The carbon footprint of green bonds: evidence from project-level data

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Abstract

We introduce a measure of green bonds' carbon footprint based on project-level data and industry guidelines. This measure captures the avoided emissions generated by green-bond-financed projects and is constructed by estimating both project emissions and the relevant counterfactual emissions. Using this metric, we revisit the inconclusive literature that evaluates green bonds using firm-level emissions data. We derive several important insights. First, green bonds deliver meaningful environmental benefits: on average, avoided emissions are roughly ten times larger than the emissions generated by the financed projects. Second, in the cross-section, larger issuers undertake projects with higher avoided-emissions intensity. Third, inferences based on our measure and those derived from firm-level emissions yield divergent patterns, particularly with respect to issuer size. Taken together, our findings suggest that the mixed results in the existing literature may reflect a level-of-analysis problem: the environmental impact of green bonds becomes diluted when measured at the firm level.

1 Introduction

> "As green bonds typically finance renewables and the improvement of energy efficiencies, it is often argued that the carbon footprint of green bonds should not necessarily be considered to be the same as the footprint of its issuers."
>
> — *London Stock Exchange Group*[1]

Do green bonds deliver environmental benefits? At present, there is no definitive answer, as the empirical evidence is mixed. On the one hand, Flammer (2021) and ElBannan and Löffler (2024) document a significant decrease in emissions after the issuance of green-bonds. On the other hand, Aswani and Rajgopal (2025) find no evidence that firms curb emissions post-issuance. Critics also question firms' motivation behind green-bond issuance, with Bhagat and Yoon (2023) arguing that green bonds are used to hide poor managerial performance, while Lam and Wurgler (2024) suggest that they are used to refinance existing projects. Critics are not limited to academia. As early as 2020, articles in the financial press questioned issuers' motives and the environmental benefits of green bonds.[2]

One potential explanation for the inconclusive evidence may be, as the opening quote suggests, the way the environmental impact is measured. To date, studies that examine the carbon footprint of green bonds do so by analyzing firm-level CO_2 emissions. While informative, these emissions do not speak directly to the bonds' impact for two reasons. First, green-bond proceeds may be too small relative to the issuer's size to make a noticeable difference (Flammer, 2021). Second, any carbon savings from green bonds may be masked by increases in emissions from other parts of the firm's operations (Ehlers et al., 2020). To overcome this level-of-analysis problem, our study employs granular, project-level data from issuers' allocation and impact reports. We use these data to revisit the environmental impact of green bonds.

[1] *LSEG* (2025), "Decarbonisation in Portfolio Benchmarks"
[2] *The Economist* (2020), "What is the point of green bonds?"

We collect data for green bonds issued by European firms over the period 2017 to 2023. We focus on Europe because the region has developed a mature and transparent market which, at the time of writing, has shown resilience in issuance levels despite recent increases in policy uncertainty (MainStreet Partners, 2025). Our first step is to calculate financed emissions—the emissions generated by each financed project—by combining project output with location-specific emissions factors that reflect the local grid mix and technology. Next, we estimate counterfactual emissions—the emissions that would have occurred in the absence of the project—and define avoided emissions as the difference between counterfactual and project emissions. We scale both financed and avoided emissions from the project-level to the bond-level using the reported use of proceeds and any existing project financing. Finally, we express these measures per unit of investment to obtain financed- and avoided-emissions intensities that are comparable across bonds.

Our first set of results is descriptive. We present stylized facts on the carbon footprint of green bonds and its dynamics over time and across sectors and countries. The analysis shows that avoided emissions from green-bond-funded projects are approximately ten times larger than realized emissions: Per €1 million invested, the average green bond is associated with about 27 tonnes of CO_2 emissions, while the average avoided emissions are approximately 271.22 tonnes. There is substantial heterogeneity across issuers' country and sector, attributable mainly to project type as well as country-specific emissions factors and baselines. Despite this heterogeneity, all bonds in our sample realize non-zero avoided emissions, indicating a net improvement relative to the counterfactual. Taken together, these findings indicate that green bonds generate meaningful environmental benefits when their carbon footprint is assessed at the appropriate level.

The second part of our empirical analysis examines the cross-sectional determinants of carbon savings. To account for issuers' self-selection into green versus conventional issuance, we employ a Heckman selection model. This selectivity arises because unobserved drivers of green-bond issuance may also correlate with the green bonds' carbon footprint. Thus, for the purpose of this analysis, we collect data on conventional bond issues. Specifically, we collect and merge data from multiple sources. Bond-level information comes from Bloomberg and LSEG Workspace. We retrieve firm-level variables from Orbis, because our sample also includes private issuers.

For identification of the selection equation, we use Google Trends search volumes as an exclusion restriction. According to Chemmanur et al. (2025), search-volume data can serve as a proxy for individual investor attention. Such attention is likely to influence the choice to issue a green bond, as firms often use green bonds to signal environmental commitment to investors (Flammer, 2021). Whether this commitment is genuine or serves to hide poor managerial performance (Bhagat and Yoon, 2023), investor attention would still be correlated with the likelihood of issuing a green bond. At the same time, Google search volumes are unlikely to directly influence project-level carbon footprints, as they do not affect the technological or operational features of the projects and there is a large time gap between the carbon-footprint measurement and the period captured by our search-volume data.

The estimates from the selection equation of our Heckman model are consistent with prior evidence on the green–conventional bond choice (Dutordoir et al., 2024a). Importantly, *Google Trends* is a significant determinant of this choice: firms receiving greater individual-investor attention are more likely to issue green rather than conventional bonds. Turning to the outcome equation(s), two results stand out. The first involves *Firm Size*. Larger issuers are associated with projects that generate higher financed emissions but also achieve higher avoided emissions. This association holds after controlling for a range of firm- and bond-level characteristics and fixed effects. Second, the *Inverse Mills Ratio* is negative and significant, indicating non-random selection into green issuance.

To unpack the size effect, we test whether it is driven by project choice (e.g., larger issuers more frequently finance high-abatement projects such as renewables) or by certification (e.g., larger issuers have greater capacity to absorb certification costs). Interestingly, *Firm Size* remains significant after controlling for project mix and certification. The results for project mix are in general consistent with expectations. For example, renewable-energy generation projects deliver, on average, greater carbon savings than green-building projects. By contrast, we do not find evidence that certification is associated with more carbon-efficient projects, a result that differs from firm-level evidence in previous studies (Flammer, 2021; Yu et al., 2024; Liu et al., 2025).Nonetheless, we refrain from making causal statements due to potential selectivity between certified and non-certified bonds, which is beyond the scope of this paper.

We interpret the issuer size–carbon footprint relationship as consistent with scale and economies-of-scale effects. Larger firms may be better able to mobilize experienced teams and undertake projects that yield higher efficiency gains per € invested, or achieve similar efficiencies at lower cost (or both). Furthermore, this size pattern is notable in light of prior evidence suggesting that larger firms often enjoy higher ESG scores not because they curb emissions more, but because they have greater resources to appear environmentally friendly (Drempetic et al., 2020). In contrast, we show that large firms—at least those issuing green bonds—invest in projects that deliver larger environmental benefits per € invested.

Our empirical analysis concludes with a firm-level difference-in-differences (DiD) exercise, which has become standard practice in the literature. At the aggregate level, our results are in line with Flammer (2021): green-bond issuers experience a decline in emissions in the years following issuance. This finding also holds when we employ a stacked DiD specification, alleviating concerns regarding inferences from staggered designs (Baker et al., 2022). However, when we examine treatment heterogeneity, we find a pattern opposite to the bond-level evidence: declines in firm-level emissions occur only among smaller issuers. In addition, comparing the bond-level top performers with the DiD-implied top performers highlights two further divergences. First, none of the leading bond-level performers appears among the leading firm-level performers. Second, the bond-level rankings highlight firms in emission-intensive industries as the top performers, whereas the firm-level evidence points to financial firms.

A plausible explanation for these inconsistencies is dilution. Green-bond proceeds are typically small relative to issuer size; in our sample, this ratio averages only 3%. Hence, even if the bonds deliver sizable environmental benefits, these benefits may be too small to materially shift firm-level emissions. This size-related dilution may help explain the opposing inferences from the two levels of analysis. It may also help reconcile the inconsistent results in the literature, as firm-level inferences can depend on the size composition of the underlying samples. This point is implicitly acknowledged by both Flammer (2021) and ElBannan and Löffler (2024), who note that their results should not be interpreted as the causal impact of green bonds on firm-level emissions because green-bond proceeds are small relative to issuer size. Our analysis reinforces this point and underscores the need for caution when using high-level firm emissions to evaluate the environmental impact of green bonds.

Our findings are important because they offer new insights on the environmental performance of green bonds by focusing on the project rather than the issuer level. Our measures also align with industry standards. The financed-emissions methodology follows the Partnership for Carbon Accounting Financials (PCAF) framework for measuring and disclosing greenhouse gas (GHG) emissions, and avoided emissions follow the impact-reporting guidelines the International Capital Market Association (ICMA) and the Nordic Public Sector Issuers. This makes the evidence presented in this paper relevant for academics, investors, and policymakers seeking to evaluate the true carbon impact of sustainable finance instruments.

The rest of the paper is structured as follows. Section 2 positions our paper to the literature and outlines our contribution. Section 3 describes our sample selection and identification strategy. Sections 4 and 5 report our bond-level and firm-level results, respectively, and Section 6 concludes the paper.

2 Related literature & contribution

The global green bond market has exhibited rapid growth in recent years, reflecting increasing momentum in sustainable finance and strong investor demand for climate-aligned assets. In 2024, total green bond issuance reached approximately USD 669 billion, bringing cumulative issuance to over USD 3.5 trillion by year-end (Climate Bonds Initiative, 2024). Data up to the third quarter of 2025 indicate sustained momentum despite heightened policy uncertainty (MainStreet Partners, 2025). In particular, the European market has shown significant resilience, supported by robust issuance activity and steady investor participation.

Yet, despite the importance of green bonds for corporate financing and climate change mitigation, they used to be underrepresented in academic research (Stroebel and Wurgler, 2021). This shortcoming can be attributed, in part, to the limited availability of data on corporate green bond issues. It is only in recent years that the number of corporate issuers has significantly increased, allowing researchers to examine the motivations and consequences of green bond issuance (Dutordoir et al., 2024a). In what follows, we review the green bond literature, organizing studies by their primary research question(s).

The growing academic literature on green bonds focuses on three main areas. First, the existence of a "greenium", a term used to describe the lower yields of green bonds compared to conventional ones. This yield difference is typically attributed to strong pro-environmental investor demand. However, evidence on the existence of a greenium is mixed. Zerbib (2019) documents a small greenium of about 2 basis points, while Caramichael and Rapp (2024) report a greenium ranging from 3 to 8 basis points. In contrast, other studies find no significant yield difference between green and conventional bonds (Karpf and Mandel, 2018; Larcker and Watts, 2020; Tang and Zhang, 2020). More recent studies show that the greenium is concentrated in specific subsamples. For example, Zhou et al. (2024) find that yields on green bonds are significantly lower than on conventional bonds when the green bonds are externally certified by a third-party institution, whereas the difference is not statistically significant for self-labeled issues. In the secondary market, Aswani and Rajgopal (2025) report that green bonds issued by financial firms trade at a greenium of about 8.2 basis points. On the contrary, they find no significant greenium for issuers operating in heavy-polluting industries.

Second, studies examine the shareholder wealth effects of green bond issuance. Early work documents positive stock market reactions around announcement dates (Baulkaran, 2019; Tang and Zhang, 2020). However, more recent evidence is mixed and suggests that any positive reaction is concentrated in specific categories of issues. For example, Yu et al. (2024) find that Chinese issuers experience positive reactions only for certified green bonds. By focusing on an international sample, Flammer (2021) reports positive cumulative abnormal returns (CARs) around the green bond announcements, but this positive reaction is limited to certified and first-time issues. By contrast, subsequent cross-country studies present less favorable evidence. Bhagat and Yoon (2023) document statistically insignificant CARs around green bond announcements, while Dutordoir et al. (2024a) report a negative market reaction, on average. Reconciling these findings, Aswani and Rajgopal (2025) show that the earlier positive market reaction is driven by a small set of high-profile U.S. issuers (e.g., Tesla) and financial firms.

Deviating from the investor perspective, a third strand of the literature examines green bonds from the issuer's side, exploring the motivations behind the issuance. Survey evidence highlights reputational benefits and pro-environmental behavior as key drivers behind green bond issuance (Sangiorgi and Schopohl, 2023). This view is also supported by empirical studies: firms use green bonds to signal their commitment to sustainability (Flammer, 2021; Liu et al., 2025), gain reputational benefits (Dutordoir et al., 2024a), align with their countries' pro-sustainability policies (Becker et al., 2025), and respond to climate-related risks (Guesmi et al., 2025). However, other studies adopt a more critical stance. Bhagat and Yoon (2023) argue that managers may opportunistically use green bond announcements to hide their poor performance.

Lam and Wurgler (2024) examine a sample of U.S. corporate and municipal bonds, and find that green bonds are frequently used to refinance existing projects, raising questions about additionality.

Surprisingly, the environmental impact of green bonds has received relatively limited attention in the academic literature. Although several studies examine the association between green bond issuance and carbon outcomes, this is often not their central focus, and the evidence is mixed. The first paper to address this question is Flammer (2021), who document that firms issuing green bonds subsequently reduce carbon emissions. In support of her findings, ElBannan and Löffler (2024) and Demski et al. (2025) also find a negative association between green bond issuance and emissions. However, other studies question the ability of green bonds to deliver sizeable environmental benefits. Guesmi et al. (2025) find no significant improvement in the carbon footprint of green bond issuers compared to matched non-issuers, and Aswani and Rajgopal (2025) show that high-emitting firms do not reduce emissions post-issuance.

A likely reason for the inconclusive evidence on green bonds' environmental impact is how that impact is measured. Most studies use firm-level emissions, even though green bonds finance specific projects rather than the entire firm. This mismatch can bias the estimated relationship between green bond issuance and firms' carbon intensity in either direction. If green bond issuers are generally greener and undertake other sustainability actions, the association with lower firm emissions may be upward biased. Conversely, project-level reductions may be offset by increased emissions in other parts of the firm's operations, leading to a downward bias (Ehlers et al., 2020). Several papers acknowledge this limitation. Flammer (2021) notes that green bond proceeds are small relative to issuer size, so her results are more likely to reflect issuers' broader commitments to sustainability rather than a causal impact of green bonds per se. ElBannan and Löffler (2024) find that larger green-bond volumes are associated with greater emissions reductions but avoid making causal claims. Instead, they argue that the observed pattern reflects the relative size of the green bonds; larger issues are more likely to have a sizable impact on firm-level emissions.

This limitation poses a challenge for the existing literature, as commonly used databases such as Bloomberg and ASSET4 report carbon emissions at the firm-level rather than the project-level. Our paper directly addresses this gap. We collect detailed data on the projects financed through green bonds and attribute the appropriate carbon footprint to each bond, taking into account the project's type, output (e.g., MWh generated), location, and existing financing structure. In doing so, our study responds to the call of the comprehensive literature review by Flottmann et al. (2025), which highlights the need for more granular, project-level analyses to evaluate how these instruments contribute to environmental objectives.

3 Sample selection & identification strategy

3.1 Sample construction

Our sample construction involves several steps and combines data from multiple sources: MainStreet Partners, Bloomberg, LSEG Workspace, Orbis, and Google Trends. The first step uses MainStreet Partners' project-level carbon footprint data for green bonds. For each bond, MainStreet Partners (MSP) collects the issuer's post-issuance report and extracts (i) use-of-proceeds allocations by project, (ii) activity/impact metrics (e.g., MWh generated, floor area, tonnes treated), and (iii) location of financed projects. When issuers disclose EU Taxonomy alignment, MSP records it; when they do not, MSP independently assesses financed projects against the EU Taxonomy's Technical Screening Criteria based on the technical details in the report. This means coverage is not limited to self-disclosing issuers and helps mitigate disclosure-driven selection. We then retain bonds with sufficient project-level information to compute financed and avoided emissions. To do so, MSP aggregates multiple financed projects to the bond-level using the reported allocation shares, and constructs category flags (e.g., renewables, buildings, transport). This database contains data for 280 green bond issues, announced between 2017 and 2023 by European corporations. Detailed information on MainStreet Partners' proprietary methodology will be provided in later sections.

The second step is to retrieve green bond–level characteristics from Bloomberg. Following the filtering criteria of Flammer (2021) and Aswani and Rajgopal (2025), we search the Bloomberg fixed-income database for corporate bonds issued by European firms and restrict to issues with the Green Bond Indicator set to "Yes." We exclude non-corporate sectors based on Bloomberg Industry Classification System (BICS) labels, namely *Sovereigns*, *Government Agencies*, *Government Regionals*, *Supranationals*, *Government Development Banks*, *Winding-up Agencies*, *Central Banks*, and *Government Local*. For each qualifying bond, we extract the issuer Ticker symbol, coupon, maturity and issue dates, bond rating, amount issued, yield at issue, and the bond's ISIN. We then link Bloomberg data to the MainStreet Partners dataset using the bonds' ISIN number. This matching process provided us with bond-level data for 271 out of the 280 green bonds of the MSP database.

The third step is to construct the conventional (non-green) bond sample. Following Dutordoir et al. (2024a), we retrieve these data from LSEG Refinitiv Workspace.[3] We apply a similar filtering with the green bond sample. Particularly, we search Refinitiv's *Universe of Government and Corporate Bonds*, and we restrict the dataset to bonds issued by European corporate issuers over the period 2017 to 2023. For each bond, we collect the same variables as in the green bond sample. This procedure yields a dataset of 6,733 conventional bonds.

The fourth step is to collect firm-level data for both green and conventional issuers from Moody's Orbis. Orbis' key advantage over Compustat Global and Worldscope is its comprehensive coverage of privately held firms. This feature is particularly relevant in our setting because many green issuers in the MSP database are private. To proceed with the matching, we manually search each issuer in Orbis using their names, tickers, and location. In cases when Bloomberg/LSEG Workspace names differ from Orbis

[3] As noted by Dutordoir et al. (2024a), using Bloomberg for conventional bonds is impractical given download limits. However, they note that by comparing raw data from both databases, they do not find any notable differences.

(e.g., renamings or subsidiary vs. parent entries), we use public sources and the firms' Website URL provided in Orbis to verify the match. Then, we extract total assets, net income, turnover, and year of incorporation, as well as the firms' *listing status* (listed vs. unlisted) and *corporate entity type* (global ultimate owner vs. controlled subsidiary). This procedure yields firm data for 247 green-bond issues and 4,946 conventional-bond issuers. Following Flammer (2021), we then consolidate multiple tranches of the same type (green or conventional) issued by the same firm on the same date into a single issuance, resulting in 203 green and 3,691 conventional bonds.

As a final step, we retrieve *Google Trends* search volume data by issuer name to proxy for individual-investor attention (Zhou et al., 2024). We use this variable as the exclusion restriction in the first stage of the Heckman selection model. A detailed definition of how we construct this variable is provided in Subsection 3.3.

3.2 Carbon footprint measures

3.2.1 Project-level financed emissions

We compute each bond's financed emissions following the project-finance boundary recommended by the Partnership for Carbon Accounting Financials (PCAF). In general, post-issuance reports disclose project types, locations, and impact metrics; however, the carbon emissions resulting from the projects financed are often overlooked. Our approach quantifies the share of project emissions attributable to the bond's use of proceeds.

Methodologically, we treat a green bond as financing a portfolio of projects. For each financed project, we (i) estimate project emissions from activity data using technology- and location-specific emission factors, and (ii) attribute emissions to the bond using the attribution factor—the ratio of the bond's allocated proceeds to the project's total financing mix (debt + equity). Formally, for bond b financing projects

$j \in \mathcal{J}_b$,

$$\textit{Financed Emissions}_b = \sum_{j \in \mathcal{J}_b} \underbrace{\left(\frac{A_{bj}}{D_j + E_j} \right)}_{\text{attribution factor}} \times \underbrace{\textit{Emissions}_j}_{\text{realized}} \tag{1}$$

where A_{bj} is the amount of proceeds from bond b allocated to project j, $D_j + E_j$ is the project's total capital (debt plus equity), and $\textit{Emissions}_j$ denotes the project's annual greenhouse-gas emissions in tonnes of CO_2-equivalent (tCO_2e). Equation (1) is appropriate in our context because (a) aggregates the different projects a single bond can finance, and (b) avoids overstating financed emissions by scaling the contribution of the project with the financing structure of the project (only the financed share is attributed to the bond).

To make bonds comparable by invested amount, we compute the financed emissions intensity by normalizing financed emissions with the amount of money that was allocated to eligible projects M_{ib}:

$$\textit{Financed Emissions Intensity}_b = \frac{\textit{Financed Emissions}_b}{\textit{Monetary Amount}_b}, \qquad M_b \equiv \sum_{j \in \mathcal{J}_b} A_{bj} \tag{2}$$

Normalizing by $\textit{Monetary Amount}_b$ (the reported allocated amount in EUR million) is crucial because issuers often report allocation to a pool of eligible assets that can exceed face value; using face value instead would inflate per-euro financed emissions. The resulting *Financed Emissions Intensity* is interpreted as green bond's b financed emissions per EUR million invested. Throughout the remainder of the study, we refer to $\textit{Financed Emissions Intensity}_b$ as *Financed Emissions* or *Financed* CO_2.

Project-level realized emissions are estimated from the project's reported activity data and technology type as disclosed in post-issuance impact reports. Specifically, we follow the PCAF guidelines and use category-specific formulas and country-specific emission factors. We classify the financed projects of our sample into the following categories: renewable energy (generation and capacity), clean transportation (vehicles and EV charging), real estate (green buildings), and sustainable forestry. To illustrate our approach, the emissions for green buildings (GB) are computed as follows:

$$Emissions_j^{(\mathrm{GB})} = \mathrm{Area}_j \Big(\underbrace{\mathrm{kWh}^{\mathrm{elec}}/\mathrm{m}^2}_{\text{building type}} \times \underbrace{\mathrm{EF}^{\mathrm{elec}}_{\mathrm{country}}}_{\text{grid factor}} + \underbrace{\mathrm{kWh}^{\mathrm{thrm}}/\mathrm{m}^2}_{\text{building type}} \times \underbrace{\mathrm{EF}^{\mathrm{thrm}}_{\mathrm{fuel}}}_{\text{fuel factor}} \Big) \quad (3)$$

where $Area_j$ is floor area, energy-use intensities reflect the building type (e.g., residential vs. industrial), $EF^{\mathrm{elec}}_{\mathrm{country}}$ maps local electricity mixes into CO_2e per kWh, and $EF^{\mathrm{thrm}}_{\mathrm{fuel}}$ captures the thermal fuel mix (e.g., natural gas, district heat).

To illustrate the use of these formulas, consider the following example: a firm issues a green bond, which allocates A_{bj} = EUR 3 million to a green building project, while the project's total capital is $D_j + E_j$ = EUR 12 million (attribution factor $= A_{bj}/(D_j + E_j) = 0.25$). The green building has an $Area_j = 10{,}000\,\mathrm{m}^2$ (area). The building-type electricity intensity is $(\mathrm{kWh}_{\mathrm{elec}}/\mathrm{m}^2)_{\mathrm{type}} = 50$, and the grid factor is $EF_{\mathrm{elec,country}} = 0.25$ kg CO_2e/kWh. The building-type thermal intensity is $(\mathrm{kWh}_{\mathrm{thrm}}/\mathrm{m}^2)_{\mathrm{type}} = 80$, and the fuel factor is $EF_{\mathrm{thrm,fuel}} = 0.184$ kg CO_2e/kWh. Plugging these into Eq. (3) gives $Emissions_j^{(GB)} = 272.2$ t CO_2e/yr (125.0 t from electricity and 147.2 t from thermal). Hence, *Financed Emissions* equal $0.25 \times 272.2 = 68.05$ t CO_2e/yr. If this is the only project, *Financed Emissions Intensity* is $68.05/3 \approx 22.7$ t CO_2e per EUR million.

Analogous activity–factor constructions are used for renewable energy (generation or capacity, with technology-specific lifecycle factors and grid adjustments), clean transportation (vehicle counts, km, and g/km by drivetrain), and forestry (on-site fuel and inputs net of sequestration). Full category-specific formulas and parameter sources are provided in the Appendix B. Note that a single bond can finance projects in several categories

3.2.2 Project-level avoided emissions

We measure avoided emissions as the difference between a benchmark baseline level of emissions and the project-level realized emissions. We define baseline emissions as the counterfactual emissions that would occur had the project not been implemented. For the green-building example described above, the counterfactual baseline is a comparable *non-green* building with the same floor area, building type, country, and climate, but with higher electricity and thermal energy-use intensities and typically a more carbon-intensive heat mix. Alternatively, in a renewable-energy project, baseline emissions are the CO_2 emissions that would have been produced if the same electricity had been generated by fossil fuels instead of renewables. For each project category, *Baseline Emissions* are calculated using an appropriate reference for the project's activity, technology, and location (e.g., a country portfolio average in green buildings, or the grid mix for electricity). More details on these calculations are included in the Appendix C.

As before, let bond b finance projects j. For each project j:

$$\textit{Avoided Emissions}_j \;=\; \underbrace{\textit{Baseline Emissions}_j}_{\text{counterfactual}} - \underbrace{\textit{Emissions}_j}_{\text{realized}}, \tag{4}$$

At the bond-level, we attribute the project's avoided emissions to the bond using the same PCAF project-finance attribution factor as in our financed-emissions measure:

$$\textit{Avoided Emissions}_b \;=\; \sum_{j \in \mathcal{J}_b} \left(\frac{A_{bj}}{D_j + E_j} \right) \textit{Avoided Emissions}_j, \tag{5}$$

with A_{bj} the proceeds from bond b allocated to project j, and $D_j{+}E_j$ the project's total capital (debt plus equity). To make results comparable by invested amount, we report avoided-emissions intensity per EUR million allocated:

$$\textit{Avoided Emissions Intensity}_b \;=\; \frac{\textit{Avoided Emissions}_b}{\textit{Monetary Amount}_b}, \qquad M_b \equiv \sum_{j \in \mathcal{J}_b} A_{bj}. \tag{6}$$

Again, *Monetary Amount*$_b$ is the bond's allocated amount to eligible projects. The estimated *Avoided Emissions Intensity*$_b$ is interpreted as green bond's b avoided emissions per EUR million invested. Throughout the remainder of the study, we refer to *Avoided Emissions Intensity*$_b$ as *Avoided Emissions* or *Avoided* CO_2..

This method of measuring project-level avoided emissions is in line with market-based guidelines from ICMA (*Handbook – Harmonised Framework for Impact Reporting*[4], June 2021) and the Nordic Public Sector Issuers (*Position Paper on Impact Reporting*[5], February 2020). It is noteworthy that our implementation follows two core principles: (i) we avoid double counting across projects and reporting periods; and (ii) we rely on *actual* realized activity rather than *potential* environmental impact. For example, in renewable energy, we do not count "MW connected" or contracted "MWh" as impact; instead, avoided emissions are computed from realized electricity generation (MWh) against a location-appropriate grid baseline, with project emissions based on technology-appropriate emission factors.

3.3 Google Trends

We construct an issuer–year attention proxy from Google Trends using a reproducible Python workflow (`pytrends`, `pandas`). We start from issuer names and standardize them into query-ready "brand" forms: we normalize punctuation and diacritics, remove generic descriptors (e.g., *Holding*, *Group*, *Finance*) and legal suffixes (e.g., AG, SA, plc) when they appear at the end of the name, and apply a small set of deterministic overrides to align with common brand usage. We preserve domain keywords (e.g., banking terms) to reduce ambiguity, then perform order-preserving de-duplication. We query Google Trends at worldwide scope for each issuer, requesting the weekly *interest-over-time* series over 2015–2024. To respect rate limits and reduce request failures, we implement retries with back-off and randomized delays, and we drop partial weeks returned by the API. We aggregate each weekly series to calendar-year averages, yielding an issuer-by-year panel of attention indices (0–100 per query). For each bond, we map the issuer's *previous calendar year* average to the bond's announcement date, producing an ex-ante attention measure that is available for both green and brown issues. We use this variable only in the green vs. brown selection equation

[4] https://www.icmagroup.org/assets/documents/Sustainable-finance/2021-updates.

[5] https://www.kuntarahoitus.fi/app/uploads/sites/2/2020/02.

as an exclusion and do not include it in the project-level savings regression.

3.4 Covariates

We use a vector of firm characteristics frequently employed in the green–bond literature. All accounting variables are retrieved from Orbis. Specifically, as in Aswani and Rajgopal (2025) we include: *Firm Size*, which is the natural logarithm of total assets, *ROA*, which is the net income over total assets, and *Sales Growth*, which is the percentage change in turnover.[6] Furthermore, we also control for *Firm Age*, which is the natural logarithm of one plus the number of years since incorporation. *Listed Issuer*, which equals 1 if the issuer is publicly listed, and 0 otherwise, *Subsidiary*, which equals 1 if the issuer is not the ultimate global ultimate owner (GUO) in Orbis, and 0 otherwise, *First Issuer*, which equals 1 if the bond is the first green bond of the issuer in our sample, and 0 expected, and *Rated Issuer*, which equals 1 if the issuer has a public credit rating at the issue, and 0 otherwise.

Following Dutordoir et al. (2024a), we include pre-issuance oil-price movements because higher energy prices can encourage firms to pursue energy-efficient innovations. *Oil Price* is defined as the average daily percentage change of real Brent crude over the 180 trading days preceding the issue date (nominal Brent deflated by U.S. CPI). We also compute a *Greenium* measure, following the methodology of Larcker and Watts (2020). *Greenium* is the yield difference at issuance between a *matched conventional bond and the green bond of the same issuer* (positive values indicate a greenium). Matching is conducted in two-steps: (i) exact match on bond rating; (ii) among candidates of the same issuer, we choose the nearest neighbour on issued amount, maturity, and coupon.

Bond-level covariates are: *Coupon Rate* (stated coupon at issuance), *Amount Issued* (the natural logarithm of the issue amount), *Maturity* (number of years from issue to

[6] We do not include *Leverage* because data availability in Orbis reduces substantially our sample, especially for green bonds. Nonetheless, its inclusion leaves our results unchanged. This is expected in light of Dutordoir et al. (2024a), who report that leverage is not a significant determinant of green-bond issuance.

maturity), and *Bond Rating* (Moody's issue rating as reported in Bloomberg/LSEG). Table A1 provides a detailed definition of the variables employed in our study.

3.5 Identification Strategy

3.5.1 Heckman selection model

Project-level data let us assess whether and to what extent green-bond-funded projects deliver environmental benefits. We then ask what determines these benefits. In identifying these determinants, there are some econometric concerns. The first is that the sampling of green-bond observations is not random: firms endogenously choose whether to issue a green or a conventional bond, and recent evidence shows that both firm and deal attributes determine this choice (Dutordoir et al., 2024a; Zhou et al., 2024; Guesmi et al., 2025). Consequently, traditional OLS is unbiased only if selection is as-good-as-random conditional on observed characteristics and fixed effects. However, if the issue-green decision also depends on unobserved factors that are correlated with project-level savings, OLS produces biased estimates. A second concern is that project-level carbon footprint is observed only for issuers that chose to issue a green bond. Given that the observed green projects are the result of a systematic selection process, simply removing conventional bonds from the analysis would not resolve the issue. Altogether, a selectivity problem arises because Y is observed only in green bonds, and the selection and the outcome errors may be correlated. Therefore, to address this selection issue, we employ a Heckman selection model.

We estimate a Heckman selection model in two steps. Let i index issuers, b bond issues, and t the issue year. Each green bond funds a distinct project, so the outcome is at the issue level. Both the firm characteristics $X_{i,t-1}$ and the exclusion variable $Z_{i,t-1}$ are measured in the previous calendar year. In our baseline, $Z_{i,t-1}$ is the issuer's previous-year average *Google Trends* and proxies for investor attention. We include fixed effects for country (α_c), issue year (α_t), and NACE industry (α_s), and we cluster standard errors at the industry level.[7]

Step 1: Selection equation Let $G_{ibt} \in \{0, 1\}$ indicate whether issue b by issuer i in year t is green (1) or conventional (0). We estimate:

$$\Pr\big(G_{ibt} = 1 \,\big|\, X_{i,t-1}, Z_{i,t-1}, \alpha_c, \alpha_t, \alpha_s\big) = \Phi\big(\eta_{ibt}\big), \tag{7}$$

with index

$$\eta_{ibt} = X'_{i,t-1}\gamma \;+\; \theta\, Z_{i,t-1} \;+\; \alpha_c \;+\; \alpha_t \;+\; \alpha_s. \tag{8}$$

From the fitted probit we obtain $\widehat{\eta}_{ibt}$ and compute the inverse Mills ratio (for green issues $G_{ibt} = 1$):

$$\widehat{\lambda}_{ibt} \;=\; \frac{\phi(\widehat{\eta}_{ibt})}{\Phi(\widehat{\eta}_{ibt})}. \tag{9}$$

Step 2: Outcome equation We then estimate the project-level outcome equation on the sample of green bond issues:

$$y_{ibt} = X'_{i,t-1}\beta \;+\; \delta\,\widehat{\lambda}_{ibt} \;+\; \alpha_c \;+\; \alpha_t \;+\; \alpha_s \;+\; u_{ibt}, \tag{10}$$

The coefficient δ captures selection on unobservables: $\delta \neq 0$ indicates that factors affecting the green-issuance decision are correlated with unobserved determinants of y_{ibt}.

Exclusion restriction. $Z_{i,t-1}$ is included in the selection equation but excluded from the outcome equation. $Z_{i,t-1}$ denotes the issuer's previous-year average *Google trends* and proxies for individual investor attention. We believe that *Google Trends* should be positively correlated with selection, satisfying the relevance condition. According to the signaling theory, firms use green bonds to send a strong signal to investors re-

[7] We follow Flammer (2021) and standard errors at the industry level to allow for within-industry correlation in residuals arising from common technologies, regulatory environments, and reporting practices. For robustness (unreported), given the modest number of industry clusters, we also compute wild-cluster bootstrap standard errors and issuer–clustered standard errors. Results are qualitatively unchanged.

garding their commitment to environment (Flammer, 2021). Therefore, more investor attention should translate to stronger incentives for firms to issue green bonds. Consistent with this expectation, Zhou et al. (2024) find that investor attention increases the likelihood of a green bond issue relative to a conventional bond, and Dutordoir et al. (2024a) document a positive association between media coverage and green bond issuance.

Moreover, the exclusion restriction is unlikely to be violated for two reasons. *First*, Google search volumes are unlikely to directly influence project-level carbon footprints, as they do not affect the technological or operational characteristics of the projects. *Second*, there is a substantial time gap between the period captured by the search-volume data and the carbon-footprint measurement. To illustrate the timing, Google searches are measured as the average daily volume in the year before the green bond issue, whereas our outcome data are taken from impact reports that are typically released around 15 months after issuance—and issuance itself can occur several months after the end of the $t-1$ year.

3.5.2 Difference-in-Differences

While our measure of project-level *carbon footprint* is observed only for green-bond–funded projects, we can observe firm-level CO_2 *emissions* for both types of issuers. This allows us to conduct the DiD analysis of Flammer (2021), which has become the common practice in the literature. In that paper, she proposes the following identification strategy: treated firms are those that issue a green bond at some point during the examination period, while control firms are conventional-bond issuers that are very similar in characteristics to the treated firms. Similarity is achieved through a standard matching approach. To account for cross-country and cross-industry heterogeneity, matching is performed by country and NACE sector. Then, matching is conducted on the basis of the following seven firm-level characteristics measured at the fiscal year-end prior to issuance: *Size*, *Tobin's Q*, *ROA*, *Leverage*, *EScore*, *SScore*, and *GScore*. This timing ensures that control firms are as similar as possible to treated firms *ex ante*.[8]

We perform the matching approach described above and estimate three firm-level DiD specifications. The first is a standard two-way fixed-effects model as in Liu et al. (2025), which accounts for time-invariant firm unobserved heterogeneity and time trends. The second replaces the year fixed effects with country-by-year and industry-by-year fixed effects. This allows us to absorb time-varying shocks at those levels and is the most commonly used specification in the literature (Flammer, 2021; Guesmi et al., 2025; Aswani and Rajgopal, 2025). The third is a stacked DiD model following Cengiz et al. (2019) and Baker et al. (2022). This approach addresses the "bad comparison" problem associated with staggered adoption, where already treated units are used as controls for later-treated units. The stacked design mitigates this concern by constructing separate event-time datasets for each cohort of green-bond issuers, stacking these cohort-specific samples into a single dataset, and estimating the treatment effect using comparisons only against never-treated controls. The first DiD model we estimate is:

$$CO_{2,it} = \alpha_i + \alpha_t + \beta\, Treated_{it} + \gamma\, X_{it-1} + \varepsilon_{it}, \tag{11}$$

where α_i are firm fixed effects, α_t are year fixed effects, and $Treated_{it}$ equals 1 for green bond issuing firms in post-issuance years and 0 otherwise. $CO_{2,it}$ stands for firm-level carbon intensity, calculated as the sum of the direct (Scope 1) and indirect (Scope 2) carbon emissions (Refinitiv item: ENERDP023) divided by the book value of total assets. $X_{i,t-1}$ is a vector of firm-level controls measured at $t-1$. The second DiD model we estimate is:

$$CO_{2,it} = \alpha_i + \alpha_{c\times t} + \alpha_{s\times t} + \beta\, Treated_{it} + \gamma\, X_{it-1} + \varepsilon_{it}, \tag{12}$$

[8]For this analysis, we collect accounting and ESG data from the LSEG Workspace (formerly Refinitiv/ASSET4). A detailed definition of these variables is provided in A1. As in Flammer (2021), the analysis is limited to publicly-listed companies due to data availability issues.

where $\alpha_{c\times t}$ are country-by-year fixed effects and $\alpha_{s\times t}$ are NACE industry–by–year fixed effects. The third DiD model we estimate is:

$$CO_{2,itg} = \alpha_{i\times g} + \alpha_{t\times g} + \beta\, Treated_{itg} + \gamma\, X_{it-1} + \varepsilon_{itg}, \tag{13}$$

where $\alpha_{i\times g}$ are firm-by-cohort fixed effects (with g denoting the issuance-year cohort), and $\alpha_{t\times g}$ are year-by-cohort fixed effects. In Eq. (11), Eq. (12), and Eq. (13), β captures the average treatment effect on firm-level CO_2 emission intensity. In the staggered DiD regressions, standard errors are clustered at the industry level, following Flammer (2021), while in the stacked DiD regressions, standard errors are clustered at the firm–cohort level, consistent with Lu (2025).

The aforementioned matching approach aims to construct a credible counterfactual—firms that are ex-ante comparable to green issuers—so that, conditional on observed pre-issuance characteristics, the assignment to treatment is as-good-as-random. Identification therefore relies on the assumption that no unobserved, time-varying factors jointly influence the decision to issue a green bond and subsequent firm-level emissions. This is a strong requirement in such settings. For example, the previous literature has identified many more determinants of the green bond issue decision, such as oil prices (Dutordoir et al., 2024a). Besides the issue decision, oil prices may also affect firms' corporate footprint, as firms may choose to reduce fuel consumption when prices hike, thereby reducing Scope 1 emissions. Since higher oil prices have been shown to increase the propensity to issue green bonds (Dutordoir et al., 2024a), improvements in firm-level CO_2 *emissions* could also reflect the need of *Treated* firms' to reduce their costly exposure to fossil fuels.

Our motivation for the firm-level analysis is to test whether the patterns we uncover at the bond-level also appear when outcomes are measured at the firm-level. This exercise provide us with a validity check on the prevailing DiD interpretation: if the DiD estimates align with the project-level results, it suggests the project effects scale to the issuer; if they diverge, it highlights how aggregation at the firm-level can mask the green bonds' actual environmental impact.

4 Bond-level emissions

4.1 Carbon Footprint Dynamics

We begin our analysis by examining how green bonds' *Carbon footprint* varies over time, across countries and sectors. Table 1 shows the evolution of both *Financed* CO_2 and *Avoided* CO_2 overtime. We observe that financed-emissions intensity (tCO_2e per EUR million allocated) increases from about 14 in 2017 to about 45 in 2023, while avoided-emissions intensity peaks around 2020 (about 405) and is lower thereafter. There is considerable time-variation, which may reflect shifts in the mix of financed activities (e.g., energy generation versus green buildings) and evolving counterfactual baselines (for example, cleaner electricity grids could reduce measured "avoided" tonnes for a given MWh). Importantly, across all 203 issues, the average *Financed* CO_2 is approximately 26.5 tCO_2e per EUR million, while the average *Avoided* CO_2 is approximately 271 tCO_2e per EUR million—roughly 10 times larger—indicating that carbon savings substantially exceed the emissions generated from the green bond funded projects.

[Insert Table 1 around here]

Table 2 summarizes patterns in *carbon footprint* by the issuer's country of origin and reveals substantial cross-country heterogeneity. The dispersion is especially pronounced for *Avoided* CO_2, consistent with differences in (i) the mix of financed activities (e.g., energy generation versus green buildings) and (ii) country-specific parameters that enter both project emissions and the counterfactual baseline. Issuers in countries where a large share of proceeds goes to renewable energy generation or capacity (Portugal, Denmark, Italy) exhibit high avoided intensities.[9] Issuers in countries

[9] Portugal's high *Avoided* CO_2 is primarily driven by multiple issues from the same electric utility company that channelled investments to renewable energy and clean-transportation projects.

where proceeds go mainly to real estate (Netherlands, Norway, Sweden, Switzerland, United Kingdom, Austria, Belgium, France) show low to moderate avoided intensities. Furthermore, issuers in Germany and Spain fund projects in both energy generation and real estate and exhibit modest carbon savings. These findings are in line with the notion that building retrofits typically deliver smaller per-euro abatement than utility-scale renewables. Finally, these patterns are consistent with differences in country-specific parameters that enter both realized emissions and the counterfactual baseline. For instance, in markets with relatively clean baselines (Sweden, Norway, United Kingdom), avoided intensities are among the lowest.

In the case of *Financed* CO_2, a country that stands out as an outlier is Finland. The large negative value is driven by three green bonds issued in 2020, 2021, and 2022 by a manufacturing company that financed forestry activities with net annual carbon removals due to carbon sequestration.[10] By comparing the two measures, we observe that *Avoided* CO_2 is smaller than average *Financed* CO_2 in some countries. However, this occurs where the number of issues is small and is not, by itself, concerning. By construction, *Avoided* CO_2 measures the gap between baseline and project emissions. Therefore, any positive value in *Avoided* CO_2 indicates a net improvement relative to the counterfactual. Moreover, our metrics are based on realized activity from post-issuance impact reports, typically published 15 months after issuance, a window in which many projects may still be in construction or ramp-up (front-loaded emissions with delayed savings).

[Insert Table 2 around here]

Table 3 reports carbon-footprint intensities by the issuer's NACE sector. On the *Financed* CO_2 side, the large negative average in *Manufacturing* is driven by three bond issues from the same Finnish manufacturing company (see the discussion of Table 2). Across the remaining sectors, average financed-emissions intensities are generally close

[10] See Appendix B.8 for a detailed description on how *sequestration* impacts *Financed* CO_2 in Sustainable forestry projects.

to the overall mean, with the exception of categories represented by a single observation (e.g., *Professional, scientific and technical activities*, *Public administration*). For *Avoided* CO_2, the highest savings are observed in the *Electricity, gas, steam and air* sector. This is consistent with the notion that firms in polluting sectors have higher capacity for carbon savings (Liu et al., 2025). Other carbon-intensive sectors such as *Manufacturing* and *Construction* also show high avoided intensities, while issuers from the *Real estate activities* sector exhibit very low *Avoided* CO_2. It is worth noting that over half of the issuers belong in the *Financial and insurance activities* sector ($\approx$ 56% of the sample). This is not surprising. In both Flammer (2021) and Dutordoir et al. (2024a), financial firms constitute around 50% of the sample. Furthermore, green bonds issued by financial firms result in some modest carbon improvements. This is also unsurprising, given those firms' ability to effectively channel funds to sustainability linked loans by screening out "brown" borrowers (Aswani and Rajgopal, 2025).

[Insert Table 3 around here]

Thus far, the key takeaway is that, on average, green bonds finance projects that deliver sizeable environmental benefits. In fact, avoided-emissions intensities are more than an order of magnitude larger than financed-emissions intensities. However, there is considerable variation in the green bonds' *Carbon footprint* over time, across issuer countries, and across sectors. While these patterns are intuitive given differences in project mix and local baselines, they also justify the inclusion of year, country, and industry fixed effects in our later regressions.

In our setting, firm fixed effects may not be appropriate for two econometric reasons highlighted by Dutordoir et al. (2024a). First, our data are not a traditional panel. Many firms appear only once, and several appear only in the green or only in the conventional bond sample. In a binary-choice model with firm fixed effects, singletons and observations without within-firm variation in the outcome are dropped. Hence, when we estimate the selection probit replacing country and industry fixed effects with firm fixed effects, the sample falls from 3,893 to 787, a reduction of about 82.5%. Beyond the loss of observations, Breuer and DeHaan (2024) advise against including firm fixed effects when firms lack an adequate time series of observations.

A second issue emerges when the key variables of interest are accounting measures such as *Firm Size*, which typically exhibit limited within-firm variation (Breuer and DeHaan, 2024). Because these variables are slow-moving, firm fixed effects risk absorbing nearly all informative variation. To evaluate the severity of the issue, Jennings et al. (2024) suggest regressing the independent variables of interest on firm fixed effects; if the R^2 of this regression exceeds 90%, inferences on that regressor become unreliable. For context, regressing *Firm Size* on firm fixed effects yields an R^2 of 99.12%, indicating that almost all variation is absorbed by the fixed effects. Strikingly, we obtain similar R^2 for the other continuous measures.[11] Consistent with Dutordoir et al. (2024a), adding firm fixed effects renders all covariates statistically insignificant. Given these econometric concerns, we do not base our inferences on specifications with firm fixed effects.

4.2 Determinants of carbon savings

Having shown that green bonds are associated with substantial carbon savings, we turn our attention to the determinants of these savings. We begin by presenting summary statistics for green and conventional bonds in Table 4. This univariate comparison allows us to examine whether there are any systematic differences in characteristics between the two groups. The last column of Table 4 reports the mean difference between green and conventional bonds, and evaluates the statistical significance using a two-tail t-test. At first glance, we observe notable differences. On average, green-bond issuers are smaller, yet more profitable and exhibit faster sales growth. Moreover, green issuers are more likely to be publicly listed and to be first-time issuers. Firms also appear more likely to issue a green (rather than a conventional) bond when *Oil*

[11] Among firm-level characteristics, all continuous variables exhibit R^2 exceeding 90% apart from *Sales Growth*, for which R^2 equals 41.20%.

Price and *Greenium* are higher.[12] Turning to bond features, green bonds carry higher coupons, have lower ratings and shorter maturities,[13] yet raise larger amounts. These systematic differences suggest selection into green issuance, reinforcing our choice of a Heckman selection model.

[Insert Table 4 around here]

Before presenting the Heckman estimates, we report pairwise correlations among the independent variables. As shown in Table 5, most correlations are modest, as all absolute values are below 0.4. The highest correlation coefficient is 0.39, and it is between *Firm Size* and *Rated Issuer*. This suggests that larger firms are also more likely to be listed on an exchange, which is also in line with economic intuition. Overall, these patterns suggest that multicollinearity is unlikely to significantly affect the precision of our estimates. As a matter of fact, average Variance Inflation Factors (VIFs) are below 10 across all specifications, further reinforcing the argument that multicollinearity is not a major concern in our setting [14]

[Insert Table 5 around here]

Table 6 reports the estimates of the Heckman selection model. Specifically, Column 1 reports the estimates of the selection equation, and Columns 2 and 3 report the estimates of the outcome equation, where the dependent variable is *Financed* CO_2 and *Avoided* CO_2, respectively. In the selection equation, two key patterns emerge. First, the coefficients on observable characteristics are similar to what has been reported in Table 4 and are in line with previous papers. For instance, as in Dutordoir et al. (2024a), green-bond issuers are more likely to be smaller, rated by Moody's, and to issue when oil prices are high; while consistent with Zhou et al. (2024), they are more

[12] The average greenium in our sample is 9 basis points, which lies at the upper end of the ranges reported by Caramichael and Rapp (2024) and Aswani and Rajgopal (2025).

[13] Out of 203 unique bond issues, 7 have no stated maturity as they are perpetual subordinated or hybrid instruments callable by the issuer. Six of these seven bonds were issued by a Spanish electric utility company.

[14] To compute VIFs for the selection equation, we ran a separate linear probability model using the same covariates solely for diagnostic purposes.

likely to be listed. Furthermore, consistent with the cost of capital explanation (Zerbib, 2019), firms issue more green bonds when *Greenium* is higher. First-time issuers are also more likely to issue green bonds, possibly to reap signaling benefits, as documented in Flammer (2021). Second, *Google Trends* is positive and statistically significant at the 1% level in the selection equation. This finding aligns with the signaling view and suggests that our exclusion variable is relevant for selection.

Moving to the outcome equation, one important result stands out: the impact of *Firm Size*. Specifically, we observe that *Firm Size* is positive and statistically significant at the 10% level in Column 2 and at the 1% level in Column 3. These results suggests that larger issuers fund projects with higher financed carbon intensity, but, more importantly, deliver larger carbon savings per €1 million invested. This latter finding contrasts with Drempetic et al. (2020), who report that larger firms allocate resources to appear environmentally friendly, but do not invest in projects that deliver measurable environmental benefits. Furthermore, *Listed Issuer* bears a negative and significant at the 5% level coefficient in Column 3, which suggests that private issuers fund more environmentally-efficient projects. This finding is also important, as it supports our choice to include unlisted firms in our sample.[15]

Inverse Mills Ratio is negative and and statistically significant at the 10% level in Column 2 and at the 1% level in Column 3. This indicates negative selection on unobservables: unobserved factors that raise the probability of selection are associated with lower outcomes. Put differently, conditional on observables, firms that are more likely to issue a green bond for unobserved reasons tend to deliver smaller *Avoided* CO_2. Several intuitive examples can explain this negative selection story. For instance, when demand from sustainable investors is strong, issuers can satisfy the market with easy-to-certify and quick-to-execute projects. This pressure to issue quickly could shift

[15] Table A2 reports the results of naïve OLS regressions that ignore sample selection. Results, especially for *Firm Size*, are similar to those from the Heckman outcome equations. The main differences arise in the *Avoided* CO_2 regressions: under OLS, *Listed Issuer* is not statistically significant, whereas *First Issuer* is positive and significant at the 5% level. We report these OLS specifications for completeness, but we do not base inference on them because they do not correct for the sample-selection problem.

the pipeline toward short-cycle activities that tick eligibility boxes but deliver smaller *Avoided* CO_2 than more transformative investments. Alternatively, firms that are already relatively efficient may find it less costly to certify and market green bonds. However, because the 'low-hanging fruit' has already been captured, the marginal carbon savings from new projects are small.

Returning to issuer size, the positive association with carbon savings may reflect scale effects, economies of scale, or a combination of the two. On the capability side, larger issuers can mobilize specialized in-house engineering and project-management teams. On the cost side, they may realize economies of scale—achieving lower per-euro transaction, engineering, and procurement costs—which translates into a lower cost per unit of carbon savings. In what follows, we will examine the stability of this relationship by accounting for other potential determinants of green bonds' *Carbon footprint*.

[Insert Table 6 around here]

Table 7 repeats the exercise of Table 6 with the addition of bond-level controls in the sample. The main reason for their exclusion in the baseline model was to alleviate concerns about conditioning on variables that are determined simultaneously with or shortly after the green-vs-conventional decision (e.g., coupon rate, bond rating). Similar approach is followed by Dutordoir et al. (2024a), who study the choice between green and conventional bond issues. Similarly to this paper, a higher *Bond Rating* is associated with a higher probability of issuing a green bond. Furthermore, in our sample, green bonds are also associated with higher coupon rates, larger issue amounts, and shorter maturities.

Moving to the outcome equations, the results for *Firm Size* and *Inverse Mills Ratio* are similar to the ones reported in Table 6, suggesting that our baseline findings hold even when we control for bond features. When it comes to these bond-level characteristics, both *Coupon Rate* and *Bond Rating* are negatively associated with *Financed* CO_2 and positively with *Avoided* CO_2. Given that higher values of *Bond Rating* values denote lower credit quality, these patterns are consistent with the interpretation that green-bond funding may ease financing difficulties for lower-rated issuers, enabling investment in emissions-reducing projects (ElBannan and Löffler, 2024).

[Insert Table 7 around here]

Lennox et al. (2012) advise examining whether inferences from Heckman selection models are sensitive to alternative exclusion restrictions. Hence, to assess the robustness of our main findings, we follow Dutordoir et al. (2024b) and use *Prior Conventional* as the alternative exclusion restriction. This variable is a dummy equal to 1 if a firm issued conventional bonds at any point prior to the green bond issuance within our sample period, and 0 otherwise. We expect *Prior Conventional* to be negatively associated with the green–conventional issuance choice. Furthemore, we have no reason to believe that previous issuance of conventional bonds would directly affect the carbon footprint of future green-bond-financed projects.

Table A3 in the Appendix reports the results of this analysis. Consistent with our expectations and in line with Dutordoir et al. (2024b), *Prior Conventional* enters the selection equation with a negative and highly statistically significant coefficient. Importantly, the coefficients of the outcome equation—most notably those on *Firm Size* and the *Inverse Mills Ratio*—remain very similar to the baseline estimates reported in Table 6, indicating that our findings are robust to the choice of exclusion restriction.

4.3 Use of Proceeds & Certification

In this section, we consider two possible interpretations of the positive association between firm size and carbon savings. The first is project mix. Larger firms may allocate more funding to energy-generation or other infrastructure-intensive projects (Hartmann et al., 2021). These projects often have higher baseline emissions and greater abatement potential, which can lead to larger reported carbon savings. The second interpretation relates to certification. Because certification entails fixed costs (Ehlers and Packer, 2017), larger firms may be more inclined to certify their issues.

Certification is also associated with stronger environmental commitments (Flammer, 2021), and certified issues often report higher avoided CO_2. Taken together, the size association may simply capture larger firms' propensity to fund projects with greater abatement potential or to seek certification for their issues.

To assess these explanations, we add dummies for project categories and a certification indicator to the outcome equation. We do not add them to the selection equation, where selection is between green and conventional bonds. We believe that this choice is not problematic for two reasons. First, these variables are not observed for conventional issues. Second, they also most likely follow the green–versus–conventional decision. For example, if a firm plans to finance a renewable-energy project, it has almost certainly already decided to issue a green bond rather than a conventional one. Likewise, if a firm intends to issue a certified green bond, certification applies only after choosing a green label because such certifications do not exist for conventional bonds.

Table 8 presents the outcome equation (both with and without bond-level controls) with the inclusion of project mix dummies. Because a bond can finance multiple categories, there is no need for a residual category. Thus, each dummy compares bonds that include that category to those that do not, holding other controls fixed. *Vehicles* and *EV Charging* show the strongest carbon savings, plausibly because they replace fossil-fuel use directly and deliver quick efficiency gains at existing sites. *Forestry* also exhibits large carbon savings and even lower financed emissions, consistent with sequestration benefits that these projects deliver. Furthermore, *Energy Generation* shows higher financed emissions because renewable plants still produce emissions from manufacturing and energy generation. However, they also deliver substantial avoided emissions by replacing fossil-fuel electricity with renewable sources such as solar and wind. By contrast, green buildings appear to deliver the smallest environmental benefits in our sample.

Two broader takeaways remain. First, the size association stays positive and statistically significant for both *Financed* CO_2 and *Avoided* CO_2. Hence, after controlling for project mix, larger issuers finance more emissions-intensive projects yet are also associated with greater carbon savings per euro. Second, the *Inverse Mills ratio* remains negative and significant in the savings equations, indicating that selection on unobservables continues to matter even after we account for project mix.

[Insert Table 8 around here]

Table 9 presents the outcome equation with the inclusion of *Certified*, a dummy equal to 1 if the green bond is certified by an independent third party. Following Flammer (2021), we obtain certification information from the Climate Bonds Initiative (CBI) database.[16] To increase coverage, we augment the CBI records with data from LSEG. Notably, the results for *Firm Size* and the *Inverse Mills Ratio* remain qualitatively similar to those reported earlier. By contrast, *Certified* is statistically indistinguishable from zero in all specifications except column (3), where it is negative and only marginally significant. Taken together, these results indicate that certification is not significantly associated with carbon savings, while there is some evidence of lower financed emissions for certified issues. A plausible interpretation is that certification emphasizes eligibility rather than additionality. In that case, issuers may select projects that qualify and look clean on the financing side but are easier to execute, low-additionality investments that do not displace much emissions.

[Insert Table 9 around here]

Overall, these findings differ from prior evidence that certified bonds are associated with stronger environmental performance (Flammer, 2021; Yu et al., 2024; Liu et al., 2025). Rather, our results are consistent with studies reporting no statistically significant association between certification and carbon-emission reductions (ElBannan and Löffler, 2024; Aswani and Rajgopal, 2025). One potential explanation for these mixed results may come from Cardot et al. (2025), who show that certification is the optimal choice when investor priors about an issuer's "greenness" are not favorable.

[16] https://www.climatebonds.net/data-insights/market-data/certified-climate-bonds-database

At this point, it is worth emphasizing that we do not make any causal claims about the impact of certification on the carbon footprint of green bonds. The certification decision is endogenous, and addressing that selection is beyond the scope of this paper. Rather, our main objective is to assess whether the baseline results continue to hold after accounting for certification.

5 Firm-level emissions

We now turn to the firm-level difference-in-differences analysis employed in previous studies (Flammer, 2021; Aswani and Rajgopal, 2025). The aim of this analysis is to assess whether our bond-level results carry at the firm level. Specifically, we test whether post-issuance, *Treated* (green bond issuers) exhibit lower firm-level emissions intensity relative to *Controls* (propensity-score-matched conventional bond issuers). As detailed in Section 3.5.2, we adopt the matching approach of Flammer (2021). Furthermore, we follow DeFond et al. (2015), and we apply a tight caliper of 0.01 on the propensity-score distance. We do so to ensure that treated and control units are very similar in treatment probability, conditional on observables.

Before presenting the DiD results, we assess match quality. Following He et al. (2025), we plot kernel density estimates of the propensity score for treated and control firms, both before and after matching. Figure 1 illustrates the quality of the matching. Prior to the matching, we observe large differences in the two distributions, indicating strong selection on observables; in particular, control firms exhibit substantially lower treatment probabilities than treated firms. However, after matching, the two distributions almost overlap, indicating strong common support in the matched sample and improved covariate balance.[17]

[Insert Figure 1 around here]

[17] Because overlap in propensity score distributions is necessary but not sufficient for covariate balance, we also test for differences in means (untabulated). While some significant differences appear before matching, the significance disappears in the PSM matched sample.

Table 10 presents the results of the DiD analysis. Columns 1 and 2 report the estimates from the staggered DiD specifications of Eq. (11) and Eq. (12), respectively, while Column 3 reports the stacked DiD estimates from Eq. (13). *Treated* is negative and statistically significant at the 10% level in Column 1 and at the 5% level in Columns 2 and 3, indicating that green bond issuers exhibit lower carbon intensity following the green bond issue. These results are consistent with prior evidence documenting improved environmental performance after green bond issuance (Flammer, 2021; Liu et al., 2025). Importantly, the persistence of statistical significance in the stacked DiD specification suggests that the mixed findings in earlier work are unlikely to be driven by the "bad comparisons" issue inherent in staggered DiD designs.

Columns 4 and 5 examine the dynamic association between green bond issuance and carbon intensity using the staggered DiD approach. We obtain two important takeaways. First, both $Year^{-2}$ and $Year^{-1}$ are statistically insignificant, providing no evidence of a pre-treatment trend. Second, $Year^{+1}$ is negative and statistically significant at the 5% level, or better, while $Year^{+1}$ is also negative but only marginally statistically significant. These results are consistent with ElBannan and Löffler (2024), who note that environmental benefits are typically observed around two years after green bond issuance. This delay mirrors the time needed for energy-efficiency retrofits and clean-energy projects to be installed, scaled, and reflected in emissions metrics. Finally, Column 6 examines the dynamic treatment effects using the stacked DiD specification. Both $Year^{+1}$ and $Year^{\geq +2}$ are negative and statistically significant at the 5% level, and the magnitude of their coefficients is similar.

[Insert Table 10 around here]

Thus far, the firm-level results reconcile with the bond-level findings. To explore this further, we examine treatment heterogeneity. In particular, we assess whether the effect of *Treated* varies by firm size, given that at the bond-level we documented a strong positive association between issuer size and carbon savings. Accordingly, we re-estimate Columns 1 to 3 of Table 10 by interacting *Treated* with two dummy variables indicating whether the green issuer is a large or a small firm. This size classification is based on the year-end prior to the green bond announcement ($Year^{-1}$), using the median *Firm Size* as the cutoff. Table 11 presents the results. *Treated* × *Large Firm* is negative but not statistically significant, whereas *Treated* × *Small Firm* is negative and statistically significant at the 5% level, or better. This finding contrasts with the bond-level evidence, as it indicates that the positive environmental impact of green bonds is observed only in small issuers.

[Insert Table 11 around here]

Two explanations may account for the apparent inconsistency in the size pattern. First, residual selection from an omitted determinant in matching. Although our propensity-score matching is standard in the literature and incorporates several firm-level characteristics, it may omit variables correlated with both firm size and post-issuance changes in emissions intensity. For example, firms' exposure to climate risk—physical and regulatory transition risk—is associated with green-bond issuance (Guesmi et al., 2025). If such exposure is not included in the match and varies with size (for example, smaller issuers with concentrated operations in flood-prone or carbon-priced jurisdictions), treated small firms can display larger post-issuance declines in intensity relative to their matched controls even after balancing financial and ESG characteristics.

A second, and possibly more intuitive explanation is a dilution effect. Green bond projects can deliver real emissions savings at the project level, yet they may be small relative to a large issuer's overall scale. As a matter or fact, in our green-bond sample, the ratio of *Amount Issued* to *Firm Size* is roughly 3%, on average. Similarly, as noted by Ehlers et al. (2020), carbon reductions financed by green bonds may be offset by increased emissions in other parts of the firm, a pattern likely more pronounced among larger issuers. Taken together, these arguments imply that the same absolute savings shift firm-level emissions-to-assets intensity much less for large firms than for small firms. Acknowledging this limitation, Flammer (2021) argues that the observed reduction in the carbon intensity of *Treated* firms is not a direct outcome of the financed projects, given that these projects are about ten times smaller than the issuer's size. She interprets those results as firms' signaling a broader organizational commitment to sustainability rather than a causal impact of the green bonds, an interpretation also adopted by ElBannan and Löffler (2024).

Finally, we compare the best-performing issuers on carbon savings using the project-level results and the firm-level DiD predictions from Eq. 12. We compute the average *Avoided* CO_2 per issuer–year in the bond-level data. This is because the DiD analysis uses firm-years as the unit of observation, and some firms had issued multiple bonds within a year.

Table 12 reports the rankings. For compliance reasons, we do not disclose issuer names. Panel A lists the top five issuers by *Avoided* CO_2. Consistent with what has been reported in Table 2, a Portuguese electric utilities company ranks first with 1,490.8 tCO_2 avoided per EUR million invested. Notably, three of the five best performing companies operate in emissions-intensive sectors, such as the *Electricity and gas* or the *Construction* sectors. Panel B lists the top five firms according to the DiD model. The percentage change (ΔCO_2) is defined as the change in firm-level emissions between $Year^{+2}$ and $Year^{-1}$, relative to $Year^{-1}$. A different picture emerges: none of the top performers in Panel A appear among the top DiD performers. This is visible from the first column of Panel B, which reports each issuer's rank from Panel A and shows that none of the top-five project-level performers are represented in the DiD rankings. With 44 unique listed issuers in the sample, these cross-rankings highlight a clear mismatch between project-level and firm-level assessments.

[Insert Table 12 around here]

Taken together, the treatment-heterogeneity results and the rankings provide suggestive evidence that firm-level emissions analyses may tell a different story than more granular, project-level data. Our reading of these findings is that researchers should be cautious in interpreting firm-level estimates as the causal impact of green bonds on firms' emissions intensity. Instead, these patterns may reflect a broader sustainability commitment, of which green bonds are one component, and which is associated with reductions in emissions intensity. This conclusion aligns with Flammer (2021) and ElBannan and Löffler (2024), who acknowledge that these designs provide limited scope for causal inference because green bonds typically finance only a small subset of projects relative to the firm's overall scale.

6 Conclusion

This study contributes to the debate on whether green bonds deliver genuine environmental benefits or simply serve as a form of greenwashing. We extend the literature by using granular project-level data and an industry-led framework to measure the carbon footprint of green bonds. Specifically, we calculate each bond's financed emissions—the emissions generated by the funded projects—by accounting for project type, resource allocation per project, project location, and activity/impact metrics (e.g., MWh generated). We then compute counterfactual emissions, that is, the emissions that would have occurred if the green-bond-funded projects had not been implemented. The difference between these two measures represents the avoided emissions. All emissions measures are standardized by the amount of funds invested, so that both financed and avoided emissions represent emission intensities.

Our first set of analyses is descriptive. We find that, on average, avoided emissions are more than ten times larger than the financed emissions. This result is particularly pronounced for energy generation projects and for the smaller subset of electric vehicle and charging infrastructure projects. We also document substantial heterogeneity in carbon savings across countries and sectors. However, even the least effective projects deliver a net improvement relative to their counterfactual scenarios. Overall, the evidence supports the view that green bonds are not a form of greenwashing. Rather, when emissions are measured appropriately, green bonds are shown to generate sizable reductions in carbon intensity.

The second part of our analysis examines the cross-sectional determinants of carbon savings. To address the selection issue inherent in green bond issuance, we estimate a Heckman selection model. We find a strong positive association between issuer size and carbon savings, robust to the inclusion of firm- and bond-level characteristics. Further analysis shows that this association is not driven by project mix (e.g., larger issuers funding more energy projects) or certification (e.g., larger issuers being more likely to certify their bonds). We interpret this finding as evidence of scale effects: larger issuers may achieve lower emissions intensities per euro invested, or attain similar carbon reductions at a lower cost.

Finally, we replicate a standard firm-level difference-in-differences design used in prior studies to compare the inferences from our project-level analysis to this setting. At first glance, the results align with our main findings, as we observe a reduction in firm-level carbon emissions following green bond issuance. However, treatment heterogeneity analysis reveals that this effect is only evident in small issuers, which contrasts with the results of our cross-sectional analysis. This discrepancy may reflect omitted variable bias in the conventional PSM-based DiD design or a dilution effect, given that green bond proceeds represent a small share of total funding for large issuers. Comparisons across issuers and sectors highlight further inconsistencies between firm-level and project-level results. Altogether, we caution against strong causal claims based solely on firm-level difference-in-differences approaches when researchers assess the environmental impact of green bonds.

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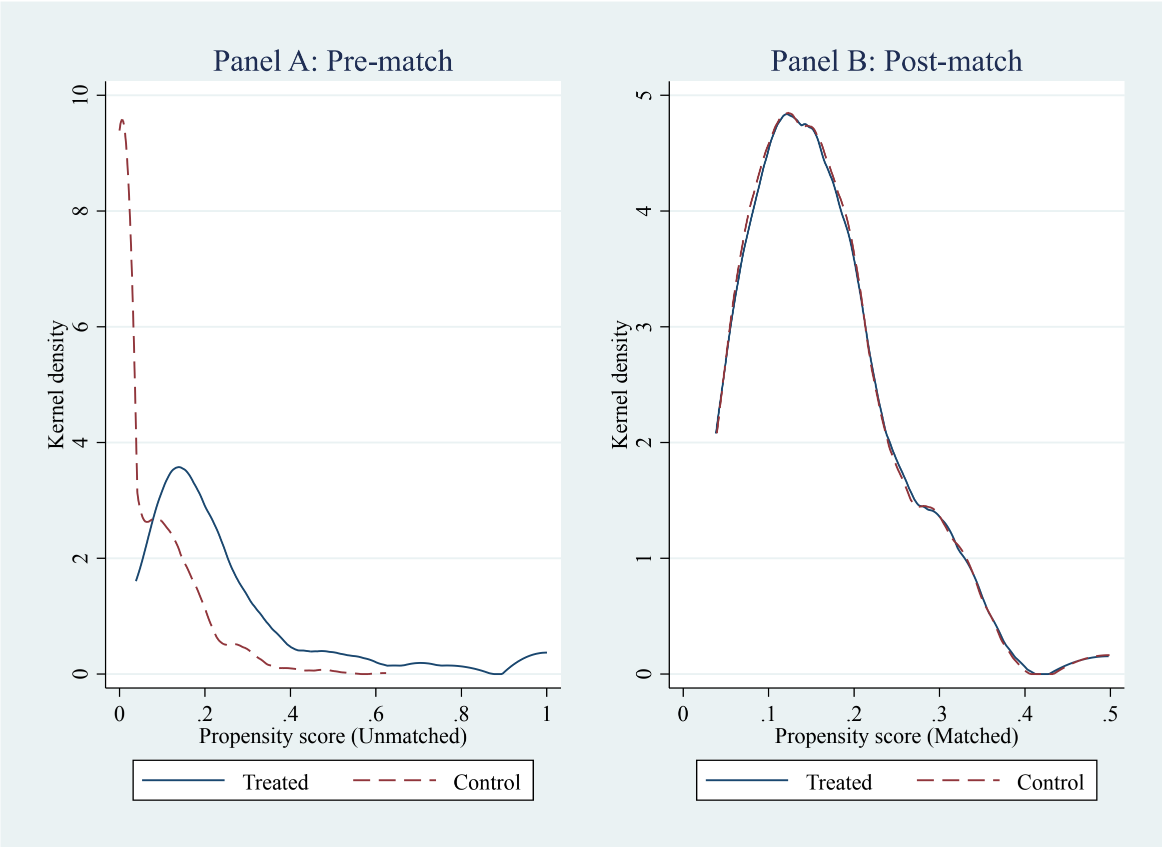
Figure 1: Quality of matching



Notes: The figure displays the kernel density of propensity scores before matching (Panel A) and after matching (Panel B). The treatment group (green bond issuers) is represented by the solid line, and the control group (PSM-matched conventional bond issuers) by the dashed line. Matching is performed by country and NACE sector, using the following seven firm-level characteristics measured at the fiscal year-end prior to issuance: *Size*, *Tobin's Q*, *ROA*, *Leverage*, *EScore*, *SScore*, and *GScore*. Nearest-neighbor matching is implemented one-to-one, without replacement, and using a caliper of 0.01.

Table 1: Carbon footprint by year

Year	Financed CO_2	Avoided CO_2	N
2017	13.74	352.61	9
2018	26.28	316.99	8
2019	10.85	353.52	17
2020	17.71	405.29	35
2021	22.83	175.99	54
2022	30.68	252.58	41
2023	44.84	238.33	39
Overall	26.49	271.22	203

Notes: The table reports the average carbon footprint (*Financed CO_2* and *Avoided CO_2*) and number of green bond issues by year.

Table 2: Carbon footprint by country

Country	Financed CO_2	Avoided CO_2	N	Top category
Austria	34.35	0.90	3	Real estate
Belgium	42.86	39.67	1	Real estate
Denmark	62.37	688.29	1	Energy capacity
Finland	−113.08	83.44	6	Forestry
France	29.43	21.52	9	Real estate
Germany	27.30	263.47	44	Energy generation / Real estate
Hungary	40.58	511.20	1	EV charging
Italy	90.01	463.10	13	Energy generation
Netherlands	28.80	44.88	46	Real estate
Norway	52.21	3.86	8	Real estate
Poland	56.59	642.89	2	Real estate / EV Charging
Portugal	10.11	1490.82	16	Energy generation
Spain	21.16	234.04	35	Real estate / Energy generation
Sweden	19.51	2.51	2	Real estate
Switzerland	14.45	7.73	4	Real estate
United Kingdom	26.31	3.96	12	Real estate
Overall	26.49	271.22	203	Real estate

Notes: The table reports the average carbon footprint (*Financed CO_2* and *Avoided CO_2*) and the number of green-bond issues by country of issue. "Top category" indicates the project category receiving the largest share of allocated proceeds in that country (based on issuer reporting). If no single category exceeds 50% of total allocations, we list the two largest categories (by share), in descending order.

Table 3: Carbon footprint by issuer NACE sector

Industry	Financed CO_2	Avoided CO_2	N
Manufacturing	−103.07	287.17	5
Electricity, gas, steam and air	15.69	781.98	42
Construction	6.48	515.76	2
Transportation and storage	21.54	14.98	2
Financial and insurance activities	36.79	162.41	114
Real estate activities	21.16	2.39	14
Professional, scientific and technical activities	222.18	311.02	1
Administrative support services	6.50	0.00	6
Public administration	62.37	688.29	1
Other service activities	22.71	10.62	16
Overall	26.49	271.22	203

Notes: The table reports the average carbon footprint (*Financed* CO_2 and *Avoided* CO_2) and number of green bond issues by the issuer's NACE sector.

Table 4: Summary statistics

	Conventional Bonds						*Green Bonds*						Mean Diff.
	N	Mean	Std.dev	p25	Median	p75	N	Mean	Std.dev	p25	Median	p75	
Google Trends	3691	3.60	1.23	3.75	4.09	4.23	203	3.84	0.63	3.72	3.96	4.17	0.24***
Firm Size	3691	12.49	1.48	11.31	13.16	13.47	203	11.21	1.61	10.02	11.32	12.56	-1.28***
ROA	3691	0.50	1.09	0.16	0.27	0.39	203	1.45	2.02	0.22	0.56	2.38	0.95***
Firm Age	3691	3.69	0.88	3.00	3.22	4.62	203	3.68	1.06	3.04	3.81	4.79	-0.01
Sales Growth	3691	3.55	17.06	−6.16	0.70	9.59	203	6.54	20.45	−6.10	3.00	11.24	2.99**
Listed Issuer	3691	0.25	0.43	0.00	0.00	0.00	203	0.66	0.48	0.00	1.00	1.00	0.41***
Subsidiary	3691	0.32	0.47	0.00	0.00	1.00	203	0.34	0.47	0.00	0.00	1.00	0.02
First Issuer	3691	0.03	0.18	0.00	0.00	0.00	203	0.33	0.47	0.00	0.00	1.00	0.30***
Rated Issuer	3691	0.73	0.44	0.00	1.00	1.00	203	0.69	0.46	0.00	1.00	1.00	-0.04
Oil Price	3691	0.08	0.18	−0.04	0.08	0.20	203	0.12	0.18	−0.03	0.12	0.26	0.04***
Greenium	3691	0.22	0.50	−0.15	0.25	0.49	203	0.31	0.49	−0.12	0.28	0.56	0.09**
Coupon Rate	3690	1.98	1.63	0.55	1.59	3.13	203	2.41	1.84	0.88	1.88	3.85	0.43***
Amount Issued	3690	4.74	1.75	3.35	4.74	6.35	203	6.36	0.53	6.21	6.40	6.72	1.62***
Maturity	3643	2.20	0.44	1.95	2.20	2.40	196	2.11	0.46	1.79	2.08	2.33	-0.09***
Bond Rating	3691	8.67	6.08	5.00	8.00	15.00	203	14.95	6.54	8.00	18.00	20.00	6.28***

Notes: This table reports the summary statistics for the firm-and bond-level characteristics of our sample. The table reports summary statistics separately for *Conventional bonds* and *Green bonds*. All variables are defined in Table A1 of the Appendix. *Mean Diffs* denote the difference in sample means (*Green* − *Conventional*). Statistical significance of the mean differences is assessed using two-tailed t-tests. Significance levels are indicated as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Google Trends														
(2) Firm Size	0.38^a													
(3) ROA	-0.00	-0.34^a												
(4) Firm Age	-0.02	-0.14^a	0.04^b											
(5) Sales Growth	-0.03	-0.14^a	0.11^a	-0.02										
(6) Listed Issuer	0.08^a	0.06^a	0.36^a	0.23^a	-0.00									
(7) Subsidiary	-0.38^a	-0.27^a	-0.05^a	0.16^a	0.00	-0.19^a								
(8) First Issuer	-0.04^b	-0.29^a	0.24^a	0.00	0.05^a	0.14^a	0.05^a							
(9) Rated Issuer	0.44^a	0.39^a	-0.06^a	0.02	-0.05^a	0.05^a	-0.34^a	-0.14^a						
(10) Oil Price	0.05^a	0.00	-0.02	0.01	0.12^a	0.02	-0.04^b	0.01	0.03^c					
(11) Greenium	-0.01	-0.05^a	-0.03^b	-0.02	0.06^a	-0.05^a	0.01	0.02	0.00	0.11^a				
(12) Coupon Rate	-0.06^a	-0.00	0.06^a	0.04^b	-0.05^a	0.15^a	0.02	0.01	-0.08^a	-0.16^a	-0.11^a			
(13) Amount Issued	-0.18^a	-0.14^a	0.22^a	0.17^a	0.03^c	0.36^a	0.23^a	0.15^a	-0.25^a	-0.03^b	-0.02	0.09^a		
(14) Maturity	-0.06^a	-0.02	-0.05^a	-0.04^b	0.06^a	-0.04^b	0.01	-0.04^b	0.02	0.04^b	0.06^a	-0.25^a	-0.17^a	
(15) Bond Rating	-0.01	-0.21^a	0.19^a	0.02	0.00	0.18^a	-0.01	0.18^a	-0.06^a	-0.01	0.01	0.17^a	0.15^a	-0.04^b

Note: This table reports pairwise Pearson correlations among the variables. All variables are defined in Table A1. Significance levels: [a] $p < 0.01$, [b] $p < 0.05$, [c] $p < 0.10$.

Table 6: Baseline Heckman model

	Green vs. Conv.	Financed CO_2	Avoided CO_2
	(1)	(2)	(3)
Google Trends	0.153***		
	(4.76)		
Firm Size	-0.131***	0.323*	0.659***
	(-7.57)	(2.17)	(7.36)
ROA	-0.111	-0.219	0.125
	(-1.18)	(-1.44)	(0.87)
Firm Age	0.070***	-0.117*	0.274
	(4.08)	(-2.44)	(1.25)
Sales Growth	0.001	0.007	-0.014
	(0.41)	(1.50)	(-0.95)
Listed Issuer	0.496***	-0.658	-1.745**
	(8.40)	(-1.75)	(-3.41)
Subsidiary	0.134**	0.088	-0.230
	(2.42)	(0.15)	(-0.48)
First Issuer	1.543***	0.078	-0.373
	(16.41)	(0.20)	(-2.07)
Rated Issuer	0.378***	-1.229	-0.256
	(10.55)	(-1.63)	(-0.32)
Oil Price	0.535***	0.190	-1.790
	(4.21)	(0.53)	(-0.61)
Grenium	0.107***	-0.127*	0.111
	(5.26)	(-2.47)	(0.53)
Inverse Mills Ratio		-0.327*	-1.809***
		(-2.29)	(-5.61)
Country fixed effects	✓	✓	✓
Industry fixed effects	✓	✓	✓
Year fixed effects	✓	✓	✓
N	3,894	203	203
Pseudo R^2/Adj. R^2	0.517	0.746	0.601

Note: This table reports the estimates from a Heckman selection model. Column 1 reports the estimates of the selection equation, where the dependent variable is a dummy variable which equals 1 for green bond issues, and 0 otherwise. Columns 2 and 3 report the estimates of the outcome equation, where the dependent variable is *Financed* CO_2 and *Avoided* CO_2, respectively. The *Inverse Mills Ratio* is computed based on the first-stage probit selection equation and is defined in Eq. 9. All variables are defined in Table A1 of the Appendix. All continuous variables are winsorized at 1% and 99% level. T-statistics, reported in parentheses, are calculated using industry-clustered standard errors. Significance levels are indicated as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Heckman model with bond characteristics

	Green vs. Conv.	Financed CO_2	Avoided CO_2
	(1)	(2)	(3)
Google Trends	0.150***		
	(4.23)		
Firm Size	-0.155***	0.299*	0.697**
	(-8.19)	(2.34)	(2.88)
Coupon	0.109***	-0.170***	0.282***
	(5.32)	(-6.57)	(4.61)
Ammount Issued	0.477***	-0.191**	0.216
	(21.74)	(-3.37)	(0.47)
Maturity	-0.133**	0.586	0.260
	(-2.00)	(2.13)	(0.46)
Bond Rating	0.029***	-0.048**	0.063***
	(9.24)	(-3.88)	(8.81)
Inverse Mills Ratio		-0.614**	-0.707**
		(-3.30)	(-3.46)
Baseline controls	✓	✓	✓
Country fixed effects	✓	✓	✓
Industry fixed effects	✓	✓	✓
Year fixed effects	✓	✓	✓
N	3,838	196	196
Pseudo R^2/Adj. R^2	0.576	0.754	0.611

Note: This table reports the estimates from a Heckman selection model with the inclusion of bond-level characteristics. Column 1 reports the estimates of the selection equation, where the dependent variable is a dummy variable which equals 1 for green bond issues, and 0 otherwise. Columns 2 and 3 report the estimates of the outcome equation, where the dependent variable is *Financed* CO_2 and *Avoided* CO_2, respectively. The *Inverse Mills Ratio* is computed based on the first-stage probit selection equation and is defined in Eq. 9. All variables are defined in Table A1 of the Appendix. All continuous variables are winsorized at 1% and 99% level. T-statistics, reported in parentheses, are calculated using industry-clustered standard errors. Significance levels are indicated as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Use of proceeds allocation

	Financed CO_2	Avoided CO_2	Financed CO_2	Avoided CO_2
	(1)	(2)	(3)	(4)
Firm Size	0.169**	0.654**	0.171**	0.697*
	(3.25)	(3.04)	(2.90)	(2.06)
Energy Generation	0.873**	1.745**	0.664***	2.171*
	(3.48)	(3.24)	(4.90)	(2.55)
Energy Capacity	0.001	-1.343**	-0.085	-1.987***
	(0.00)	(-2.92)	(-0.15)	(-5.50)
Vehicle	0.962	16.876***	1.202	16.045***
	(0.84)	(10.46)	(1.02)	(8.08)
EV Charging	2.217	6.055**	1.950	6.546***
	(1.40)	(3.24)	(1.28)	(5.14)
Real Estate	1.980***	-1.095	1.571***	-0.309
	(10.35)	(-1.72)	(11.99)	(-0.22)
Forestry	-4.910**	2.468**	-5.463***	2.043**
	(-4.05)	(3.84)	(-4.71)	(3.21)
Inverse Mills Ratio	0.107	-1.278***	0.250	-0.804***
	(0.52)	(-5.35)	(1.30)	(-5.36)
Baseline controls	✓	✓	✓	✓
Bond-level controls	×	×	✓	✓
Country fixed effects	✓	✓	✓	✓
Industry fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
N	203	203	196	196
Adj. R^2	0.834	0.750	0.843	0.755

Note: This table reports estimates from the *outcome equation only*, augmented with project-mix dummy variables. The dependent variable is *Financed* CO_2 (Columns 1 and 3) and *Avoided* CO_2 (Columns 2 and 4). The *Inverse Mills Ratio* is computed based on the first-stage probit selection equation (not reported here) and is defined in Eq. 9. All variables are defined in Table A1 in the Appendix. All continuous variables are winsorized at the 1% and 99% levels. T-statistics, reported in parentheses, are calculated using industry-clustered standard errors. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Certified Green Bonds

	Financed CO_2	Avoided CO_2	Financed CO_2	Avoided CO_2
	(1)	(2)	(3)	(4)
Certified	-0.335	-0.074	-0.498*	0.060
	(-1.05)	(-0.29)	(-2.15)	(0.18)
Firm Size	0.321*	0.658***	0.285*	0.699**
	(2.11)	(7.09)	(2.24)	(2.93)
Inverse Mills Ratio	-0.292	-1.803***	-0.537**	-0.716**
	(-1.33)	(-5.19)	(-3.88)	(-3.68)
Baseline controls	✓	✓	✓	✓
Bond-level controls	×	×	✓	✓
Country fixed effects	✓	✓	✓	✓
Industry fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
N	203	203	196	196
Adj. R^2	0.746	0.598	0.757	0.608

Note: This table reports estimates from the *outcome equation only*, augmented with the certification dummy *Certified*). The dependent variable is *Financed* CO_2 (Columns 1 and 3) and *Avoided* CO_2 (Columns 2 and 4). The *Inverse Mills Ratio* is computed based on the first-stage probit selection equation (not reported here) and is defined in Eq. 9. All variables are defined in Table A1 in the Appendix. All continuous variables are winsorized at the 1% and 99% levels. T-statistics, reported in parentheses, are calculated using industry-clustered standard errors. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Difference-in-Differences

	(1)	(2)	(3)	(4)	(5)	(6)
Treated	-0.035*	-0.026**	-0.028**			
	(-1.66)	(-2.10)	(-2.51)			
$Year^{-2}$				0.015	0.004	0.008
				(1.48)	(0.40)	(1.21)
$Year^{-1}$				0.001	-0.021	-0.010
				(0.11)	(-1.58)	(-1.65)
$Year^{0}$				-0.003	-0.024*	-0.011
				(-0.25)	(-1.70)	(-1.40)
$Year^{+1}$				-0.020*	-0.029*	-0.033**
				(-1.79)	(-1.85)	(-3.02)
$Year^{\geq +2}$				-0.037***	-0.034**	-0.031**
				(-3.45)	(-2.02)	(-2.70)
Firm-level controls	✓	✓	✓	✓	✓	✓
Firm fixed effects	✓	✓	×	✓	✓	×
Year fixed effects	✓	×	×	✓	×	×
Country × Year fixed effects	×	✓	×	×	✓	×
Industry × Year fixed effects	×	✓	×	×	✓	×
Firm × Cohort fixed effects	×	×	✓	×	×	✓
Year × Cohort fixed effects	×	×	✓	×	×	✓
N	794	709	3515	835	751	3515
Adj. R^2	0.909	0.941	0.917	0.911	0.942	0.917

Note: This table reports estimates from difference-in-differences specifications. Columns 1 and 2 present staggered DiD estimates corresponding to Eq. (11) and Eq. (12), while Column 3 reports stacked DiD estimates based on Eq. (13). *Treated* is a dummy variable equal to 1 for green bond issuers in all post-issuance years and 0 otherwise. Columns 4 to 6 report results for the dynamic effects of green bond issuance. $Year^{-2}$, $Year^{-1}$, $Year^{0}$, $Year^{+1}$, and $Year^{\geq +2}$ denote year dummies, where 0 represents the green bond issuance year. All variables are defined in Table A1 in the Appendix. All continuous variables are winsorized at the 1% and 99% levels. T-statistics, reported in parentheses, are calculated using industry-clustered standard errors for the staggered DiD models and firm–cohort clustered standard errors for the stacked DiD models. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Treatment heterogeneity

	(1)	(2)	(3)
Treated × Large Firm	-0.013	-0.011	-0.018
	(-1.33)	(-0.98)	(-0.92)
Treated × Small Firm	-0.065***	-0.050***	-0.044**
	(-5.30)	(-3.89)	(-2.09)
Firm-level controls	✓	✓	✓
Firm fixed effects	✓	✓	×
Year fixed effects	✓	×	×
Country × Year fixed effects	×	✓	×
Industry × Year fixed effects	×	✓	×
Firm × Cohort fixed effects	×	×	✓
Year × Cohort fixed effects	×	×	✓
N	794	709	3515
Adj. R^2	0.909	0.943	0.916

Note: This Table presents results on treatment heterogeneity. Columns 1 to 3 extend the corresponding specifications reported in Columns 1 to 3 of Table 10 by interacting *Treated* with two dummy variables, *Large Firm* and *Large Firm*. The size classification is based on the year-end prior to the green bond announcement ($Year^{-1}$), using the median *Firm Size* as the cutoff. All variables are defined in Table A1 in the Appendix. All continuous variables are winsorized at the 1% and 99% levels. T-statistics, reported in parentheses, are calculated using industry-clustered standard errors for the staggered DiD models and firm–cohort clustered standard errors for the stacked DiD models. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Comparison of Bond-level and DiD Estimates

Panel A: Bond-level			
Rank	Country	NACE Sector	Avoided CO_2
1	Portugal	Electricity and gas	1490.819
2	Spain	Construction	1017.796
3	Germany	Financial and insurance	820.939
4	Germany	Wholesale and retail	633.139
5	Italy	Electricity and gas	468.000

Panel B: DiD Estimates			
Rank in A	Country	NACE Sector	ΔCO_2
7	Spain	Financial and insurance	-61.52%
11	Germany	Professional activities	-38.56%
13	Spain	Financial and insurance	-37.32%
16	Switzerland	Financial and insurance	-36.71%
20	Italy	Financial and insurance	-33.45%

Note: This table reports the rankings of the top-5 best-performing green bond issuers. Panel A presents the rankings at the bond-level, using *Avoided* CO_2 as the performance criterion. For every issuer–year observation, the average *Avoided* CO_2 is reported. Panel B reports the rankings according to the firm-level difference-in-differences predictions from Eq. (12). ΔCO_2 is defined as the change in firm-level emissions between $Year^{+2}$ and $Year^{-1}$, relative to $Year^{-1}$. Issuer identities are not disclosed for confidentiality and compliance reasons.

Appendix A. Variables definition & additional results

Table A1: Variables definitions

Variable	**Definition**	**Source**
Bond-level analysis		
Financed CO_2	Emissions from green-bond projects divided by total allocated amount	MainStreet Partners
Avoided CO_2	Baseline (counterfactual) emissions minus financed emissions.	MainStreet Partners
Project dummies	Equals 1 if the bond funds projects in any specific category (e.g., Energy generation, ...), 0 otherwise	MainStreet Partners
Google Trends	Yearly mean of the daily search index	Google Trends
Firm Size	The natural logarithm of firm's total assets	Orbis (TOAS)
ROA	The ratio of net income and total assets	Orbis (PL, TOAS)
Firm Age	The natural logarithm of 1 plus the number of years since incorporation	Orbis (Incorporation date)
Sales Growth	YoY % change in turnover	Orbis (OPRE)
Listed Issuer	Equals 1 if the issuer is publicly listed, 0 otherwise	Orbis (Listing status)
Subsidiary	Equals 1 if the issuer is a controlled subsidiary, 0 otherwise	Orbis (Corporate entity type)
First Issuer	Equals 1 if it is the firm's first bond issue, 0 otherwise	Bloomberg, LSEG
Rated Issuer	Equals 1 if the issuer is rated by Moody's, 0 otherwise	Bloomberg, LSEG
Oil Price	Avg daily % change in real Brent over prior 180 trading days	FRED
Greenium	Issuance yield difference between conventional and matched green bonds from the same issuer.	Bloomberg, LSEG
Coupon	Coupon rate (avg across tranches).	Bloomberg, LSEG
Amount Issued	Issue amount (avg across tranches)	Bloomberg, LSEG
Maturity	The natural logarithm of 1 plus the number of year to maturity (avg across tranches).	Bloomberg, LSEG
Bond Rating	The bond's rating from Moody's, converted in numerical values (1 represents the highest rating)	Bloomberg, LSEG
Certified	Equals 1 if the bond is third-party certified, 0 otherwise	CBI, LSEG
Prior Conventional	Equals 1 if the firm has issued conventional bonds prior to the current bond offering, and 0 otherwise	CBI, LSEG
Firm-level analysis (LSEG only)		
CO_2	The sum of Scope 1 and Scope 2 emissions divided by total assets.	ENERDP023, WC0299
Firm Size	The natural logarithm of firm's total assets.	WC0299
Tobin's Q	Total assets minus book value of equity plus market value of equity divided by book value of total assets	WC0299, WC03501, MV
ROA	The ratio of earnings before extraordinary items andtotal assets.	WC083261, WC0299
Leverage	the ratio of total liabilities and total assets.	WC03551, WC0299
E score	Environmental pillar score	ENVSCORE
S score	Social pillar score	SOCSCORE
G score	Governance pillar score	CGVSCORE

Table A2: OLS model

	Financed CO_2	Avoided CO_2
	(1)	(2)
Firm Size	0.316*	0.613***
	(2.14)	(9.82)
ROA	-0.249	-0.044
	(-1.77)	(-0.40)
Firm Age	-0.107	0.333
	(-2.08)	(1.17)
Sales Growth	0.008	-0.009
	(1.62)	(-0.67)
Listed Issuer	-0.512	-0.943
	(-1.49)	(-1.28)
Subsidiary	0.096	-0.182
	(0.16)	(-0.36)
First Issuer	0.341	1.137**
	(0.87)	(4.19)
Rated Issuer	-1.145	0.217
	(-1.48)	(0.30)
Oil Price	0.225	-1.534
	(0.61)	(-0.51)
Greenium	-0.113*	0.194
	(-2.52)	(0.78)
Country fixed effects	✓	✓
Industry fixed effects	✓	✓
Year fixed effects	✓	✓
N	203	203
Adj. R^2	0.747	0.596

Note: This table reports estimates of OLS regressions that ignore sample selection. The dependent variable is *Financed* CO_2 in Column 1 and *Avoided* CO_2 in Column 2, respectively. The list of covariates are the same as the ones presented in Columns 2 and 3 of Table 6. All continuous variables are winsorized at 1% and 99% level. Standard errors are obtained via a clustered bootstrap at the industry level. T-statistics are in parentheses, and significance levels are indicated as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Heckman model with alternative exclusion restriction

	Green vs. Conv.	Financed CO_2	Avoided CO_2
	(1)	(2)	(3)
Prior Conventional	-1.567***		
	(-13.35)		
Firm Size	0.016	0.348*	0.669***
	(0.85)	(2.17)	(12.69)
ROA	-0.067	-0.225	-0.005
	(-1.32)	(-1.48)	(-0.03)
Firm Age	0.120***	-0.132**	0.292
	(9.08)	(-3.46)	(1.01)
Sales Growth	0.004*	0.007	-0.011
	(1.88)	(1.52)	(-0.72)
Listed Issuer	0.450***	-0.698	-1.253**
	(25.53)	(-1.58)	(-2.94)
Subsidiary	0.136**	0.122	-0.135
	(2.11)	(0.21)	(-0.28)
First Issuer	0.600***	0.192	0.881*
	(3.86)	(0.59)	(2.58)
Rated Issuer	0.346***	-1.307	-0.059
	(5.81)	(-1.57)	(-0.07)
Oil Price	0.620***	0.098	-1.764
	(2.66)	(0.31)	(-0.56)
Greenium	0.074**	-0.126	0.169
	(2.44)	(-1.96)	(0.73)
Inverse Mills Ratio		-0.393*	-0.651**
		(-2.14)	(-2.54)
Country fixed effects	✓	✓	✓
Industry fixed effects	✓	✓	✓
Year fixed effects	✓	✓	✓
N	3963	203	203
Pseudo R^2	0.541	0.748	0.597

Note: This table reports the estimates from a Heckman selection model. Column 1 reports the estimates of the selection equation, where the dependent variable is a dummy variable which equals 1 for green bond issues, and 0 otherwise. Columns 2 and 3 report the estimates of the outcome equation, where the dependent variable is *Financed* CO_2 and *Avoided* CO_2, respectively. The *Inverse Mills Ratio* is computed based on the first-stage probit selection equation and is defined in Eq. 9. All variables are defined in Table A1 of the Appendix. All continuous variables are winsorized at 1% and 99% level. T-statistics, reported in parentheses, are calculated using industry-clustered standard errors. Significance levels are indicated as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix B. Category-specific project emissions

This appendix details the project-level emissions formulas used to construct $Emissions_j$ by Use-of-Proceeds (UoP) category and country/technology. Bond-level financed emissions and intensities follow Eqs. (1)–(2) in the main text by applying the attribution factor and the monetary normalization.

Throughout, EF denotes an emissions factor (e.g., gCO_2e per kWh or per ton). All quantities are converted to tCO_2e using appropriate unit conversions.

B.1: Energy Generation

For projects where energy output is observed or forecast:

$$Emissions_j^{(\text{RE-Gen})} = \underbrace{\text{EnergyGenerated}_j}_{\text{MWh/yr}} \times \underbrace{\text{EF}^{\text{elec}}_{\text{country/tech}}}_{\text{gCO}_2\text{e / kWh}}. \tag{B1}$$

$\text{EF}^{\text{elec}}_{\text{country/tech}}$ reflects the technology lifecycle factor (e.g., wind, solar, hydro, biomass) and, where relevant, the local grid mix.

B.2: Energy Capacity

When capacity and utilization are available (no direct MWh reporting):

$$Emissions_j^{(\text{RE-Cap})} = \underbrace{\text{Capacity}_j}_{\text{MW}} \times \underbrace{\text{CF}_j}_{\text{capacity factor}} \times \underbrace{8760}_{\text{hours/yr}} \times \underbrace{\text{EF}^{\text{elec}}_{\text{country/tech}}}_{\text{gCO}_2\text{e / kWh}}. \tag{B2}$$

B.3: Vehicles

If a project finances multiple vehicle types v (e.g., ICE, hybrid, EV; cars, trains):

$$Emissions_j^{(\text{Transp})} = \sum_v \underbrace{N_{jv}}_{\#\text{ vehicles}} \times \underbrace{\text{km}_{jv}}_{\text{km/yr}} \times \underbrace{\text{EI}_v}_{\text{gCO}_2\text{e / km}}. \tag{B3}$$

with EI_v chosen by drivetrain/use (passenger vs. freight). For rail, use train-km and train intensity.

B.4: EV Charging

When energy delivered is observed or forecast:

$$Emissions_j^{(\text{EV-Chg})} = \underbrace{\text{EnergyDelivered}_j}_{\text{kWh/yr}} \times \underbrace{\text{EF}^{\text{elec}}_{\text{country}}}_{\text{gCO}_2\text{e / kWh}}. \tag{B4}$$

If only power and utilization are known, $\text{EnergyDelivered}_j \approx \text{Power}_j \times \text{Util}_j \times \text{hours/yr}$.

B.5: Real Estate (Green Buildings)

$$\mathit{Emissions}_j^{(\mathrm{GB})} = \underbrace{\mathrm{Area}_j}_{\mathrm{m}^2}\Big(\underbrace{\mathrm{EUI}_j^{\mathrm{elec}}}_{\mathrm{kWh/m}^2}\times\underbrace{\mathrm{EF}_{\mathrm{country}}^{\mathrm{elec}}}_{\mathrm{gCO_2e\ /\ kWh}} + \underbrace{\mathrm{EUI}_j^{\mathrm{therm}}}_{\mathrm{kWh/m}^2}\times\underbrace{\mathrm{EF}_{\mathrm{fuel}}^{\mathrm{therm}}}_{\mathrm{gCO_2e\ /\ kWh}}\Big). \tag{B5}$$

where $\mathrm{EUI}_j^{\mathrm{elec}}$ and $\mathrm{EUI}_j^{\mathrm{therm}}$ depend on building type (residential/industrial/office), and $\mathrm{EF}_{\mathrm{fuel}}^{\mathrm{therm}}$ reflects the thermal fuel mix (e.g., gas, district heat).

B.6: Forestry

Decompose process emissions and biological fluxes:

$$\mathit{Emissions}_j^{(\mathrm{Forestry})} = \Big(\underbrace{\mathrm{FuelUse}_j\times\mathrm{EF}_{\mathrm{fuel}}^{\mathrm{comb}}}_{\text{on-site fuel}} + \underbrace{\mathrm{FertilizerUse}_j\times\mathrm{EF}^{\mathrm{fert}}}_{\text{inputs}}\Big) - \underbrace{\mathrm{Sequestration}_j}_{\mathrm{tCO_2e/yr}}, \tag{B6}$$

so that net negative values occur when sequestration exceeds process emissions.

From projects to bonds. For any category c, the bond-level financed emissions contribution is

$$FE_b^{(c)} = \sum_{j\in c}\left(\frac{A_{bj}}{D_j+E_j}\right)\mathit{Emissions}_j^{(c)}, \qquad FEI_b^{(c)} = \frac{FE_b^{(c)}}{M_b}, \tag{B7}$$

and totals satisfy $FE_b = \sum_c FE_b^{(c)}$ and $FEI_b = \sum_c FEI_b^{(c)}$, with $M_b = \sum_j A_{bj}$ the allocated monetary base (main-text Eq. (2)).

Appendix C. Counterfactual (baseline) avoided emissions

Baselines are defined according to MainStreet Partners' proprietary methodology, consistent with ICMA's *Harmonised Framework for Impact Reporting* and the Nordic Public Sector Issuers' *Position Paper on Impact Reporting*. Baselines are category-specific and location-adjusted to reflect a relevant counterfactual for the same service in the same geography. For *green buildings*, a standard benchmark is a representative national property portfolio:

$$\mathit{BaselineEmissions}_j^{(\mathrm{GB})} = \mathrm{Area}_j\Big(\mathrm{EUI}_{\mathrm{base}}^{\mathrm{elec}} \times \mathrm{EF}_{\mathrm{country}}^{\mathrm{elec}} + \mathrm{EUI}_{\mathrm{base}}^{\mathrm{therm}} \times \mathrm{EF}_{\mathrm{fuel}}^{\mathrm{therm}}\Big), \tag{C4}$$

$$\mathit{Emissions}_j^{(\mathrm{GB})} = \mathrm{Area}_j\Big(\mathrm{EUI}_{\mathrm{proj}}^{\mathrm{elec}} \times \mathrm{EF}_{\mathrm{country}}^{\mathrm{elec}} + \mathrm{EUI}_{\mathrm{proj}}^{\mathrm{therm}} \times \mathrm{EF}_{\mathrm{fuel}}^{\mathrm{therm}}\Big), \tag{C5}$$

$$\mathit{AvoidedEmissions}_j^{(\mathrm{GB})} = \mathit{BaselineEmissions}_j^{(\mathrm{GB})} - \mathit{Emissions}_j^{(\mathrm{GB})}. \tag{C6}$$

For *renewable energy*, the baseline is the grid mix for the same MWh, while project emissions reflect technology lifecycle (or operational) factors:

$$\mathit{BaselineEmissions}_j^{(\mathrm{RE})} = \mathrm{MWh}_j \times \mathrm{EF}_{\mathrm{grid}}^{\mathrm{elec}}, \tag{C7}$$

$$\mathit{Emissions}_j^{(\mathrm{RE})} = \mathrm{MWh}_j \times \mathrm{EF}_{\mathrm{tech}}^{\mathrm{elec}}, \tag{C8}$$

$$\mathit{AvoidedEmissions}_j^{(\mathrm{RE})} = \mathrm{MWh}_j\big(\mathrm{EF}_{\mathrm{grid}}^{\mathrm{elec}} - \mathrm{EF}_{\mathrm{tech}}^{\mathrm{elec}}\big). \tag{C9}$$

Baseline definitions for transportation and forestry adhere to the same principle—selecting the conventional alternative for the same service and geography.