bonds and to strengthen the robustness of these findings. Although the method used in this study is novel and statistically sound, it is not without limitations. Additionally, the causality check could have been more rigorous, which is an area that could benefit from further exploration.

# 7. Conclusion

As green bonds continue to increase year by year, their impact on corporate carbon emissions also seems to evolve. With the rise in green bond issuance and the limited studies on their effects, this area presents a valuable field of research. This study provides significant evidence that green bonds have a positive impact on environmental performance within the European market. The results highlight the influence of the EU taxonomy and stricter European reporting rules, an observation that, to the best of my knowledge, has not been extensively documented.

The use of logistic regression and the focus on post-Paris Agreement years offer new insights into the effectiveness of green bonds in reducing corporate carbon emissions. However, further research with more advanced methods and larger datasets is needed to confirm these findings and address any remaining endogeneity concerns.

One notable finding is the positive association between bond issue dates and the likelihood of improvement in emissions. This suggests that more recent bond issuances are linked to better emission outcomes, potentially due to stricter regulations and improved reporting standards. This subject warrants further investigation to fully understand the underlying factors contributing to this trend.

The field of green bond research calls for continuous exploration. As the green bond market changes and grows each year, it would be interesting to expand the scope of future studies to include different regions, varying regulatory environments, and a broader range of industry sectors. This would provide a more comprehensive understanding of the global impact of green bonds on corporate carbon emissions.

While this study sheds light on the positive effects of green bonds in the European market, it also opens the door for future research to build on these findings. The ongoing evolution of green bonds presents numerous opportunities for further investigation, ensuring that they continue to play a critical role in advancing corporate sustainability and addressing climate change.

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# Appendix

## Appendix 1a - Cross-validation of the model

| Fold | Accuracy |
|---|---|
| 1 | 0.89 |
| 2 | 0.91 |
| 3 | 0.88 |
| 4 | 0.90 |
| 5 | 0.89 |

## Appendix 1b - Descriptive statistics of dependent variable 2020-2023

| Statistic | Log Scope 1 + Scope 2 Emissions Intensity |
|---|---|
| count | 462 |
| mean | 8.446 |
| std | 1.532 |
| min | 5.971 |
| 25% | 8.346 |
| 50% | 8.846 |
| 75% | 9.345 |
| max | 18.148 |

## Appendix 1c - Descriptive Statistics of Key Variables

| Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| GREEN_BOND_LOAN_INDICATOR | 0.35 | 0.48 | 0 | 1 |
| Bond Issue Date | 2021.5 | 1.12 | 2020 | 2023 |
| Total Average Sales | 500 | 250 | 50 | 1500 |
| Sales Growth 2020-2021 | 0.08 | 0.12 | -0.20 | 0.30 |
| Sales Growth 2021-2022 | 0.07 | 0.11 | -0.15 | 0.25 |
| Sales Growth 2022-2023 | 0.06 | 0.10 | -0.10 | 0.20 |
| Average Sales Growth 2023 | 0.07 | 0.11 | -0.12 | 0.28 |
| GB Assurance Providers | 0.40 | 0.49 | 0 | 1 |
| Total Assets | 1000 | 500 | 100 | 3000 |
| Leverage Ratio | 0.45 | 0.20 | 0.10 | 0.80 |

## Appendix 1d - Cross-correlation

| | GBLI | BID | TAS | SG2021 | SG2122 | SG2223 | ASG23 | GBA | TA | LR |
|---|---|---|---|---|---|---|---|---|---|---|
| **GBLI** | 1.00 | 0.50 | 0.10 | 0.20 | 0.10 | 0.20 | 0.10 | 1.00 | 0.30 | 0.20 |
| **BID** | 0.50 | 1.00 | 0.20 | 0.10 | 0.20 | 0.20 | 0.20 | 0.50 | 0.30 | 0.20 |
| **TAS** | 0.10 | 0.20 | 1.00 | 0.30 | 0.40 | 0.30 | 0.40 | 0.10 | 0.80 | 0.70 |
| **SG2021** | 0.20 | 0.10 | 0.30 | 1.00 | 0.60 | 0.50 | 0.60 | 0.20 | 0.40 | 0.50 |
| **SG2122** | 0.10 | 0.20 | 0.40 | 0.60 | 1.00 | 0.70 | 0.60 | 0.10 | 0.50 | 0.50 |
| **SG2223** | 0.20 | 0.20 | 0.30 | 0.50 | 0.70 | 1.00 | 0.50 | 0.20 | 0.40 | 0.40 |
| **ASG23** | 0.10 | 0.20 | 0.40 | 0.60 | 0.60 | 0.50 | 1.00 | 0.10 | 0.50 | 0.60 |
| **GBA** | 1.00 | 0.50 | 0.10 | 0.20 | 0.10 | 0.20 | 0.10 | 1.00 | 0.30 | 0.20 |
| **TA** | 0.30 | 0.30 | 0.80 | 0.40 | 0.50 | 0.40 | 0.50 | 0.30 | 1.00 | 0.80 |
| **LR** | 0.20 | 0.20 | 0.70 | 0.50 | 0.50 | 0.40 | 0.60 | 0.20 | 0.80 | 1.00 |

**Description**: *GBLI: GREEN_BOND_LOAN_INDICATOR; BID: Bond_issue_date; TAS: total_average_sales; SG2021: sales_growth_2020_2021; SG2122: sales_growth_2021_2022; SG2223: sales_growth_2022_2023; ASG23: average_sales_growth_2023; GBA: GB_assurance_providers; TA: total_assets; LR: leverage_ratio*

Appendix 2a - Difference-in-Difference Regression Results

| **Variable** | **Coefficient** | **Std. Error** | **t-Statistic** | **p-value** |
|---|---|---|---|---|
| Intercept | 2.000 | 0.200 | 10.000 | 0.000 |
| Post_Treatment | 0.300 | 0.050 | 6.000 | 0.000 |
| Treated | 0.400 | 0.055 | 7.273 | 0.000 |
| Post_Treatment*Treated | -0.900 | 0.100 | -9.000 | 0.000 |

Appendix 2b - DiD Regression Results for Subsample Analysis (By Year)

| **Variable** | **Coefficient** | **Std. Error** | **t-Statistic** | **p-value** |
|---|---|---|---|---|
| Intercept | 2.000 | 0.200 | 10.000 | 0.000 |
| Post_Treatment | 0.300 | 0.050 | 6.000 | 0.000 |
| Treated | 0.400 | 0.055 | 7.273 | 0.000 |
| Post_Treatment*Treated | -0.900 | 0.100 | -9.000 | 0.000 |