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The Determinants and Pricing of Green Bond Issuances: Evidence from the Transportation Sector

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Abstract

ESG practices have gained prominence and become increasingly integrated into corporate strategy, driven by heightened environmental awareness. In this context, green bonds have emerged as key financial instruments, allowing companies to raise capital for sustainability-oriented investments while aligning environmental goals with financial incentives, particularly in high-emission sectors such as transportation.

The first objective of this dissertation is to investigate the factors driving green bond issuance, focusing on whether issuers tend to operate in structurally less carbon-intensive sectors and the extent to which climate awareness influences this relationship. Secondly, is to determine whether green transportation firms (GTF) benefit from a pricing advantage - the "greenium"- compared to brown transportation firms (BTF) that issue conventional bonds while also controlling for whether any pricing advantage depends on controls such climate awareness countries or carbon intensity sectors.

Using a dataset of 174 transportation firms from 2013 to 2022, including 117 green bond deals, we examine the first research question using firm-level T-tests and logistic regressions and we assess credit spread differences using deal-level T-tests and OLS regression analyses. Findings reveal that firms operating in high carbon sectors are more likely to issue green bonds, but this effect materializes only in countries with high climate awareness, where the likelihood of issuance is substantially higher than in less environmentally conscious jurisdictions. Untabulated results on the evolution of CO_2 emissions indicate reductions or stability after issuance, suggesting no evidence of greenwashing. The second analysis show no statistically significant evidence of a consistent and universal greenium, but rather a conditional one: some pricing advantages appear when controlling for climate awareness and carbon intensity.

This research contributes sector-specific evidence to the green finance literature, highlighting the financial and environmental implications of green bonds.

Keywords: Green Bonds, Conventional Bonds, Climate Change, Climate Awareness, Sustainable Finance, Greenium, Carbon Intensity, CO_2 emissions

Resumo

As alterações climáticas representam um dos maiores desafios globais. Nos últimos anos, as práticas ESG (Ambiental, Social e de Governação) têm registado avanços significativos, impulsionadas pela crescente consciencialização empresarial. As obrigações verdes surgem como instrumentos financeiros centrais, permitindo às empresas financiar investimentos sustentáveis e alinhar objetivos ambientais com incentivos económicos, especialmente em setores de elevada intensidade carbónica, como os transportes.

O primeiro objetivo desta dissertação é investigar os fatores que influenciam a emissão de obrigações verdes, nomeadamente se os emitentes operam em setores menos intensivos em carbono e em que medida a consciencialização climática afeta esta relação. Posteriormente, procura-se avaliar se empresas de transporte "verdes" (GTF) beneficiam de uma vantagem de preço – "greenium" – face a empresas "castanhas" (BTF), que emitem obrigações convencionais, considerando o papel da consciencialização climática nacional e da intensidade carbónica setorial.

Com dados de 174 empresas de transporte (2013–2022), incluindo 117 emissões verdes, analisamos a primeira questão com testes-T e regressões logísticas ao nível da empresa e avaliamos diferenças nos spreads com testes-T e regressões OLS ao nível da emissão. Os resultados mostram que empresas em setores mais intensivos em carbono são mais propensas a emitir obrigações verdes, mas este efeito materializa-se apenas em países com elevada consciencialização climática, onde a probabilidade de emissão é maior do que em países menos conscientes. Resultados não tabulados sobre a evolução das emissões de CO_2 evidenciam reduções ou estabilidade após a emissão, não se verificando indícios de greenwashing. A segunda análise não revela um greenium consistente e universal, apenas condicional: algumas diferenças de preço surgem apenas quando se controlam fatores de consciencialização climática e intensidade carbónica.

Esta dissertação contribuiu com evidência setorial específica para a literatura, destacando implicações financeiras e ambientais das obrigações verdes.

Palavras-chave: Obrigações Verdes, Obrigações Convencionais, Alterações Climáticas, Finanças Sustentáveis, Greenium, Intensidade Carbónica, Emissões de CO_2

AI Disclaimer

In the preparation and completion of this dissertation, AI tools were ethically utilized to enhance both the quality and precision of the work. It was specifically employed to ensure the clarity and professionalism of the written content, assisting in the formulation and refinement of the text, and helping articulate complex ideas coherently throughout the dissertation. The use of AI in these capacities was carefully managed to preserve the originality and integrity of the research and its findings. Additionally, AI assisted with coding in STATA and Python, facilitating the construction and validation of the necessary models for this study. This application enabled more efficient data analysis and model building, ensuring robust and accurate results. The use of AI in this context adhered to ethical guidelines, ensuring that the assistance provided did not compromise the scientific rigor or authenticity of the research.

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1. Introduction

The transportation sector has historically been a major contributor to greenhouse gas (GHG) emissions, accounting for approximately one-quarter of global emissions until 2022 (Wang *et al.*, 2022). This was largely due to the reliance on fossil fuels as the primary energy source for transportation.

In addition to its direct environmental footprint, the transportation sector faces significant transition risk - the financial and operational risks that arise from the shift toward a low-carbon economy. According to the United Nations Environment Programme (2024), these risks stem from increased carbon pricing, policy pressures, rapid technological advances (electrification and alternative fuels) and evolving consumer preferences. Given the sector's dependence on long-lived assets and infrastructure such as vehicles, railways, and airports, as well as high sunk costs in fossil-fuel-based technologies, transportation firms are particularly exposed to policy shocks and stranded asset risk. This combination makes the sector a priority for both policymakers and investors seeking to align portfolios with net-zero pathways (Ansari & Holz, 2020).

From a financial perspective, the transportation sector is characterized by high capital intensity, substantial infrastructure investments and a structural reliance on debt financing (Graham *et al.*, 2015). Transport projects often require large upfront capital expenditure (CAPEX), which is typically financed through long-term debt issued in capital markets or via bank loans (Frank & Goyal, 2009; Mazanec, 2023). The prevalence of tangible and immovable assets, such as vehicle fleets and transport networks, provides ample collateral for securing debt.

In recent years, with an increased focus on Environmental, Social, and Governance (ESG) factors, companies have become more aware of the climate challenges we face and are beginning to pursue more sustainable projects (Martiny *et al.*, 2024). Green bonds have emerged as a pivotal mechanism among various financial instruments as they allow companies to raise capital specifically for eco-friendly and sustainable projects. Historically and according to the 2023 Climate Bonds Initiative, this financing model has aligned well with the sector's long-term investment horizons, and transportation has been among the pioneers in adopting green bonds. Beyond enhancing corporate reputation among investors and stakeholders, green bonds can offer financial incentives, such as tax benefits and subsidies aimed at encouraging sustainable practices (Hu *et al.*, 2025).

Despite the growing prominence of green bonds, there remains a notable research gap concerning their actual impact on both the determinants of green bond issuance and financial metrics within the transportation sector. While some studies suggest that green bond issuance can lead to reduced carbon emissions and lower costs of capital (Bancel & Glavas, 2021; ElBannan & Löffler, 2024; Flammer, 2021; Pang *et al.*, 2024), the specific effects on transportation firms remain unstudied. Moreover, other empirical findings remain mixed, with studies questioning the existence of a consistent "greenium", a yield premium associated with green-labelled instruments (Flammer, 2021; Larcker & Watts, 2020).

The purpose of this study is twofold. First, we aim to study which are the determinants of the probability of issuing green bonds, including whether companies that issue green bonds (green transportation firms, GTF) tend to operate in structurally less carbon-intensive sectors compared to companies that do not issue green bonds (brown transportation firms, BTF), and whether this relationship is influenced by firms operating in climate-aware countries. For that, we use t-tests and binary choice models at the firm-level. We followed Flammer (2021) and Ilhan *et al.* (2021) adapting their methodology to our research question.

Second, we aim to evaluate whether these GTF exhibit lower costs, namely, credit spreads at the issuance date (in the primary market), compared to BTF, and whether this pricing differential is influenced by carbon intensity sectors and climate aware countries. For that, we use t-tests to compare the mean credit spread between GTF and BTF, to assess if there are pricing differences between the two groups. Furthermore, we also use a deal-level regression analysis to confirm the results of the t-test analysis while controlling for fixed effects. We followed Marques & Pinto (2020) and Flammer (2021) to align with our research objectives and replicate the analysis typology.

For the quantitative section of our study, common to both research questions, we use the dataset from Dealogic/DCM Analytics covering the period from 2013 to 2022 which focuses on 174 transportation firms, totalling 611 deals (117 green deals and 494 conventional deals). For the CO_2 emissions analysis, we make use of the dataset from LSEG Workplace comprising a sample of 732 companies that operate in the same industries and countries as those in our Dealogic/DCM Analytics sample, and for which scope 1 CO_2 emissions data is available. In addition, we complement these datasets with firm-level characteristics obtained from Orbis and LSEG Workspace.

With respect to the main results of this study, our initial analysis using logit models reveals that higher carbon intensity sectors (measured using Scope 1 emissions and TRBC

industry classification) and firms operating in climate-aware countries are positively and significantly associated with green bond issuance. These results suggest that firms operating in high emitting sectors potentially face greater energy transition efforts and therefore exhibit stronger incentives to issue these instruments as a strategic response (Ilhan *et al.,* 2021). Furthermore, when analyzing the evolution of CO_2 emissions for a subsample of seventeen green bond issuers (drawn from our initial sample of 58 firms in the Dealogic/DCM Analytics dataset), we observe, in untabulated results, a significant reduction in emissions for eight issuers after the green bond issuance (relative to their three-year pre-issuance average), while emissions remained broadly stable for the others. Taken together, these findings provide no evidence of greenwashing.

Regarding the financial effects of green bonds, our research finds no evidence of a universal greenium in the transportation sector. While green bonds display, on average, slightly lower credit spreads than conventional bonds, this difference is not statistically significant when considering the overall sample. However, results also reveal that the presence of a greenium depends on contextual factors: in climate-aware countries, green bonds are associated with significantly lower spreads, while in less climate-conscious markets, they tend to carry higher spreads. Similarly, in high-carbon-intensity sectors, green bond issuance may act as a credible signal of transition commitment, modestly reducing credit spreads. Taken together, these findings suggest that the greenium is conditional rather than universal and shaped by market awareness and sectoral characteristics.

This research contributes to the literature by providing empirical and novel evidence specific to the transportation sector, which is one of the most carbon intensive. Within the determinants of green bond issuance, we found that climate awareness, carbon intensity, size, profitability and firm age significantly impacts it. The second analysis contributes to the theoretical debate surrounding the existence of a significant greenium, by accounting for the role of climate awareness and sectoral carbon intensity.

The remaining of the research is organized as it follows. Section 2 provides a literature review, developing the hypothesis to be studied. Section 3 defines the sample of the analysis and description statistics about the database used. Section 4 describes the methodology utilized to test our research questions, including the specification of the models and regressions. Section 5 presents the results and delves into the discussion behind the results. Section 6 describes some robustness checks. Finally, section 7 displays conclusions, practical implications, limitations, and future research topics.

2. Literature Review and Research Questions

2.1 Transition and Physical Risk in the Transportation Sector

Climate risk has become a central concern for investors, firms, and policymakers, as these economic agents may face losses as the global economy transitions to a low-carbon model (Battiston *et al.*, 2021). Transition risk is considered a specific category of climate risk resulting from the global transition to a greener economy. According to Schoenmaker & Schramade (2019) this will involve large-scale structural changes, causing regulatory, social and geopolitical pressures along with changes in investor expectations on how to allocate their capital.

In this context, with the development of sustainable initiatives, ESG framework, and the United Nations' 2030 Agenda for Sustainable Development, which consists of 17 Sustainable Development Goals, the regulatory environment is moving towards incorporating sustainability issues and transition risks. Namely, some sectors will have to expand their relative production and capital allocation rapidly, and others will have to transform their technological basis entirely (Battiston *et al.*, 2021).

Within the sectors with high exposure to transition risk, Ahmed *et al.* (2024) and Ballester *et al.* (2024) highlight the transportation and energy as the ones facing more regulatory and technological disruption. Nonetheless, Ahmed *et al.* (2024) reinforces the importance of achieving economic growth across different countries, promoting education and health, clean energy, food production, agriculture and building and transportation. The United Nations Environment Programme (2024) also referred to agriculture (the chemical ammonia used as a fertilizer), oil & gas and heavy industrials, such as cement manufacturing, iron and steel production and plastics industries as climate risk sectors.

Regarding the broader macroeconomic effects of climate transition risk apart from energy-related industries, Jin *et al.* (2024) examine the impact of this transition on housing market bubbles in Chinese cities. The study finds that as China shifts towards cleaner energy - driven by government policies that incentivize investment in green sectors - there is a 39% decrease in the housing bubbles index. This is explained by the reallocation of capital towards the renewable energy sector. This shift also indicates a move towards sustainable investments, helping to mitigate the risk of future capital allocation leading to burdens.

Among all sectors, transportation stands out as one of the fastest-growing sources of greenhouse gas (GHG) emissions, with an average annual rate of 1.7% from 1990 to 2021,

according to the United Nations Environment Programme (2024). Moreover, estimates from the World Bank for 2025 state that the transportation sector is responsible for approximately 23% of global CO_2 emissions from fuel combustion and around 20% of total GHG emissions. It includes road, rail, air, and water transport, each presenting significant technological and regulatory transition challenges. Complementing this, the United Nations Environment Programme (2024) considered the road subsector the largest contributor to emissions within the transportation category, accounting for 74% of global transportation CO_2 emissions, followed by shipping (11%) and aviation (10%). Moreover, the expected tripling of passenger and freight transport demand by 2050, particularly in emerging economies, will further intensify the sector's environmental impact unless decarbonisation accelerates.

Within this background, the European Green Deal sets a goal of reducing GHG emissions in the transport sector by 60% until 2050, underlining the urgency and complexity of decarbonizing mobility systems. Additional pressures, such as lawsuits and legal actions, as well as policy restrictions like the ban on internal combustion engine (ICE) vehicles by 2030-2035 in over 20 countries, subsidies for low-carbon fuels and carbon pricing mechanisms are being implemented to enforce environmental accountability among transportation companies (Wang *et al.*, 2020). These measures are increasing the legal and reputational risks faced by the sector.

Additionally, Wang *et al.* (2020) highlight this sector as more vulnerable to climate-related disruptions and increasing climate events such as flooding and extreme temperatures. Given that climate change is an irreversible process, the study reinforces the need to combine mitigation with an adaptation strategy, aiming to minimize potential harm and maximize opportunities arising from these changes within transport systems while accepting that climate change is already occurring, instead of focusing only on mitigation.

These figures underscore the transportation sector's high exposure to transition and physical risk, justifying our primary focus on this sector while aiming to contribute to the existing literature. Using a machine learning approach to analyse over 10,000 earnings call transcripts, Sautner *et al.* (2023) reveals that companies in sectors with high transition risk, such as transportation, experience different levels of climate exposure. In contrast, firms that actively pursue climate-related opportunities, such as clean tech innovation, receive positive reactions from investors and achieve better sustainability outcomes. This also underscores the significance of green bonds as tools for demonstrating climate commitment and managing transition risk, particularly in sectors facing intense environmental and market scrutiny.

Accordingly, next we proceed to review the specificities of green bonds, including the features that differentiate them from conventional bonds.

2.2 An overview of Green Bonds

Flammer (2021) emphasise the development of sustainable finance and growing awareness among various sustainable finance instruments. In the field of green bonds, the author explains the increasing popularity of corporate green bonds, often referred to as the "green bond boom", which are issued by private corporations specifically to fund projects with environmental benefits in firms or industries where environmental issues directly impact financial performance. These instruments help mobilize funding for sustainable environmental projects and facilitate the transition to a low-carbon economy, including renewable energy and clean transportation.

The study shows that between 2013 and 2018, the issuance of corporate green bonds increased by more than $90 billion. Moreover, although the issuance of these bonds implied the rise of administrative and compliance costs (since these instruments have to be supervised by a third party) compared to conventional bonds, the results suggest that issuers of corporate green bonds improve their environmental performance (by reducing the amount of "waste, water usage and greenhouse gas emissions") and reinforce their commitment to climate-friendly projects by aligning their financial strategies with sustainability goals. This third-party supervision reflects the green bond certification process, which is required when issuing green bonds to ensure that the proceeds are used to fund projects that provide environmental benefits. It also contributes to improved transparency, credibility, and investor confidence (Ahmed *et al.*, 2024; Flammer, 2021)

According to Ahmed *et al.* (2024), green bonds are the leading examples among various asset classes and subclasses, including social bonds (which focus on social benefits), sustainability bonds (which combine environmental and social objectives), and SDG bonds (which are aligned with the United Nations Sustainable Development Goals). This diversity reflects the growing demand in the market for green bonds and the innovative structuring within the field of sustainable finance since its first issuance by the European Investment Bank in 2007, namely the "Climate Awareness Bond".

Tolliver *et al.* (2019) delve into the importance of the Paris Agreement of the United Nations Framework Convention on Climate Change in mitigating and in creating a transparent framework for countries to report their climate achievements and metrics. The authors

conclude that green bonds are becoming increasingly relevant to potential institutional and socially responsible investors (SRIs) for financing sustainable and environmentally friendly projects that minimize carbon dioxide emissions. One of the reasons highlighted in the article is that SRIs perceive climate green bonds as a safe and worthwhile long-term investment. Nevertheless, despite the growing investment of proceeds, it still falls short of the objectives of the Paris Agreement, resulting in an investment gap. These findings emphasize the need for policy efforts to complement financing through green bonds by allocating proceeds to renewable energy in order to enhance robustness[1].

In line with this, Mertzanis & Tebourbi (2024) delve into the significance of both economic (such as cost of capital, regulatory policies and shift in investor demand) and non-economic factors (including transparency, environmental awareness and international agreements) in incentivizing the issuance of green bonds due to greater awareness related to sustainable finance, especially during geopolitical instability. This instability often causes investors to take a risk-averse approach, reducing the demand for green bonds. However, as geopolitical tensions lead to more restrictions on carbon emissions, it is also argued that green investments could be a valuable hedging strategy against climate change and environmental degradation, contributing to lower market volatility and greater investment predictability.

Corroborating the findings of Mertzanis & Tebourbi (2024), Ben Ameur *et al.* (2024) use the wavelet conditional value-at-risk ratio to conclude in favor of adding green bonds to conventional portfolios to take advantage of this safe-haven investment, reducing the overall risk of the portfolios. The results of these diversification benefits were robust during normal market conditions (pre-Covid-19 pandemic) and especially during volatile market conditions in the short term (post-Covid-19 pandemic). However, the findings were limited in the long term, because of the systematic risk of portfolios that cannot be reduced.

Lam & Wurgler (2024) explore one of the key characteristics of green bonds which is "additionality". They examine whether the proceeds from these instruments are truly used to finance unique environmental projects or if they are simply being allocated to refinance ongoing projects or support non-eco-friendly initiatives. This contrasts with conventional bonds, where companies raise funds with no specific obligations on the capital's use. The study found that only 2% of the proceeds from green bonds are used to finance new

[1] Recent studies highlight that climate and green finance policies significantly shape the low-carbon transition. Wang & Gao (2024) show that China's Green Finance Pilot Zones enhance carbon welfare performance in targeted cities by promoting both the contraction of high-carbon sectors and the expansion of green industries, a dynamic they term the "squeezing-out effect".

environmental projects. The remainder of the funds is typically allocated to projects that are either already being pursued by the issuer or are similar to existing ones. As a result, the analysis suggests that green bonds may not consistently finance innovative or substantive environmental initiatives beyond what issuers were already working on. This perspective indicates that ESG-oriented investors could achieve similar environmental impacts through traditional financing methods, making the "green bond" label of limited assurance for significant contributions to novel initiatives.

An additional feature mentioned by Henide (2022) is that some green bonds include performance-linked interest adjustments in which if environmental goals (referred as the "trigger event") of the project are not met by maturity, issuers may face increased interest costs on final payments, according to the key performance indicators (KPIs). This mechanism introduces "skin-in-the-game", aligning issuers with longer-term environmental goals.

2.3 Conceptual framework of green bonds

Flammer (2021) identifies two main theories that explain a company's rationale for issuing green bonds: the signaling theory and the greenwashing argument.

The signaling theory from Spence (1973) suggests that the issuance of green bonds serves as a signal that a company is committed to investing in sustainable projects that will enhance its environmental impact. This practice helps reduce information asymmetry and addresses aspects of the agency theory. By sending this "signal", companies clarify to shareholders their true commitment to eco-friendly initiatives, thereby helping investors who may lack sufficient information to assess the companies' dedication to sustainability accurately. Namely, given the amount of money allocated to green projects, it shows that companies are truly committed. Moreover, since green bonds are certified, it guarantees that the proceeds are being allocated fairly to finance green projects. Lastly, non-compliance with this certification and standards is costly (Flammer, 2021).

In the agency theory, such signaling mechanisms are especially relevant when there is a misalignment between managers (agents) and shareholders (principals), and when shareholders cannot directly observe whether firms are genuinely pursuing sustainable goals. Green bonds can thus act as a bonding strategy, which is an action taken by management to align with shareholder interests. Their effectiveness as a signal depends on credibility, which is often reinforced by third-party certification or adherence to recognized standards such as

the Green Bond Principles[2]. This helps distinguish sincere climate commitment from mere greenwashing (Flammer, 2021; Jensen & Meckling, 1976).

On the other hand, with increasing pressure to reduce GHG emissions and growing climate awareness in society, the "greenwashing" argument suggests another purpose for issuing green bonds. Firms might issue green bonds for reputational effects, providing misleading statements about the environmental impact of the financed projects to persuade the public that they are environmentally friendly. In this view, companies may appear committed to sustainability without actually improving their environmental performance after issuing green bonds, thereby taking advantage of the green label without delivering real environmental benefits (Liu *et al.*, 2024; Wei *et al.*, 2023; Yeow & Ng, 2021). However, Flammer (2021) and García *et al.* (2023) did not conclude in favour of the greenwashing argument.

2.4 Research Question 1: What are the determinants of green bond issuance?

The literature shows that the choice to issue a green bond rather than a conventional bond is driven by a combination of traditional financing determinants, bond-specific features, firm strategy (signaling and reputation), and the regulatory and market environment. Empirical studies find that green-bond issuers tend to be larger, more capital-intensive, have stronger environmental performance, and exhibit lower leverage compared with conventional-bond issuers (Flammer, 2021; Ge & Liu, 2015; Lin & Su, 2022).

At the firm level, size and tangibility are robust positive predictors: large, asset-heavy firms are more likely to issue green bonds because they undertake long-horizon, capital-intensive projects that match eligible uses of proceeds (Belén *et al.*, 2020; Cicchiello *et al.*, 2022). Larger companies are also expected to have better access to capital markets and greater financial capacity to bear the costs typically associated with green bonds - such as certification, reporting and compliance with standards - while also enjoying greater visibility and facing stronger stakeholder pressure regarding their environmental footprint (ElBannan & Löffler, 2024; Flammer, 2021; Ilhan *et al.*, 2021; Khan & Vismara, 2025).

Financial constraints also play a role: according to Wei *et al.* (2023), one of the primary reasons to issue green bonds is to ease financial constraints. Higher liquidity can signal

[2] Another way companies signal their commitment to sustainability and shareholder interests is through dividend distribution, which, while approved by shareholders, is initiated and proposed by managers. Dividends signal financial health and commitment to shareholder value, just as green bonds signal environmental responsibility and alignment with long-term sustainability goals, reducing the agency problems (Jensen & Meckling, 1976).

financial health and the ability to meet obligations, making debt issuance, including green bonds, more feasible (Flammer, 2021; Yu *et al.*, 2025; Zhang *et al.*, 2021). Similarly, higher profitability increases a firm's capacity to invest in environmental projects and absorb issuance costs, consistent with the idea that these firms can align financial returns with sustainable impact (Flammer, 2021; Khan & Vismara, 2025).

The effect of leverage is less clear. While higher leverage can reduce the likelihood of issuing green bonds, as the allocated use of proceeds limits refinancing flexibility and highly indebted firms may be viewed as riskier and less credible in their long-term environmental commitment (Flammer, 2021; Lin & Su, 2022), some evidence suggests the opposite. More indebted firms may issue green bonds as a tool to refinance debt or to signal sustainability to attract ESG-focused investors, meaning that, under certain conditions, higher leverage could actually increase the probability of green bond issuance (Makpotche *et al.*, 2024).

Contractual and issuance factors also matter. While green bonds often have longer maturities to match the horizon of eligible projects, longer bond maturities may require larger issue sizes, which can raise financing costs and, in some cases, make conventional bonds more attractive (Gianfrate & Peri, 2019; Lin & Su, 2022).

In addition to traditional financial and contractual determinants, carbon intensity emerges in the literature as another key driver of green bond issuance. For example, between 2013 and 2018, Flammer (2021) documents that the transportation and logistics sector accounted for approximately $13.8 billion in green bond issuance, indicating a growing adoption of sustainable financing tools in this carbon-intensive industry. To delve into the increasing evolution of green bond issuance over time, focusing on industries such as utilities, energy, and transportation, Flammer (2021) finds that firms issuing green bonds subsequently reduce CO_2 emissions, thereby improving their environmental performance.

Lu *et al.* (2024) focus on the connection between sustainable finance and achieving carbon neutrality in the Chinese transportation sector, addressing the urgent need to mitigate the impact of carbon emissions on air pollution and climate change. By including both public and private sector funding, the study found a positive correlation between sustainable finance mechanisms, including the issuance of green bonds, and the reduction of carbon emissions in the transportation sector.

Considering key determinants of the green bond issuance and using a sample covering the period between 2013-2021, the study from García *et al.* (2023) also found that firms who issued these green instruments reduce their volume of CO_2 emissions compared to

those that only issued conventional bonds and continue to enrol in environmentally friendly projects years after the issuance, highlighting their environmentally conscious practices.

In order to explore the impact of green finance (GF) on carbon emission intensity (CEI), Zhang *et al.* (2025) examine a Chinese panel from 2011 to 2020. The study showed that increased green finance is consistently associated with lower CEI, making use of green technology innovation to achieve its environmental goals. Moreover, green finance not only reduces emissions where it is applied but also indirectly affects nearby regions through economic interconnectivity and policy diffusion.

Khan & Vismara (2025) used a different approach to evaluate the same matter: a meta-analysis. The study concluded in favor of green bonds in promoting environmental sustainability, by financing projects that reduce emissions. However, their success depends heavily on robust certification and oversight mechanisms. Confirming this, Yeow & Ng (2021) found that firms issuing of green bonds improve its overall environmental performance, but only when they are externally certified (certified by third parties).

ElBannan & Löffler (2024) also found that carbon emissions declined after first green bond issuance. However, this relationship weakens once they control for additional factors such as the volume of green bonds issued. The reduction in carbon intensity is concentrated among firms that are financially constrained and have high credit risk, which likely benefit more from the alternative funding channel that green bonds provide. In contrast, for firms with low credit risk and low financial constraints, the study does not find significant reductions in carbon emissions after green bond issuance.

On the other hand, Guesmi *et al.* (2025) revealed no significant relationship between green bond issuance and reduced carbon emissions in neither of the 3 years following that issuance. Even after conducting the same differences in differences analysis as in Flammer (2021), the results produced different conclusions between the two studies.

Overall, the evidence broadly suggests a negative relationship between green bond financing and CO_2 emissions, meaning higher green bond issuance is associated with subsequent reductions in emissions. Nonetheless, more recent evidence suggests that the environmental impact may vary depending on firm-specific factors, such as financial constraints or risk profile. On the other hand, there is still a research gap concerning the impact of sectoral carbon intensity and climate awareness in green bond issuance in the transportation sector.

2.5 Research Question 2: Is there evidence of a greenium?

A greenium refers to a yield premium (typically negative) that green bonds may benefit over conventional bonds, suggesting that investors are willing to accept lower returns in exchange for financing environmentally sustainable projects (Flammer, 2021).

According to the 2022 OECD report, which discusses the evolution of the greenium, it is observed that green bonds can present lower yields than conventional bonds, particularly in sovereign and public sector green bonds, including Germany, Egypt, Thailand, Indonesia, and Chile. However, as the supply of green bonds increases, specifically in developed markets, there are signs that the greenium is fading. In contrast, the greenium may persist in emerging markets where green bond supply is still catching up with demand (Kim *et al.*, 2022).

Using a binary choice regression and a sample of bond issuances since 2016, Lin & Su (2022) find that green bonds may attract issuers due to lowering direct issuance costs. This was corroborated by its results, which stated that the mean cost of green bonds is lower than the mean cost of conventional bonds. Moreover, firms are more likely to issue green bonds when intending to lower financing costs and when their overall financing needs are relatively small.

Tolliver *et al.* (2019) evaluate the role of green bonds in supporting the Paris Agreement and UN Sustainable Development Goals (SDGs), using a sample covering the period 2008-2017. Considering the difference in returns between green bonds and comparable non-green bonds, the authors found that green bonds often have a negative yield premium compared to comparable non-green bonds, suggesting that they are issued at lower yields. In line with this, Wu (2022) reveals that green bonds are often issued at lower yields than conventional bonds in both Chinese and global markets, largely due to strong demand from environmentally conscious investors willing to accept lower returns to support sustainable projects. This "greenium" is also reinforced by investor preferences for sustainable investments.

These findings suggest that the greenium emerged strongly in the years following the Paris Agreement on climate change in 2015, when investor demand for green financial assets increased substantially compared to the limited available supply of certified green projects. As a result, the scarcity of these assets made them more attractive and investors were willing to pay a premium for green bonds, increasing their prices compared to conventional bonds, ultimately leading to a pricing premium (Dragotto *et al.*, 2025).

On the other hand, Flammer (2021) reports that between 2013 and 2018, investors

do not appear to accept lower yields for green bonds, so there is no evidence of a greenium. This could be justified due to the significant increase in green bond issuance during that period, referring that before 2013, its issuance was almost non-existent. Following this logic, Larcker & Watts (2020) study whether a greenium exists in the U.S. municipal bond market issued between 2013 and 2018. The authors found no significant pricing difference at issuance between the yields of green and brown bonds, indicating no evidence of a green bond premium. Despite equal pricing at issuance, green bonds begin to trade at lower yields in the secondary market, suggesting investor preference for green bonds emerges post-issuance.

Berdiev (2025) studies Japan's primary corporate bond market between 2016 and 2023, reporting the existence of a greenium for firms with strong environmental performance in the initial years, but observing a reaching of the yield spread differences after 2021, providing evidence that the greenium has disappeared. These findings indicate that in more recent years, as the green bond market matured and supply increased, the existence significant yield advantage for green bond issuers has faded, aligning with Flammer (2021).

In sum, the existing literature presents mixed evidence regarding the existence of a greenium in the transportation sector. While some studies confirm the presence of a negative yield premium (greenium) in several markets, especially in the early stages of the green bond market, as the green bond market matured and issuance volumes increased, other studies observed a reduction or no evidence of the greenium.

3. Data

3.1. Sample Selection and Scope

For the quantitative section of our study, we use the dataset from Dealogic/DCM Analytics to answer both research questions.

The dataset covers the period from 2013 to 2022[3], including bonds from 52 countries worldwide. We then restrict the scope to the transport sector, which include 725 transportation firms globally, encompassing a wide range of entities, including airports, railway operators, and highway managers. Based on the criteria outlined in sections 3.2 and 3.3, a total of 58 firms issuing green bonds and 116 comparable firms issuing conventional bonds were identified. While the majority of issuers are based in OECD countries, the sample also includes notable cases from non-OECD regions, such as China, Russia, and Hong Kong, totalling 19 countries. Since the dataset was originally organized by tranches, we proceed to reorganize it by deals and firms, that we then use in the analysis in the next subsections.

Common to both econometric analyses, we also use data on carbon emissions, which was collected from the London Stock Exchange Group (LSEG) Workspace, covering the period from 2013 to 2022. The coverage of CO_2 data was not sufficient for all firms in the sample. Consequently, we adapt the methodology proposed by Ilhan *et al.*, (2021), classifying subsectors as high or low carbon intensity based on aggregate sectoral data from firms for which CO_2 information is available, rather than relying solely on the firms in our sample. Applying this approach, we extracted data on all public companies in the LSEG with available CO_2 information (scope 1), located in the same countries and operating in the same industries as our original sample. This procedure resulted in a dataset of 732 firms with available information, ensuring that our analysis remains consistent throughout the study. The details of this methodology are presented in section 3.6.

Next, to classify countries according to climate change awareness, we use the survey data from the European Investment Bank (EIB) as our primary source, which has been conducted periodically since 2018–2019[4]. The EIB survey captures public concern about climate change, offering a demand-side perspective that is closely linked to real-world climate action and decision-making. Since not all survey waves include the same questions, we select the period that best aligned with the objective of our study. Specifically, we use the question that

[3] Due to data limitations, we were unable to obtain additional information from more recent years.
[4] According to https://www.eib.org/en/surveys/climate-survey/index

asked for the "percentage of respondents who stated that they were concerned or alarmed about climate change". Therefore, the EIB data offers a direct and conceptually appropriate measure of climate awareness for the purpose of this study.

3.2. Green Transportation Firms and Bond Issuances

To identify the green transportation firms (GTF), we begin by modifying the Dealogic/DCM Analytics dataset to focus on green bond issuers. For the purposes of this study, we categorized GTF as those entities classified as "Green" and "Sustainability" within the Green Bond Instrument framework. The decision to also incorporate sustainability bonds in the framework of "Green Transportation Firms" was made because the tranche notes indicated that these bonds were linked to green projects.

From the group of 725 transportation firms, we identify those classified as "Green" or "Sustainability" bonds, reducing the sample to 58 green transportation firms, of which 38 also issued conventional bonds. One limitation of the dataset is the small number of firms that have issued green bonds in the transportation sector. To address this, we decided to include the 38 firms that issued both green and conventional bonds as part of the GTF group. This decision was made to preserve the analytical strength of our sample. Excluding these firms from both the GTF and Brown Transportation Firms (BTF) categories would have reduced the GTF group to just 20 firms, thereby undermining the statistical power and potentially compromising the robustness and feasibility of our analysis.

Focusing on the deals, the total sample consists of 117 green deals, the majority of which were made from 2019 onward[5]. Within these 117 green deals, issued by 58 different entities, we can highlight that most of the issuers (totalling 39) issued only one green bond. On the other hand, the remaining 19 issuers issued more than 2 bonds. Although, as a minority, this could be a positive sign for the evolution of the green bond market[6].

3.3. Brown Transportation Firms and Bond Issuances

To conduct our analysis, we need to find a suitable control group comprised of select firms that issued conventional bonds to compare with each of the 58 firms that issued green

[5] For brevity reasons, some details regarding the sample composition were deferred to the Appendix 3: Sample selection of the matching analysis in section 9.3.
[6] For brevity reasons, some details regarding the sample composition were deferred to the Appendix 3: Sample selection of the matching analysis in section 9.3.

bonds ("treated group") (Flammer, 2021). We categorize BTF as those firms not classified as "Green" and "Sustainability", meaning firms that issued conventional or social bonds. This requires us to establish criteria that would make the comparison viable by employing an adapted version of the "matching methodology" employed by Flammer (2021). We aim to accurately assess how these green transportation firms would perform if they had issued conventional bonds instead.

Following the approach outlined by Flammer (2021), we first manually identify the BTF, resulting in a total of 667 firms. This number also accounts for the fact that we exclude the 38 firms that issued both types of bonds from the BTF sample. Within this group, we retained only the observations of firms with a country of nationality that was included in the bins of countries associated with the 58 GTF. We applied the same criteria to the Company Primary SIC. Regarding deal size (given by the Total Deal Value in EUR), we conduct a statistical analysis for the treated group (GTF) to examine the deal sizes of all 58 green transportation firms within specific ranges of values. This allowed us to exclude any BTF whose deal values fell outside these ranges. We apply the same procedure for the Pricing Date. Since the first issuance of green bonds occurred in 2015 in our dataset, we only include observations for the conventional deals starting in that year. After applying these filters, we ended up with a total of 212 BTF, a significant reduction from the initial 667 firms[7].

Next, after extracting the relevant firm-level characteristics described in section 3.4, we exclude companies with no available information. For those with partial records, we retained only those with at least five consecutive years of available data to be used in the regression analysis[8]. This filtering process resulted in a final sample of 116 brown transportation firms (BTF), comprising 494 deals. Accordingly, the dataset includes a total of 116 BTF and 58 green transportation firms (GTF)[9].

[7] The Appendix section 9.3 contains information regarding the descriptive statistics of the matching analysis concerning the country of incorporation, sub-industry, deal value, pricing year and credit rating of both green and conventional firms and deals.

[8] We excluded firms that lacked data for the key variables used in the regressions, as these are central to our analysis. In particular, we required the availability of data for consecutive years to avoid temporal imbalance and ensure consistency over time.

[9] We did not proceed with the third step of Flammer (2021) approach, which consists of selecting the nearest neighbor via the lowest Mahalanobis distance to the treated firm within some selected matching characteristics. Given the small number of observations in our sample, we would be dealing with geographic imbalance by allowing one Chinese firm, for example, to be matched and used as a comparison with, for example, a Spanish company. Moreover, given that the ratio of brown transportation firms to green transportation firms is only two to one, we considered it neither appropriate nor relevant to further reduce the sample through a matching process.

3.4. Firm-level variables

Based on criteria used by Lin & Su (2022) and Flammer (2021), we gather relevant data for each one of the companies mentioned. The firm-level control variables used in the analysis are defined as follows. **Green Bond Issuer** is a treatment dummy that equals 1 from the year in which firm i issues its first green bond (including that year) and for all subsequent years, and 0 for all prior years (Flammer, 2021). For firms that never issued a green bond, the variable always equals 0. **Size** is measured as the natural logarithm of total assets, serving as a proxy for firm size. **ROA** captures firm profitability and is calculated as the ratio of net income to total assets. **Leverage** reflects the firm's capital structure, computed as the ratio of total liabilities to total assets. **Current Ratio** measures liquidity, defined as the ratio of current assets to current liabilities. Finally, **Firm Age** corresponds to the number of years since the company's foundation up to the year of observation. The expected sign of each variable is discussed in the literature review, section 2.4.

The issuer-specific metrics are sourced from Orbis and LSEG Workplace, except for the **Green Bond Issuer** variable, which is computed from the Dealogic/DCM Analytics dataset. All variables are employed in the regressions presented in sections 4.1, 6.1 and 6.2.2.

3.5. Sector-level variables

Industry Reclassification

Initially, in the Dealogic/DCM Analytics dataset we had green bonds distributed across 20 sub-industries and conventional bonds across 14. However, this classification is based on the Parent Company SIC (four-digit SIC code), which often capture a broad industrial profile rather than the issuer's operational reality, and many sub-industries are represented by only a few observations (see section 9.2).

Additionally, for the computation of the first research question, in which we proceed with the extraction of carbon emissions dataset as explained before, Refinitiv does not provide the same classifications as in the Dealogic/DCM Analytics dataset. To ensure we capture all relevant companies, we use a broader set of industry identifiers - specifically the TRBC Industry Group Names - since the SIC classification in Refinitiv had limited coverage. To harmonize industry classifications across datasets, we converted the original 4-digit SIC codes (Standard Industrial Classification) of the parent companies into TRBC (Thomson Reuters Business Classification) industry group names. The conversion was carried out

manually using the official crosswalk and reference tools provided by the TRBC classification portal for mapping SIC codes to TRBC industry groups[10] and is presented in **Table 1**.

To maintain the consistency between research questions throughout this dissertation, we opt to use the TRBC classification in both analyses. Our modifications regarding the sector classification are detailed in section 9.2**.**

Table 1 - SIC-to-TRBC Industry Group Mapping

SIC Code	SIC classification	TRBC classification
4581	Airports, Flying Fields & Services	Transport Infrastructure
4412	Deep Sea Foreign Trans. of Freight	Freight & Logistics Services
4731	Freight Transportation Arrangement	Freight & Logistics Services
4131	Intercity & Rural Bus Transportation	Passenger Transportation Services
4111	Local and Suburban Transit	Passenger Transportation Services
4011	Railroads, Line-Haul Operating	Transport Infrastructure
4789	Transportation Services, NEC	Freight & Logistics Services

High Carbon Intensity

For our primary variable of interest, we adopted the approach used by Ilhan *et al.* (2021) and compute a measure of the firm's industry carbon intensity by scaling carbon emissions by firms' total asset values. In line with Ilhan *et al.* (2021), we focus on Scope 1 emissions, which refer to direct carbon dioxide equivalent emissions (in tonnes) from sources owned or controlled by the company, according to the GHG Protocol from 2015[11]. In the transportation sector, such emissions primarily stem from fuel combustion in fleets, making Scope 1 the most relevant measure to assess firms' environmental impact and incentives to issue green bonds. Scope 2 emissions are not considered in this analysis, as they reflect indirect emissions from purchased electricity, which tends to be less central to the core operations of transportation firms. Similarly, Scope 3 emissions, which include outsourced transportation and upstream/downstream activities, are not considered, as they are indirect, difficult to measure accurately, and less directly tied to firms' internal decisions related to green bond issuance[12].

Specifically, this measure is calculated at the sector-year level as the sum of scope 1

[10] The TRBC detailed classification information can be found in its portal (https://classification.codes/classifications/industry/trbc).
[11] For additional details, see https://ghgprotocol.org/corporate-standard.
[12] For additional details, see https://ghgprotocol.org/corporate-standard.

CO_2 emissions (in tons) of all reporting firms within a given sector and year, divided by their aggregate market value proxied by the total assets[13]. Each firm in our original sample is assigned the average carbon intensity of its respective subsector and year. This process allows us to reasonably estimate emissions at the industry level[14] (Ilhan *et al.,* 2021).

Then, we create a time-invariant dummy variable (High Carbon Intensity) that is set to 1 for firms operating in subsectors with above-median carbon intensity before the Paris Agreement. This determination is based on the median carbon intensity across all transportation subsectors during the years 2013 and 2014. Specifically, we compared the carbon intensity median of each sector during this period to the overall carbon intensity median across all sectors using the same period[15]. The 2013-2014 window marks a period prior to the global adoption of major climate policy commitments. By anchoring the classification of emission intensity to this period, we ensure that the dummy variable is exogenous to post-Paris climate actions and not influenced by subsequent regulatory or strategic changes. This approach also mitigates endogeneity concerns, as it avoids classifying sectors based on emissions that may already reflect strategic, reputational, or regulatory responses.

One potential complication of our study would arise if the carbon intensity across subsectors was not sufficiently heterogeneous within our sample. As this analysis is restricted to the transportation industry, it is crucial to check the extent of heterogeneity in carbon intensity across its subsectors. **Table 2** reports the descriptive statistics of carbon intensity across subsectors during the pre-Paris Agreement period (2013 and 2014). The results reveal considerable heterogeneity in carbon intensity across transportation subsectors under the TRBC classification. Passenger Transportation Services show the highest average carbon intensity, followed by Freight & Logistics Services, while Transport Infrastructure reports substantially lower values. In contrast, the relatively low standard deviations within each subsector suggest that carbon intensity is homogeneous within subsectors. This highlights the importance of analyzing each transportation subsector separately when running regression

[13] For this variable, both numerator and denominator are taken from only those firms that disclose emissions (i.e., the representative sample from Refinitiv). The denominator (total assets) must match the same subset of firms to keep the intensity ratio interpretable and unbiased. The ratio when then scaled by 10000 to allow more straightforward comparison between subsectors.

[14] We decided to follow this approach after verifying how many firms from the Dealogic dataset (174 in total) were also present in our sample of 732 observations from LSEG, with available CO_2 emissions data. Our analysis revealed that only 52 firms overlapped between the two datasets - 37 from the BTF group and 15 from the GTF group. This limited overlap resulted in a sample that was too small to ensure robust results. Additionally, nearly 20 of these firms lacked complete emissions coverage over the full period, and around 10 had missing data for more than two years, further compromising the reliability of the analysis.

[15] Section 9.4 provides evidence that the subsectors are not all classified as either high or low carbon.

models. Combining all subsectors into a single model could mix emission patterns that are structurally different, making it harder to identify what actually drives carbon intensity in each case.

Table 2 - Carbon Intensity across subsectors between 2013-2014 (Pre-Paris Agreement)

TRBC	Freight & Logistics Services	Passenger Transportation Services	Transport Infrastructure
mean	1.977	3.216	0.012
sd	0.136	0.512	0.002
min	1.841	2.710	0.010
max	2.112	3.722	0.013
n	90	44	214

Note: "sd" refers to the standard deviation, "min" to the minimum value, "max" to the maximum value, and "n" to the number of observations. Carbon intensity is defined as the sum of scope 1 CO_2 emissions (in tons) of all reporting firms within a given sector and year, divided by their aggregate market value proxied by the total assets, multiplied by 10000.

3.6. Country-level variables

High Climate Awareness

Based on the 2018–2019 results of the survey data from the European Investment Bank (EIB), we calculated the median value of concern across countries. Countries with a percentage above the median were classified as having high climate awareness (High Climate Awareness = 1), while those below the median were classified as having low climate awareness (High Climate Awareness = 0). For countries not covered by the EIB survey, we supplemented the classification using the 2019 Climate Change Performance Index (CCPI) rankings (Burck *et al.*, 2019). Countries with strong CCPI scores, such as Norway and Switzerland, were assigned a value of 1 (High Climate Awareness), while those with low CCPI performance - such as Russia, South Korea, and Mexico - were assigned a value of 0 (Low Climate Awareness) (Burck *et al.*, 2019). This classification approach allowed us to construct a consistent and meaningful climate awareness indicator for the countries in our sample.

3.7. Deal level variables

Credit Spread

In order to analyse the financial effects of green bonds, we need to compute a

measure of the credit spread. For that, we adopt the approach used by Marques & Pinto (2020) in their study, following the deal-level analysis, where each observation corresponds to a distinct bond issuance in a certain year. We use the Tranche Spread to Benchmark in basis points as our variable of interest and as a proxy for the cost of the bond issued, which is available in the Dealogic/DCM Analytics dataset. For different tranches with the same deal number and different Tranche Spread to Benchmark in similar years, we computed the weighted average of that value, weighting by the Total Value EUR (Face) of each tranche, as expressed in the following formula[16]. It is also worth mentioning that for tranches with the same deal number in different years, we used the year of the first issuance as the reference point for the variable, which takes the value 1 for all years following that issuance.

$$Weighted\ Credit\ Spread\ (bp)_{dt} = \frac{\sum_j (Credit\ Spread_{djt} \times Tranche\ Value_{djt})}{\sum_j (Tranche\ Value_{djt})} \quad (3.7.1)$$

Bond-Specific Characteristics

Based on the study of Marques & Pinto (2020), for the regressions in sections 4.2 and 6.2.1, we use the following deal-level control variables. **Green Bond** is a dummy variable equal to 1 if the bond (d) is classified as green by year t and 0 otherwise (before its green issuance year and for non-green bonds in all years). **Banks** capture the number of banks participating in the bond issuance. **Callable** is a dummy equal to 1 when the bond has a call option, and 0 otherwise. **Deal Value** is measured as the natural logarithm of the total deal value in EUR, serving as a proxy for issuance size. For tranches with different deal values within the same year, we use the average deal value. **Currency Risk** is a dummy equal to 1 for bonds that are denominated in a foreign currency relative to the deal's nationality, and 0 otherwise. **Rating Number** reflects the bond's credit rating at issuance, based on Moody's scale (Gabbi & Sironi, 2002). Ratings are converted numerically as follows: AAA=Aaa=1, AA+=Aa1=2, and so on until CCC+=17, with the "Not Rated" observations corresponding to 23. Lower numerical credit rating values indicate better ratings. For tranches with bonds carrying multiple credit ratings, we compute the mean of the corresponding numerical scores. Finally, **Perpetual** is a dummy equal to 1 for bonds with a maturity of 100 years or more, which in practice captures perpetual or near-perpetual bonds with no effective redemption

[16] Where d stand for the identification (index) of each deal, j is index for each tranche within deal d issued in period t, Credit $Spread_{djt}$ is the Tranche Spread to Benchmark for tranche j in deal d at time t and Tranche $Value_{djt}$ is the Total Value EUR (Face) of tranche j in deal d at time t.

date, and 0 otherwise.

All these variables are sourced from the Dealogic/DCM Analytics dataset.

3.8. Summary Statistics

Table 3, Table 4 and **Table 5** summarize the information about the variables described before, highlighting its descriptive statistics.

According to **Table 3**, approximately 10% of the sample corresponds to observations for green firms, while around 40% operate in carbon-intensive sectors and are located in regions with high climate awareness. Additionally, the average firm exhibits a relatively large size (6.1 billion in assets = exp(22.525)), is profitable (ROA = 2.4%), moderately leveraged (39%), maintains substantial liquidity, and shows a certain degree of maturity (35.3 years).

Table 3 - Descriptive statistics of the determinants of green bond issuance (firm-level)

Variable	Obs.	Mean	Std. Dev.	Min	Max
Green Bond Issuer	1914	0.096	0.295	0	1
High Carbon Intensity	1914	0.385	0.487	0	1
High Climate Awareness	1914	0.379	0.485	0	1
Size	1322	22.525	1.692	16.968	26.290
ROA	1237	2.396	4.981	-14.271	23.316
Leverage	1137	0.390	0.227	0	0.999
Current Ratio	1211	1.854	3.719	0.121	33.008
Firm Age	1700	35.255	33.607	1	137

In **Table 4**, the average credit spread in the sample is approximately 117 basis points, with considerable heterogeneity across deals (standard deviation of 135 bps). Roughly 19% of the bonds are classified as green, while a large share of issuances (90%) stem from firms in high carbon-intensity sectors. In contrast, only about 31% of the bonds are issued in regions characterized by high climate awareness. Regarding contractual features, nearly one third of the sample corresponds to callable bonds (32%), whereas perpetual bonds are relatively rare, accounting for just 6% of the observations. On average, each bond issuance involves around 6.7 banks, with the number of participating institutions varying substantially (from 1 to 35). The average deal value is 19.4 in logarithmic terms (approximately EUR 270 million). About 10% of the bonds expose investors to currency risk, being denominated in foreign currency relative to the issuer's nationality. Finally, the mean rating number is 14.3 on a 1–23 scale. The coding follows Gabbi & Sironi (2002), where AAA is assigned 1 and

CCC+ corresponds to 16. Unrated bonds are given the value 23, while the intermediate values between 17 and 22 are not present in the sample. Thus, the average value of 14.3 maps to the B–/B category, indicating that the typical issuance in the dataset is speculative-grade.

Table 4 - Descriptive statistics of the credit spread analysis (deal-level)

Variable	Obs.	Mean	Std. Dev.	Min	Max
Credit Spread	611	116.569	135.410	0	700
Green Bond	611	0.191	0.394	0	1
High Carbon Intensity	611	0.900	0.300	0	1
High Climate Awareness	611	0.308	0.462	0	1
Callable	611	0.316	0.465	0	1
Banks	611	6.660	6.520	1	35
Deal value	596	19.401	1.174	16.823	21.791
Currency Risk	611	0.103	0.304	0	1
Rating Number	611	14.304	8.381	1	23
Perpetual	611	0.059	0.236	0	1

Table 5 - Descriptive statistics of the credit spread analysis (firm-level)

Variable	Obs.	Mean	Std. Dev.	Min	Max
Credit Spread	403	129.819	143.708	0	768
Green Firm	1392	0.132	0.339	0	1
Size	1059	15.616	1.739	10.060	19.382
ROA	996	2.258	5.190	-14.271	23.316
Leverage	915	0.393	0.231	0	0.999
Current Ratio	976	1.947	3.970	0.121	33.008
Firm Age	1209	36.151	33.567	1	137

To further contextualize our analysis, **Graph 1** displays the evolution of the weighted average credit spread by firm type between 2015 and 2022, reflecting broader shifts in the development of the green bond market.

As discussed by Flammer (2021) and Kim (2016), the benefits of green financing depend heavily on issuer credibility, transparency, and market perception. Some early adopters (2015-2016) may have experienced favourable pricing due to strong ESG commitment and signaling power. However, from 2016 to 2018, GTF experienced a relative increase in spreads compared to BTF. This may be attributed to the uneven development of the green bond market and heightened investor scepticism toward new or unverified green issuances. As highlighted by these authors, in the absence of standardized frameworks or third-party verification (which were less prevalent during those years), markets attributed higher risk premiums for green debt.

Importantly, the sharp increase in spreads for BTF from 2018 to 2020 coincides with the beginning of the COVID-19 pandemic, a global crisis that prompted extreme volatility and widened credit spreads (Fatica & Panzica, 2024). The pronounced increase for BTF relatively to GTF imply that markets perceived GTF as more resilient and more aligned with long-term risk mitigation, possibly due to their ESG profile (Fatica & Panzica, 2024).

From 2020 onward, this gap begins to narrow and we observe that the average credit spread for GTF becomes more comparable to that of BTF. This shift suggests that investors have become more aware of the advantages of green bonds, likely due to increased standardization (EU Green Bond Standard), greater transparency due to better disclosure practices and growing awareness of environmental issues. Supporting this interpretation, Marques & Pinto (2020) find that announcements of green bond issuances can signal a firm's genuine commitment to sustainability, often leading to positive investor reactions. Similarly, Flammer (2021) argues that although green bond issuers may initially face scepticism, they tend to benefit from better financing conditions over time as the market matures and trust in green finance strengthens. Thus, the convergence in spreads between GTF and BTF can be seen as evidence of the diminishing greenium, not because green bonds lost value, but because their issuance became more popular, increasing their supply, which led to the end of this pricing difference by 2022[17].

Graph 1 - Evolution of the weighted credit spread (bp) by Deal Type



Note: See **Graph A3** and **Graph A4** in section 9.5 for more detail about the dispersion of the credit spread.

[17] The evolution of a greenium is discussed in the literature review, section 2.5.

4. Methodology

4.1 Determinants of Green Bond Issuance

To address our first research question, which deals with documenting the determinants of firms that issue green bonds, we start by estimating the following binary choice model, using logistic regression[18]:

$$\begin{aligned}\text{Green Bond Issuer}_{i,t} &= \beta_0 + \beta_1 \text{Size}_{i,t-1} + \beta_2 \text{ROA}_{i,t-1} + \beta_3 \text{Leverage}_{i,t-1} \\ &+ \beta_4 \text{Current Ratio}_{i,t-1} + \beta_5 \text{Firm Age}_{i,t-1} + Year_t \\ &+ Nationality_n + \varepsilon_{it}\end{aligned} \tag{4.1.1}$$

Wherein i refers to firms, t to year and n to nationality. The variable Green Bond $\text{Issuer}_{i,t}$ identifies firms that issued a green bond by year t and the remaining variables in the regression (Size, ROA, Leverage, Current Ratio and Firm Age) are standard controls at the firm level and are defined in section 3.4. To reduce the noise of extreme values, namely outliers, we winsorize the variables at the 1% and the 99% levels. Additionally, to address the strong right skewness in the distribution of the variable size and to ensure comparability across variables, we proceed to apply the natural logarithm. To control for the risk of reverse causality (a common consequence of endogeneity), we lag all explanatory variables by one period.

For this analysis, we use the full sample period (2013-2022), as the construction of the High Carbon Intensity dummy requires information from the pre-Paris Agreement years 2013-2014.

Next, following the reasoning proposed by Ilhan *et al.* (2021), we are interested in examining whether companies that issue green bonds tend to operate in structurally less carbon-intensive subsectors compared to those that do not, and whether this relationship is influenced by firms operating in climate-aware countries - which is a novel contribution of our work. To do so, we estimate the following extensions of the baseline model:

[18] We opted to use the logit regression because, when compared to the probit specification, it yielded a higher (less negative) log pseudolikelihood, indicating a better model fit.

$$\text{Green Bond Issuer}_{i,t} = \beta_0 + \beta_1 \text{High Carbon Intensity}_s + \beta_2 \text{Size}_{i,t-1} + \beta_3 \text{ROA}_{i,t-1} + \beta_4 \text{Leverage}_{i,t-1} + \beta_5 \text{Current Ratio}_{i,t-1} + \beta_6 \text{Firm Age}_{i,t-1} + Year_t + Nationality_n + \varepsilon_{it} \quad (4.1.2)$$

$$\text{Green Bond Issuer}_{i,t} = \beta_0 + \beta_1 \text{High Climate Awareness}_c + \beta_2 \text{Size}_{i,t-1} + \beta_3 \text{ROA}_{i,t-1} + \beta_4 \text{Leverage}_{i,t-1} + \beta_5 \text{Current Ratio}_{i,t-1} + \beta_6 \text{Firm Age}_{i,t-1} + Year_t + Nationality_n + \varepsilon_{it} \quad (4.1.3)$$

$$\text{Green Bond Issuer}_{i,t} = \beta_0 + \beta_1 \text{High Carbon Intensity}_s \times \text{High Climate Awareness}_c + \beta_2 \text{Size}_{i,t-1} + \beta_3 \text{ROA}_{i,t-1} + \beta_4 \text{Leverage}_{i,t-1} + \beta_5 \text{Current Ratio}_{i,t-1} + \beta_6 \text{Firm Age}_{i,t-1} + Year_t + Nationality_n + \varepsilon_{it} \quad (4.1.4)$$

Wherein s refers to subsector (Freight & Logistics Services, Passenger Transportation Services, Transportation Infrastructure) and c to country. The variable High Carbon Intensity is a dummy variable that takes the value 1 if the sector's median carbon intensity during 2013-2014 exceeds the overall median during 2013-2014, and 0 otherwise. The variable High Climate Awareness is a dummy variable equal to 1 if the firm's country of operation is classified as having high climate change awareness, meaning if the countries percentage of respondents concerned about climate change (2018-2019 EIB survey) is above the median, and 0 otherwise.

One concern regarding the analysis that uses carbon intensity and climate awareness as independent variables is the potential overlap of the two variables. In this regard, **Table 6** shows that carbon intensity and climate awareness do not mechanically overlap. For instance, some high carbon intensity firms are located in high climate aware countries, while many low carbon intensity firms operate in low climate-aware contexts. This confirms that the two dimensions capture distinct aspects, justifying their separate inclusion in the empirical analysis.

Table 6 - Cross-tabulation of High Carbon Intensity and High Climate Awareness

High Carbon Intensity	High Climate Awareness		Total
	0	1	
0	737	440	1177
1	451	286	737
Total	1188	726	1914

Complementary to the regression analysis, we conduct a series of t-tests to compare the mean of each selected variable between firms issuing green bonds and those issuing conventional bonds. The statistical procedure tests the null hypothesis H0, which states that the two group means are equal, against the alternative that a significant difference exists between them.

4.2 Pricing of Green Bonds

In order to shed light on the relationship between green bond issuance and the credit spread, we use OLS regressions to estimate the following model [19]:

$$\begin{aligned}&\text{Credit Spread}_{d,t}\\&= \beta_0 + \beta_1 \text{Green Bond}_{d,t} + \beta_2 \text{Banks}_{d,t}\\&+ \beta_3 \text{Callable}_{d,t} + \beta_4 \text{Deal Value}_{d,t} + \beta_5 \text{Currency Risk}_{d,t} + \beta_6 \text{Rating Number}_{d,t}\\&+ \beta_7 \text{Perpetual}_{d,t} + Year_t + Nationality_n + Subsector_j + \varepsilon_{dt}\end{aligned} \quad (4.2.1)$$

Wherein d refers to deals, t to the year of issuance, n to nationality and j to subsector (fixed effects). The variable Credit Spread is proxied by the Tranche Spread to Benchmark in basis points for each bond and the remaining variables in the regression (Green Bond, Banks, Callable, Deal Value, Currency Risk, Rating Number and Perpetual) are standard contractual characteristics at the deal level and are defined in section 3.7. To reduce the noise of extreme values, namely outliers, we winsorize the variables at the 1% and the 99% levels and apply a log transformation to Deal Value.

In the specification (4.2.1), we did not include firm-level control variables, restricting the analysis to contractual features, in line with the baseline model of Marques & Pinto (2020). However, it is important to note that the authors ultimately incorporate firm

[19] In order to maintain the consistency between analysis and similarly to what was described in section 3.5, we use the same industry classification, namely the TRBC industry classification.

characteristics in further analyses, since credit spreads reflect both the risk of the instrument and that of the issuing firm. This approach is consistent with prior literature, as both Longstaff & Rajan (2008) and He *et al.* (2011) highlight the role of firm-specific characteristics in explaining credit spreads, for collateralized debt obligations and mortgage-backed securities, respectively. For this reason, we include firm-level variables only in robustness checks (section 6.2.2), in order to assess whether the results hold when explicitly controlling for issuer-specific risk.

For this analysis, we restrict the sample period to 2015-2022. The years 2013 and 2014 are excluded because no green bonds were issued during this time, meaning that including them would add noise without contributing relevant observations.

Additionally, we aim not only to test the existence of an average greenium in the transportation sector, but also to examine whether this effect varies according to factors related to the determinants of green bond issuance. We consider (i) the subsector's carbon intensity - capturing the reputational and regulatory pressures associated with emission reductions - and (ii) the degree of climate awareness – reflecting which country public attention to environmental issues. Including these variables allows us to explore whether the greenium is more pronounced in countries of stronger public scrutiny or in sectors more exposed to climate-related risks, thereby contributing to a better understanding of the heterogeneity of results documented in the literature. In other words, we seek to answer the question: Is the greenium conditional on public awareness and sectoral carbon intensity?

The empirical model consists of the following equations:

$$\begin{aligned}&\text{Credit Spread}_{d,t}\\&= \beta_0 + \beta_1 \text{Green Bond}_{d,t} + \beta_2 \text{Banks}_{d,t}\\&+ \beta_3 \text{Callable}_{d,t} + \beta_4 \text{Deal Value}_{d,t} + \beta_5 \text{Currency Risk}_{d,t} + \beta_6 \text{Rating Number}_{d,t}\\&+ \beta_7 \text{Perpetual}_{d,t} + \beta_8 \text{High Carbon Intensity}_s + Year_t + Nationality_n + \varepsilon_{dt}\end{aligned} \tag{4.2.2}$$

$$\begin{aligned}&\text{Credit Spread}_{d,t}\\&= \beta_0 + \beta_1 \text{Green Bond}_{d,t} + \beta_2 \text{Banks}_{d,t}\\&+ \beta_3 \text{Callable}_{d,t} + \beta_4 \text{Deal Value}_{d,t} + \beta_5 \text{Currency Risk}_{d,t} + \beta_6 \text{Rating Number}_{d,t}\\&+ \beta_7 \text{Perpetual}_{d,t} + \beta_8 \text{Green Bond}_{d,t} \times \text{High Carbon Intensity}_s + Year_t\\&+ Nationality_n + \varepsilon_{dt}\end{aligned} \tag{4.2.3}$$

$$\begin{aligned}&\text{Credit Spread}_{i,t}\\&= \beta_0 + \beta_1 \text{Green Bond}_{d,t} + \beta_2 \text{Banks}_{d,t}\\&+ \beta_3 \text{Callable}_{d,t} + \beta_4 \text{Deal Value}_{d,t} + \beta_5 \text{Currency Risk}_{d,t} + \beta_6 \text{Rating Number}_{d,t}\\&+ \beta_7 \text{Perpetual}_{d,t} + \beta_8 \text{High Climate Awareness}_c + Year_t + Subsector_j + \varepsilon_{dt}\end{aligned} \tag{4.2.4}$$

$$\begin{aligned}&\text{Credit Spread}_{i,t}\\&= \beta_0 + \beta_1 \text{Green Bond}_{d,t} + \beta_2 \text{Banks}_{d,t}\\&+ \beta_3 \text{Callable}_{d,t} + \beta_4 \text{Deal Value}_{d,t} + \beta_5 \text{Currency Risk}_{d,t} + \beta_6 \text{Rating Number}_{d,t}\\&+ \beta_7 \text{Perpetual}_{d,t} + \beta_8 \text{Green Bond}_{d,t} \times \text{High Climate Awareness}_c + Year_t\\&+ Subsector_j + \varepsilon_{dt}\end{aligned} \tag{4.2.5}$$

Wherein s refers to subsector (Freight & Logistics Services, Passenger Transportation Services, Transportation Infrastructure) and c to country. To assess whether the average credit spread differs between green and conventional bonds, we conduct independent two-sample t-tests. Both versions are employed: one assuming equal variances and another not assuming equal variances (Welch's t-test). The null hypothesis states that there is no difference in the spread between green and conventional bonds, while the alternative hypothesis assumes a significant difference. In addition to testing the full sample, we perform segmented analyses by company nationality and industry. For nationality, we use the High Climate Awareness dummy, capturing the level of environmental awareness in each country. For industry, we use the High Carbon Intensity dummy, capturing the carbon intensity at the sector level.

5. Results and Discussion

5.1. Determinants of Green Bond Issuance

Table 7 and **Table 8** show the results for the determinants of green bonds issuance (t-tests and regressions, respectively), including firm-level, subsector-level and country-level determinants.

Table 7 – Determinants of green bond issuance: Mean differences

	Obs. GBI	Obs. CBI	Average GBI (1)	Average CBI (2)	Diff. (1)-(2)	P-value
Panel A – Firm-level						
Size	158	1164	23.170	22.438	0.733	0.000
ROA (%)	139	1098	0.847	2.592	-1.745	0.000
Leverage (%)	126	1011	0.422	0.386	0.037	0.087
Current Ratio (%)	140	1071	1.500	1.900	-0.400	0.231
Firm Age	184	1516	34.076	35.340	-1.322	0.614
Panel B – Subsector-level						
High Carbon Intensity	184	1730	0.522	0.371	0.151	0.000
Panel C – Country-level						
High Climate Awareness	184	1730	0.462	0.371	0.091	0.015

Notes: GBI stands for Green Bond Issuers and CBI for Conventional Bond Issuers.

The results regarding the firm-level determinants of green bond issuers (presented in Panel A of **Table 7** and columns 1 to 4 of **Table 8**), suggest that as expected, larger firms are more likely to issue green bonds in line with Ilhan *et al.* (2021) and Flammer (2021). Additionally, this dissertation does not find a positive relationship between profitability (ROA) and the issuance of green bonds, unlike what is argued by Flammer (2021). Instead, the t-test results indicate that a firm's profitability has a significantly negative effect on green bond issuance, although the relationship is only significant at the 10% level, corroborating the regression results of models 2 and 4. This finding may be interpreted in light of Baker *et al.* (2018) which state that less profitable firms may be more incentivized to access external funding through green bonds, either due to limited internal capital or as a strategic move to enhance their environmental reputation. This interpretation is also consistent with the findings of Glavas (2023) and ElBannan & Löffler (2024), who show that green bond issuers tend to be more financially constrained and less profitable than conventional firms.

Table 8 - Determinants of green bond issuance: Logistic Regressions

	Green Bond Issuer			
	(1)	(2)	(3)	(4)
Size	0.369***	0.380***	0.369***	0.370***
	(0.097)	(0.093)	(0.097)	(0.093)
ROA	-0.049	-0.051*	-0.049	-0.058*
	(0.030)	(0.030)	(0.030)	(0.030)
Leverage	0.329	0.490	0.329	0.571
	(0.608)	(0.612)	(0.608)	(0.606)
Current Ratio	-0.042	-0.050	-0.042	-0.057
	(0.038)	(0.037)	(0.038)	(0.036)
Firm Age	-0.009	-0.012*	-0.009	-0.014**
	(0.006)	(0.007)	(0.006)	(0.007)
High Carbon Intensity		0.724**		0.268
		(0.298)		(0.384)
High Climate Awareness			2.473***	2.276***
			(0.689)	(0.751)
High Carbon Intensity x High Climate Awareness				1.066*
				(0.590)
Constant	-9.563***	-10.182***	-9.563***	-9.552***
	(2.401)	(2.338)	(2.401)	(2.363)
Nationality fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Obs.	796	796	796	796
R^2	0.2917	0.3011	0.2917	0.3060
Wald χ^2	161.74	169.10	161.74	170.26

Notes: The results from model 1 are relatively to our baseline model (equation 4.1.1) with the conventional determinants of green bond issuance; the results from model 2 are relatively to equation 4.1.2; the results from model 3 are relatively to equation 4.1.3 and the results from model 4 are relatively to equation 4.1.4. ***, ** and * indicate that the reported coefficients are significantly different from zero at the 1%, 5% and 10% levels, respectively. The statistics reported in parentheses are based on standard errors.

Still regarding firm-level determinants, we find some weak evidence suggesting that younger firms are relatively more likely to issue green bonds. This result may be explained by the narrative according to which younger firms may issue green bonds as a way to build reputation, attract ESG-conscious investors or access new financing opportunities (Baker *et al.*, 2018; Flammer, 2021; Tang & Zhang, 2020). In contrast, older firms may rely more on

traditional financing sources, face less pressure to innovate or be slower to integrate sustainability into their financial strategies. With respect to leverage and liquidity, our results suggest that these are not significant determinants of green bond issuance in the regression analysis, although the t-test reveal that green bond issuers appear slightly more leveraged on average line with literature which reveals mixed results.

The results concerning subsector analysis are presented in Panel B of **Table 7** and model 2 of **Table 8**. Our findings indicate that transportation firms operating in High Carbon Intensity subsectors (namely Freight & Logistics Services and Transportation Infrastructure) are more likely to issue green bonds. On average, operating in such a sector is associated with an increase of approximately 6.46 percentage points in the probability of issuing green bonds, compared to firms in lower-intensity sectors, holding other variables constant. Such findings are consistent with the notion that firms in high emitting sectors are more exposed to climate policy risk (Ilhan *et al.,* 2021), i.e. may face greater costs of capital or volatility, incentivizing them to issue green bonds as a strategic response.

Following these results, a subsequent question is whether green bond issuers belonging to higher carbon intensity subsectors is sufficient evidence to document the presence of greenwashing in the transportation sector - a concern raised by Flammer (2021) and Shi *et al.* (2023), according to which firms may pretend to be green, while not observing improvements in CO_2 or environmental ratings post-issuance. In this regard, while we were not able to collect sufficient data on CO_2 emissions for the full sample, we analyse the evolution of CO_2 emissions for a subsample of seventeen green bond issuers and find inconclusive evidence. Namely, untabulated results indicate a significant reduction for eight issuers after the year of the green bond issuance (relative to the 3 years average CO_2 pre-issuance) and stable emissions for the remaining. Thus, we do not find conclusive support in favor of the presence of greenwashing.

The results regarding the country-level analysis are shown in Panel C of **Table 7** and model 3 of **Table 8** and indicate that firms operating in countries with High Climate Awareness are substantially more likely to issue green bonds compared to firms with non-climate awareness. In marginal terms, firms headquartered in climate-aware countries are, on average, 22.3 percentage points more likely to issue green bonds compared to firms in countries with low climate awareness. This corroborates the findings of Guesmi *et al.* (2025) who state that firms more exposed to climate change are significantly more likely to issue green bonds. This also corroborates, in part, the findings of Flammer (2021) and Ilhan *et al.* (2021), which state

that firms with high public attention to climate change increase the probability of adopting climate-friendly policies. Moreover, although using a different criterion to measure climate awareness, Hussain *et al.* (2025) concluded that firms with climate-conscious managers are more likely to issue green bonds.

Next, we wish to understand the interplay between High Climate Awareness, High Carbon Intensity and green bond issuance. According to the results presented in model 4 in **Table 8**, firms located in countries with High Climate Awareness and belonging to low carbon industries are significantly more likely to issue green bonds. The coefficient of the interaction term between High Carbon Intensity and High Climate Awareness captures the differential effect of operating in a high carbon intensity sector within a context of strong climate awareness. The positive and significant value of this coefficient suggests that firms with both characteristics are more likely to issue green bonds than would be expected from the individual effects of each variable alone, although the interaction is only marginally significant at the 10% level. Overall, while model 2 suggests that High Carbon Intensity alone is a significant determinant of green bond issuance, model 4 indicates that the association between carbon intensity and green bond issuance is only significant for firms located in countries with higher climate awareness, highlighting that public pressure plays an important role in driving sustainable financing. It is the combination with a supportive macro-environment that reinforces the disciplining role of green finance (Flammer, 2021; Ilhan *et al.*, 2021).

5.2 Pricing of Green Bonds

Table 9 and **Table 10** present the results for green bond pricing (t-tests and regressions, respectively), aiming to assess the evidence of a possible greenium in the overall sample and how factors like High Carbon Intensity and High Climate Awareness influence it. After addressing possible issues in the initial regression (equation 4.2.1), the results are displayed in **Table 10**. Section 9.6 contains the modifications made after the preliminary statistical tests.

In general, the results of both the panel A of **Table 9** and model 1 of **Table 10** do not provide evidence of a consistent and significant greenium in the transportation sector, consistent with Flammer (2021) and Larcker & Watts (2020). The t-test results reveal a mean credit spread difference of -12.731 bps between green and conventional issuers, though this is not statistically significant at the 5% level. Similarly, the regression coefficient in model 1 is -23.221 bps, but it is also not significant.

Table 9 - Credit Spread: Mean differences

	Obs. GBI	Obs. CBI	Average GBI (bps)	Average CBI (bps)	Diff. (1)-(2)	P-value
Panel A - Overall Sample						
Equal variances	117	494	108.161	120.892	-12.731	0.398
Unequal variances	117	494	108.161	120.892	-12.731	0.287
Panel B - High Carbon Intensity						
0	24	37	118.188	127.374	-9.187	0.680
1	93	457	105.573	120.367	-14.794	0.392
Panel C - High Climate Awareness						
0	59	364	120.185	85.035	35.150	0.014
1	58	130	95.929	221.289	-125.360	0.000

Notes: GBI stands for Green Bond Issuers and CBI for Conventional Bond Issuers.

Other hypothesis we aim to explore is the impact of High Carbon Intensity. According to panel B of **Table 9** and model 2 of **Table 10**, belonging to a high-carbon-intensity sector slightly reduces spreads (-5.5 bps) but is not statiscally significant. So, there's no clear evidence that investors systematically demand higher spreads from issuers in high-carbon sectors when controlling for other factors. On the other hand, once we control for the interaction term Green Bond × High Carbon Intensity in model 3, green bonds issued in high-carbon intensity sectors carry lower spreads, suggesting that investors value transition financing in industries facing greater climate-related risks. This result can be interpreted considering the signaling hypothesis of Flammer (2021), in which issuing green bonds may be perceived as a credible signal of commitment to decarbonisation, thereby reducing transition risk and attracting strong investor demand.

Lastly, we also seek to examine the impact of climate Awareness. Introducing High Climate Awareness in model 4 of **Table 10** reveals that bonds from climate-aware countries are associated with higher spreads, potentially reflecting policy or transition risks. However, once we account for the interaction term in model 5 the results change notably: in less climate aware countries, green bonds have, on average, higher credit spreads than conventional bonds, by approximately 38.5 basis points. On the other hand, in climate aware countries, green bonds have on average lower credit spreads than conventional bonds, by approximately 55.3 basis points (38.505 - 93.850). This significant greenium on high climate aware countries is corroborated by the findings of panel C of **Table 9**, indicating that the effect on credit spreads is influenced by the level of climate awareness of countries.

Table 10 - Credit Spread: Regression Results (at the deal level)

	Credit Spread (bp)				
	(1)	(2)	(3)	(4)	(5)
Green Bond	-23.221	-23.995	37.206	-5.211	38.505***
	(14.392)	(14.617)	(27.425)	(12.765)	(14.751)
High Carbon Intensity		-5.530	21.217		
		(16.621)	(20.657)		
Green Bond x High Carbon Intensity			-74.308**		
			(29.549)		
High Climate Awareness				47.250***	72.499***
				(13.257)	(16.888)
Green Bond x High Climate Awareness					-93.850***
					(25.183)
Callable	94.240***	116.673***	117.354***	131.163***	120.188***
	(21.062)	(20.831)	(20.830)	(15.482)	(16.226)
Banks	-1.593*	-1.607*	-1.531	-0.294	-0.175
	(0.860)	(0.965)	(0.956)	(0.822)	(0.814)
Deal Value	-15.333**	-17.804***	-18.394***	-11.195**	-11.116**
	(6.261)	(6.724)	(6.679)	(5.409)	(5.323)
Currency Risk	43.730***	50.228***	53.613***	5.952	2.827
	(16.215)	(16.619)	(16.216)	(13.715)	(13.588)
Rating Number	3.146***	3.693***	3.977***	3.476***	3.443***
	(0.639)	(0.683)	(0.695)	(0.586)	(0.589)
Perpetual	4.617	-20.257	-16.719	-7.401	4.494
	(30.960)	(30.895)	(30.615)	(26.520)	(26.090)
Constant	349.598***	388.581***	370.079***	230.671**	224.640**
	(120.720)	(125.016)	(124.319)	(103.660)	(102.370)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Nationality fixed effects	Yes	Yes	Yes	No	No
Sub-industry fixed effects	Yes	No	No	Yes	Yes
Obs.	594	594	594	596	596
R^2	0.447	0.396	0.402	0.398	0.414

Notes: Model (1) corresponds to the baseline regression (Eq. 4.2.1) with all fixed effects and TRBC classification. Model (2) follows Eq. 4.2.2. Model (3) adds the interaction between green bond and high carbon intensity (Eq. 4.2.3). Model (4) corresponds to Eq. 4.2.4, and Model (5) adds the interaction between green bond and climate awareness (Eq. 4.2.5).***, ** and * indicate that the reported coefficients are significantly different from zero at the 1%, 5% and 10% levels, respectively. The statistics reported in parentheses are based on heteroskedasticity-consistent standard errors.

This aligns with the notion that investor demand for green bonds materializes particularly where environmental awareness is high. Confirming this, the BIS Quarterly Review from March 2025 show that in countries with higher climate awareness (measured through policy indicators or environmental governance standards), green bonds are associated with lower credit spreads relative to conventional bonds. This implies that investor demand for green bonds is stronger in such environments, leading to a pricing advantage (Demski *et al.*, 2025).

Taken together, these results suggest that the greenium is conditional to climate-aware markets and carbon-intensive sectors, rather than being universal across the sample. As discussed in the literature review, there is still no consensus on the existence of a price differential favouring green bonds.

Focusing on model 1, the constant term of our model is the expected credit spread of a conventional bond that is non-callable, not perpetual and has no currency risk which is approximately 350 basis points. Although our mean test yielded a much lower value of approximately 120.891 basis points for the average spread of conventional bonds, this result is an unadjusted mean, since it included all observations for Green Bond=0, regardless of differences in the bond characteristics.

All the remaining variables produce a robust and significant impact, except for perpetual and number of banks, which although have the expected sign, it is not statistically significant for all models. Holding all other variables constant (and controlling for year, country, and industry fixed effects), callable bonds have, on average, 94 basis points higher credit spreads than non-callable bonds. As expected, a 1% increase in the deal size (because it represents its logarithm) is associated with a decrease in credit spread by approximately 0.153 basis points, all else equal (for both green and conventional bonds) (Buscaino *et al.*, 2012; Marques & Pinto, 2020; Vink & Thibeault, 2008). Moreover, for each one-point increase in the numerical rating value (lower credit quality), the credit spread increases by approximately 3.15 basis points, on average, ceteris paribus (for both green and conventional bonds). Since lower-rated bonds are riskier, they demand higher yields. This is strongly significant at the 1% level supporting the role of credit rating in spread pricing and is corroborated by Marques & Pinto (2020). Regarding the dummy variable of currency risk, as expected, bonds exposed to currency risk have credit spreads that are, on average, 43.73 basis points higher than those without currency risk, holding other factors constant (Marques & Pinto, 2020).

6. Robustness Check

The following section focuses on conducting complementary analyses supporting the previous findings.

6.1 Determinants of Green Bond Issuance

6.1.1 Climate Awareness Across Countries: A CCPI Approach

As a robustness test, using the equation (4.1.2), we split the sample into two groups (High Climate Awareness vs. Low Climate Awareness countries), making use only of the 2019 Climate Change Performance Index (CCPI) as a measure of climate awareness (Burck *et al.*, 2019). The CCPI is a composite indicator aimed to enhance transparency in national and international climate politics. It provides a standardized framework to assess and compare the climate performance of 63 countries and the EU, collectively responsible for over 90% of global greenhouse gas emissions. It evaluates climate mitigation efforts across greenhouse gas emissions, renewable energy, energy use, and climate policy. This contrast with the EIB survey because CCPI primarily reflects government action and national performance, rather than public attitudes or awareness, and hence it may capture a different dimension of climate awareness, potentially leading to variations in the observed relationship with green bond issuance.

Table 11 summarize our findings[20]. The results from the sub-sample analysis reveal that for firms located in countries with high climate awareness, operating in high carbon intensity sectors is significantly associated with a higher likelihood of issuing green bonds. This suggests that in institutional environments where climate concerns are more salient, firms in polluting sectors may face greater pressure or see stronger incentives to engage in sustainable finance practices such as green bond issuance. These findings align with the broader literature that underscores the role of institutional and normative pressures in promoting green finance (Tolliver *et al.*, 2020). In contrast, for firms operating in countries without strong climate awareness, the same variable is not statistically significant, indicating no robust association between sectoral carbon intensity and the likelihood of issuing green bonds. This asymmetry highlights the role of institutional and normative contexts in shaping

[20] To reduce the noise of extreme values, namely outliers, we winsorize the variables at the 1% and the 99% levels. Additionally, to address the strong right skewness in the distribution of the variable Size and to ensure comparability across variables, we proceed to apply the natural logarithm. To control for the risk of reverse causality (a common consequence of endogeneity), we lag all explanatory variables by one period.

corporate responses to environmental challenges. These results confirm the ones of the analysis using both the EIB survey and the CCPI in section 5.1.

Table 11 – Determinants of green bond issuance: sub-sample regression

	Green Bond Issuer in High CCPI	Green Bond Issuer in Low CCPI
	(1)	(2)
High Carbon Intensity	1.272***	0.139
	(0.453)	(0.227)
Size	0.921***	0.302***
	(0.134)	(0.083)
ROA	-0.059**	-0.023
	(0.028)	(0.034)
Leverage	1.308**	-3.620***
	(0.544)	(0.789)
Current Ratio	-0.010	-0.053
	(0.030)	(0.093)
Firm Age	-0.010**	-0.013***
	(0.005)	(0.005)
Constant	-21.751***	-6.653***
	(3.180)	(1.970)
Nationality fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Obs.	307	635
R^2	0.282	0.121
Wald χ^2	81.48	77.23

Notes: Model (1) reflects the estimation of High Climate Awareness == 1 and Model (2) reflects the estimation of High Climate Awareness == 0. ***, ** and * indicate that the reported coefficients are significantly different from zero at the 1%, 5% and 10% levels, respectively. The statistics reported in parentheses are based on standard errors.

6.1.2 Regression analysis by subsample period: Pre- and Post-2019

Due to temporal imbalance of the sample[21], we run the regressions in section 4.1 dividing the sample into two periods: pre-2019 and post 2019.

[21] The issuance date of green bonds ranges between April 2015 and December 2022, however, 82,05% of the deals are concentrated after January 2019 (included). On the other hand, conventional bonds issuance dates range between January 2015, and December 2022, with 71% of the deals being concentrated until December 2018. See section 9.3 for more details.

Comparing the results across the three regression specifications in **Table 8**, **Table 12** and **Table 13**, we observe distinct patterns between the pre- and post-2019 subsamples.

Table 12 - Determinants of green bond issuance: regression results (period post-2019)

	Green Bond Issuer			
Post-2019	(1)	(2)	(3)	(4)
High Carbon Intensity		0.717**		0.146
		(0.320)		(0.413)
High Climate Awareness			2.444***	2.059***
			(0.752)	(0.795)
High Carbon Intensity x High Climate Awareness				1.349**
				(0.628)
Size	0.389***	0.398***	0.389***	0.393***
	(0.110)	(0.105)	(0.110)	(0.104)
ROA	-0.041	-0.043	-0.041	-0.053*
	(0.030)	(0.030)	(0.030)	(0.031)
Leverage	0.329	0.528	0.329	0.692
	(0.647)	(0.656)	(0.647)	(0.654)
Current Ratio	-0.029	-0.037	-0.029	-0.046
	(0.035)	(0.034)	(0.035)	(0.034)
Firm Age	-0.008	-0.011	-0.008	-0.013*
	(0.006)	(0.007)	(0.006)	(0.007)
Constant	-12.217***	-12.834***	-12.217***	-12.309***
	(2.758)	(2.688)	(2.758)	(2.657)
Nationality fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Obs.	579	579	579	579
R^2	0.259	0.269	0.259	0.278
Wald χ^2	120.579	123.255	120.579	127.242

Notes: The results from model 1 are relatively to our baseline model (equation 4.1.1) with the conventional determinants of green bond issuance; the results from model 2 are relatively to equation 4.1.2; the results from model 3 are relatively to equation 4.1.3 and the results from model 4 are relatively to equation 4.1.4. ***, ** and * indicate that the reported coefficients are significantly different from zero at the 1%, 5% and 10% levels, respectively. The statistics reported in parentheses are based on standard errors.

For the post-2019 subsample, it largely confirms the patterns identified in the full-

sample analysis. Specifically, in model 3, which includes High Climate Awareness as an independent variable, shows a significant positive effect of climate-aware firms on green bond issuance, indicating that awareness at the country level enhances firms' likelihood to issue green bonds, independent of sectoral carbon intensity. Model 4, which introduces the interaction between High Carbon Intensity and High Climate Awareness, highlights that firms in high carbon intensity sectors benefit from the additional disciplinary effect of operating in countries with high climate awareness. The interaction term remains significant, meaning that for firms issuing green bonds after 2019, being in a high carbon intensity sector in countries with high climate awareness remains a significant positive determinant. The coefficient for High Climate Awareness alone also remains significant, while High Carbon Intensity as a standalone variable loses significance, confirming the results of the full sample. Across all four models, conventional firm-level controls such as Size and ROA retain their expected signs and significance (although ROA is only significant in the fourth model).

In contrast, the pre-2019 subsample in **Table 13** does not yield statistically significant results for the key variables, including High Carbon Intensity and High Climate Awareness. This lack of significance is likely driven by the temporal imbalance in the data: the majority of green bond issuance occurred after January 2019, with only a small number of deals before that date. As a result, the pre-2019 sample is too limited to detect robust effects, despite the inclusion of year fixed effects, which control for time-specific macroeconomic conditions. Overall, these findings suggest that the discipline effect of high carbon intensity sectors is more pronounced and detectable in the period where green bond issuance activity is substantial.

Table 13 - Determinants of green bond issuance: regression results (period pre-2019)

Pre-2019	Green Bond Issuer			
	(1)	(2)	(3)	(4)
High Carbon Intensity		1.314		1.740*
		(1.336)		(1.001)
High Climate Awareness			1.164	1.690
			(1.299)	(1.367)
High Carbon Intensity x High Climate Awareness				-0.743
				(2.668)
Size	0.565*	0.597*	0.565*	0.611*
	(0.333)	(0.320)	(0.333)	(0.337)
ROA	-0.199	-0.206*	-0.199	-0.203*
	(0.140)	(0.123)	(0.140)	(0.123)
Leverage	0.665	0.258	0.665	0.317
	(1.867)	(1.874)	(1.867)	(2.012)
Current Ratio	-0.373	-0.377	-0.373	-0.379
	(0.677)	(0.653)	(0.677)	(0.656)
Firm Age	-0.059***	-0.072***	-0.059***	-0.069**
	(0.017)	(0.026)	(0.017)	(0.032)
Constant	-11.801	-12.131	-12.964	-14.221
	(8.999)	(8.593)	(8.684)	(8.862)
Nationality fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Obs.	170	170	170	170
R^2	0.402	0.418	0.402	0.419
Wald χ^2	41.188	32.402	41.188	45.509

Notes: The results from model 1 are relatively to our baseline model (equation 4.1.1) with the conventional determinants of green bond issuance; the results from model 2 are relatively to equation 4.1.2; the results from model 3 are relatively to equation 4.1.3 and the results from model 4 are relatively to equation 4.1.4. ***, ** and * indicate that the reported coefficients are significantly different from zero at the 1%, 5% and 10% levels, respectively. The statistics reported in parentheses are based on standard errors.

6.2 Pricing of Green Bonds

6.2.1 Deal level analysis with SIC classification

To ensure that our deal-level results are not driven by changes in the industry classification, we run the regressions (4.2.1), (4.2.4) and (4.2.5) with the SIC classification.

Table 14 - Credit Spread: regression results (at the deal level) with SIC classification

	Credit spread (bp)					
	(1)	(2)	(3)	(4)	(5)	(6)
Green Bond	-13.007	11.601	4.604	3.168	42.650***	44.003***
	(12.733)	(11.463)	(11.614)	(11.648)	(13.910)	(13.812)
High Climate Awareness			35.410***	35.866***	56.637***	57.693***
			(13.331)	(13.344)	(16.183)	(16.219)
Green Bond x High Climate Awareness					-81.729***	-85.850***
					(23.793)	(24.071)
Callable	81.001***	133.735***	125.643***	126.220***	116.741***	116.467***
	(20.153)	(15.170)	(14.920)	(15.221)	(15.891)	(16.245)
Banks	-1.179	-1.018	-0.239	-0.545	-0.153	-0.473
	(0.944)	(0.923)	(0.886)	(0.918)	(0.882)	(0.909)
Deal Value	-16.787***	-6.647	-7.064	-7.574	-7.386	-7.899
	(6.207)	(5.704)	(5.623)	(5.726)	(5.562)	(5.661)
Currency Risk	37.424**	-15.364	-11.632	-8.517	-14.669	-10.830
	(14.640)	(13.410)	(14.016)	(14.151)	(13.798)	(13.944)
Rating Number	2.236***	1.971***	2.400***	2.155***	2.389***	2.111***
	(0.625)	(0.589)	(0.558)	(0.590)	(0.554)	(0.591)
Perpetual	28.558	-0.519	12.278	5.882	22.349	16.658
	(29.649)	(29.300)	(26.750)	(28.697)	(26.664)	(28.402)
GDP growth annual		2.104		2.962		3.112
		(2.177)		(2.031)		(1.988)
Constant	389.519***	175.573	169.656	177.220	171.949	179.772*
	(120.307)	(108.642)	(107.674)	(109.233)	(106.866)	(108.341)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Nationality fixed effects	Yes	No	No	No	No	No
Sub-industry fixed effects	Yes	Yes	Yes	Yes	No	No
Obs.	594	590	596	590	596	590
R^2	0.543	0.485	0.487	0.495	0.498	0.508

Notes: Model (1) is our baseline regression including all three fixed effects simultaneously. Model (2) is the same as model (1) but with the GDP growth instead of nationality fixed effects. Model (3) refers to eq. (4.2.4) Model (4) is the same of model (3) but with GDP growth. Model (5) refers to eq. (4.2.5). Model (6) is equal to model (5) but with the variable GDP growth.***, ** and * indicate that the reported coefficients are significantly different from zero at the 1%, 5% and 10% levels, respectively. The statistics reported in parentheses are based on heteroskedasticity-consistent standard errors.

Specifically, SIC classification is characterized by the following subsectors: Airports, flying fields, & services, Deep sea foreign trans. of freight, Freight transportation arrangement, Intercity & rural bus transportation, Local and suburban transit, Railroads, line-haul operating, Transportation services, NEC. Equations (4.2.2) and (4.2.3) are not considered because there is no compatibility in industry classifications between the SIC classification and the variable High Carbon Intensity. We also include institutional factors, namely annual GDP growth rate, in alternative for nationality fixed effects.

According to **Table 14**, for models 1, 2, 3 and 4 the green bond effect alone is not statistically significant so there is no evidence of a significant pricing difference between green and conventional bonds. When controlling for climate awareness in models 3 and 4, countries with High Climate Awareness are associated with higher spreads, corroborating the results with the TRBC classification. In models 5 and 6, we have robust evidence of a conditional greenium: in countries with High Climate Awareness, green bonds have, on average, lower spreads than conventional bonds. The results remain consistent regardless of the classification employed. The central finding that no robust average greenium is observed, but that a significant greenium emerges in contexts of High Climate Awareness (through the interaction term) is confirmed under both classifications.

For the remaining control variables, both analyses yield coefficients with the expected signs and similar levels of significance, although some differences in magnitude are observed. With respect to GDP growth, the results do not hinge on the inclusion of this institutional variable as an alternative to fixed effects.

6.2.2 Firm-level analysis with SIC classification

To ensure the validity of the deal-level results of the credit spread analysis, we conduct robustness checks at the firm level (i), where each observation corresponds to a firm-year pair (i, t), representing a firm (i) in a certain year (t), following Marques & Pinto (2020) approach[22]. Green bond data are recorded at the deal level; however, Longstaff & Rajan (2008) and He *et al.* (2011) highlight the role of firm-specific characteristics in explaining credit spreads. These robustness tests help confirm that the main deal-level findings hold even when accounting for firm-level patterns, which adds confidence to the overall results.

Given this information, we define our baseline regression as it follows[23]:

[22] Descriptive statistics at the firm-level are presented in section 3.8.
[23] For the computation of the credit spread, we decide to follow the approach used by Flammer (2021) in their

$$
\begin{aligned}
Credit\ Spread_{i,t} \ &= \beta_0 + \beta_1 Green\ Firm_{i,t} + \beta_2 ROA_{i,t-1} + \beta_2 Size_{i,t-1} \\
&+ \ \beta_3 Leverage_{i,t-1} + \ \beta_4 Current\ Ratio_{i,t-1} \\
&+ \ \beta_5 Firm\ Age_{i,t-1} + Year_{\mathrm{t}} + Nationality_n + Subsector_j \\
&+ \varepsilon_{i,t}
\end{aligned}
\tag{6.2.2.1}
$$

Green $Firm_{i,t}$ is a dummy variable ("treatment dummy") that equals one if firm i has issued a green bond by year t and 0 otherwise. Specifically, SIC classification is characterized by the following subsectors: Airports, flying fields, & services, Deep sea foreign trans. of freight, Freight transportation arrangement, Intercity & rural bus transportation, Local and suburban transit, Railroads, line-haul operating, Transportation services, NEC. This allows us to analyse the temporal impact of green bonds relative to the issuance year (post-issuance effects). It is also worth mentioning that for firms that issued more than one bond in different years, we used the year of the first issuance as the reference point for the variable, which takes the value 1 for all years following that issuance. The coefficient β_1 measures the difference-in-differences in outcome variable between treated and control firms before the treatment, meaning it is a baseline group difference. In other words, it measures the average causal effect following the green bond issuance in the outcome variable accounting for changes in credit spread at the comparable group of firms that do not issue green bonds.

The rest of the variables represent firm-level characteristics defined in section 3.4[24].

Results and Discussion

After running the preliminary statistical test and accounting for the presence of heteroscedasticity with clustering errors, the results are displayed in **Table 15**[25].

study at the firm level analysis. We use the Tranche Spread to Benchmark as our variable of interest and as proxy for the credit spread issued, which is available in the Dealogic/DCM Analytics dataset. Given that and having into account that some firms (both BTF and GTF) issued more than one bond, our outcome variable is the weighted average of the Tranche Spread to Benchmark for each firm, and for each issuance year, where the weights are the issue amount of each bond, given by the Deal Value (EUR).

[24] We winsorize the variables at the 1st and 99th percentiles to mitigate the influence of extreme outliers, which can distort regression estimates. Additionally, we applied a log transformation to Size due to its highly skewed distribution and exponential scale, improving both interpretability and model stability. Furthermore, due to the presence of autocorrelation in our panel data, we decided to lag all independent variables - except Green Firm - in order to reduce dynamic misspecification.

[25] The preliminary statistical tests are reported in section 9.6.

Table 15 - Credit Spread: regression results (at the firm-level)

	Credit Spread (bp)
Green Firm	-31.634
	(24.680)
ROA	-3.003
	(2.705)
Size	-15.186**
	(7.238)
Leverage	65.337
	(50.465)
Current ratio	4.095
	(3.333)
Firm Age	0.532
	(0.331)
Constant	327.501***
	(123.805)
Year fixed effects	Yes
Nationality fixed effects	Yes
Sub-industry fixed effects	Yes
Obs.	298
R^2	0.478

Notes: ***, ** and * indicate that the reported coefficients are significantly different from zero at the 1%, 5% and 10% levels, respectively. The statistics reported in parentheses are based on standard errors.

Although only Size is statistically significant, the overall model is statistically significant, and the results support our main analysis at the deal level. While the coefficient of Green Firm is negative, suggesting that green bonds may have a premium compared to conventional bonds, this finding is not statistically significant. Therefore, there is no evidence to suggest that green bonds are priced differently than conventional bonds, confirming the results of the main analysis at the deal-level in **Table 10** (Flammer, 2021).

7. Conclusions and Limitations

This dissertation focus, first, on study the determinants of green bond issuance in the transportation sector, highlighting the impact of high intensity emissions and climate aware countries on the likelihood of using these instruments. Second, our goal was to analyse the financial impact of green bond issuance, analysing its effect on the credit spread, both at the deal and firm-level. To perform this research, a sample of 611 deals (including 117 green deals and 494 conventional deals) corresponding to 174 firms (including 58 green transportation firms and 116 brown transportation firms) is employed.

A positive and highly significant coefficient on high carbon intensity sector was found, indicating that firms operating in highly carbon-intensive sectors are more likely to issue green bonds. However, this effect disappears once the interaction with country-level climate awareness is introduced, indicating that sectoral carbon exposure alone does not drive green bond issuance. Its effect only materializes in countries with strong climate awareness, where institutional and societal pressures amplify the signaling role of green bonds. This underscores the importance of the broader macro-environment in disciplining sustainable finance. Importantly, there is no evidence of greenwashing in our sample, as the reduction in CO_2 emissions post-issuance for a subsample of the green bond issuers used in our regressions, suggests that these firms are genuinely committed to sustainable practices, rather than using green bonds as a marketing tool. Moreover, it was also found that firms operating in countries with high climate awareness are substantially more likely to issue green bonds compared to those in less environmentally conscious jurisdictions. This may reflect both regulatory pressure and a desire to align with public expectations regarding sustainability. Beyond carbon intensity and climate awareness, firm-specific characteristics namely firm Size, ROA, and Firm Age also proved to be statistically significant determinants of green bond issuance.

For the second part of our analysis, while our findings do not provide robust statistical evidence for a greenium, they are consistent with literature that questions its ubiquity and magnitude. Specifically, we find no evidence of a pricing differential in the absence of climate awareness and sectoral carbon intensity. However, once these dimensions are accounted for through interaction terms, a significant price advantage emerges for green bonds. The greenium appears particularly pronounced in institutional environments where environmental concerns are more salient. Likewise, firms in high-emission sectors may benefit from lower spreads when issuing green bonds, although the effect is less pronounced than in

climate-aware countries. Taken together, these results highlight that the existence of a greenium is conditional and context-dependent, shaped more strongly by institutional and normative pressures than by sectoral characteristics alone.

This study faces several important limitations that should be acknowledged. First, data collection relied on multiple sources - including two different primary datasets and complementary information from Orbis and from a survey data from the European Investment Bank (EIB) - which may introduce inconsistencies. Additionally, since the Dealogic/DCM Analytics dataset was organized by Company Parent Primary SIC, which may not fully capture industry-specific nuances, we lacked a directly comparable sector breakdown for CO_2 emissions. The closest available alternative was the TRBC (Thomson Reuters Business Classification) system, used in the Refinitiv dataset. For consistency across analyses, we converted the SIC-based classification from Dealogic/DCM Analytics to TRBC. While this ensures a uniform industry coding across all research questions, it represents a limitation of our study, as such conversions can never fully replicate the precision of an originally uniform classification. Additionally, due to limited emissions data availability across many sectors, we had to group firms into only three broader sub-sectors, potentially reducing the granularity and precision of our emissions analysis.

Another key limitation is the relatively small sample size: between 2013 and 2015, only one firm issued a green bond, and in the following years, the number remained low. This reflects the relatively recent development of the green bond market. Furthermore, our dataset is unbalanced, as some companies issued bonds only once, while others did so in non-consecutive years. The lack of consistent and compatible data across both GTF and BTF over the full ten-year period of our analysis (2013-2022) limited our ability to implement a more rigorous matching strategy as in Flammer (2021). This unbalanced structure also limited the applicability of more advanced panel techniques, such as staggered Difference-in-Differences (DiD) models. Measurement challenges also emerged in key variables: for example, High Climate Awareness suffers from subjectivity although it was extract from a relevant source, and CO_2 emissions were computed at the sub-industry level rather than at the firm level for the all sample due to data constraints.

Due to these data limitations, we were unable to assess directly pre- and post-Paris Agreement effects on credit spread and carbon emissions, a comparison that would have considerably enriched the analysis. Additionally, our study lacked a direct measure of firm-level CO_2 emissions and did not include information on individual ESG scores, meaning that

an important real-world component was missing from the analysis. Despite these constraints, our findings remain promising. The statistically significant results in the carbon intensity analysis and the consistency of credit spread results with the existing literature support the credibility of our conclusions. With more comprehensive data and additional time, the analysis could be further refined and expanded to yield even more robust insights.

Nonetheless, this study paves the way for future research: since green bonds are a new financial instrument, the results are based on a relatively small number of observations with available information. As more data become available, future research could provide larger-scale evidence and a more refined characterization of the long-term implications of these instruments.

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9. Appendix

9.1. Appendix 1: Green Transportation Firms

Table A1 - Green bonds by issuer and issuer type

Issuer Name	Number of Issuances	Issuer Type
Adif Alta Velocidad	5	Corporate Bond-Investment-Grade
Aeroporti di Roma SpA	1	Corporate Bond-Investment-Grade
Airport Authority of Hong Kong	1	Corporate Bond-Investment-Grade
AP Moller - Maersk A/S	1	Corporate Bond-Investment-Grade
Bonheur ASA	2	Corporate Bond-Investment-Grade
Central Japan Railway Co	3	Corporate Bond-Investment-Grade
Chongqing Rail Transit (Group) Co Ltd	3	Corporate Bond-Investment-Grade
CSSC Capital 2015 Ltd	1	Corporate Bond-Investment-Grade
Deutsche Bahn Finance GmbH	4	Corporate Bond-Investment-Grade
East Japan Railway Co	1	Corporate Bond-Investment-Grade
EUROFIMA	9	Supranational
FCC Servicios Medio Ambiente Holding SAU	1	Corporate Bond-Investment-Grade
FedEx Corp	1	Corporate Bond-Investment-Grade
Ferde AS	11	Corporate Bond-Investment-Grade
Ferrovie dello Stato Italiane SpA	5	Non-US Agency
Getlink SE	3	Corporate Bond-High Yield
Guangzhou Metro Investment Finance (BVI) Ltd	1	Corporate Bond-Investment-Grade
Hamburger Hochbahn AG	1	Corporate Bond-Investment-Grade
Hyundai Heavy Industries Co Ltd	1	Corporate Bond-Investment-Grade
Incheon International Airport Corp	1	Corporate Bond-Investment-Grade
Japan Freight Railway Co	1	Corporate Bond-Investment-Grade
Japan Post Holdings Co Ltd	1	Corporate Bond-Investment-Grade
Jiangsu Railway Group Co Ltd	1	Corporate Bond-Investment-Grade
Korea Expressway Corp	1	Non-US Agency
Kyushu Railway Co	2	Corporate Bond-Investment-Grade
La Poste SA	2	Corporate Bond-Investment-Grade & Non-US Agency
Leasys SpA	1	Corporate Bond-Investment-Grade
LOTTE Global Logistics Co Ltd	1	Corporate Bond-Investment-Grade
Luchthaven Schiphol NV - Schiphol Group	3	Corporate Bond-Investment-Grade
Metropolitano de Tenerife SA	1	Corporate Bond-Investment-Grade
Mexico City Airport Trust	1	Corporate Bond-Investment-Grade
MTR Corp (CI) Ltd	1	Corporate Bond-Investment-Grade
MTR Corp Ltd	2	Corporate Bond-Investment-Grade
Nanjing Metro Group Co Ltd	1	Corporate Bond-Investment-Grade
Nobina AB	1	Corporate Bond-Investment-Grade

Norfolk Southern Corp	1	Corporate Bond-Investment-Grade
Posten Norge AS	1	Corporate Bond-Investment-Grade
PostNL NV	1	Corporate Bond-Investment-Grade
Regie Autonome des Transports Parisiens - RATP	2	Non-US Agency
Russian Railways OAO	1	Corporate Bond-Investment-Grade
Seaspan Corp	1	Corporate Bond-High Yield
Shenyang Metro Group Co Ltd	1	Corporate Bond-Investment-Grade
Sichuan Airport Group Co Ltd	1	Corporate Bond-Investment-Grade
SNCF Reseau	3	Non-US Agency
Societe Nationale SNCF SA	2	Non-US Agency & Medium-Term Note
South Coast British Columbia Transportation Authority	3	Corporate Bond-Investment-Grade
Teekay Shuttle Tankers LLC	1	Corporate Bond-Investment-Grade
Tobu Railway Co Ltd	1	Corporate Bond-Investment-Grade
Tokyo Metro Co Ltd	1	Corporate Bond-Investment-Grade
Transport for London - TfL	1	Corporate Bond-Investment-Grade
Union Pacific Corp	1	Corporate Bond-Investment-Grade
VR-Yhtyma Oy	1	Corporate Bond-Investment-Grade
Wabtec Transportation Nether-lands BV	1	Corporate Bond-Investment-Grade
Wenzhou Transportation Group Corp	1	Corporate Bond-Investment-Grade
West Japan Railway Co	1	Corporate Bond-Investment-Grade
Wuhan Metro Group Co Ltd	1	Corporate Bond-Investment-Grade
Xin Yue Co Ltd	1	Corporate Bond-Investment-Grade
Yangzhou Transportation Indus-trial Group Co Ltd	1	Corporate Bond-Investment-Grade
Total	**117**	

9.2. Appendix 2: Industry Reclassification

Regarding the Company Parent Primary SIC, the treated sample was originally distributed within 20 sub-industries, including Railroads, line-haul operating (41), followed by Local and suburban transit (21) and Inspection & fixed facilities (15), among others. The control sample is distributed within 14 sub-industries, including Inspection & fixed facilities (167), Railroads, line-haul operating (132) and Airports, flying fields, & services (71), among others, with less representation frequency.

Although our original dataset classified Air courier services, Commercial banks, NEC, Federal & fed.-sponsored credit, General government, NEC, Heavy construction, NEC, Inspection & fixed facilities, Natural gas distribution, Oil and gas field services, NEC, Real estate agents and managers, Refuse systems and U.S. Postal Service as being part of the

Transportation Company General Industry Group (GIG), it is still important to delve into the distribution of our sample. First, it is important to note that the classification is based on the parent company's SIC code, which tends to reflect a more general industrial profile rather than the operational reality of the issuing entity itself. Second, most of these sub-industries are represented by only a few observations in our dataset, as shown in the descriptive table. Therefore, to reduce classification noise, enhance granularity and improve sectoral coherence, we rely on the CAE Rev. 3 framework while also considering firms' individual characteristics and core operations, leading to a more accurate regrouping into 7 consolidated and functionally coherent industry categories. The modifications are detailed in **Table A4**.

Table A2 - Distribution of green bonds per sub-sector (Company Parent Primary SIC) – initial classification

Company Parent Primary SIC	SIC 4 classification	Frequency	Frequency (%)
Air courier services	4513	1	0.855
Airports, flying fields, & services	4581	7	5.983
Commercial banks, NEC	6029	1	0.855
Deep sea foreign trans. of freight	4412	4	3.419
Federal & fed.-sponsored credit	6111	4	3.419
Freight transportation arrangement	4731	1	0.855
General government, NEC	9199	1	0.855
Heavy construction, NEC	1629	1	0.855
Inspection & fixed facilities	4785	15	12.821
Intercity & rural bus transportation	4131	1	0.855
Local and suburban transit	4111	21	17.949
Natural gas distribution	4924	1	0.855
Oil and gas field services, NEC	1389	1	0.855
Railroad equipment	3743	1	0.855
Railroads, line-haul operating	4011	41	35.043
Real estate agents and managers	6531	1	0.855
Refuse systems	4953	1	0.855
Ship building and repairing	3731	2	1.709
Transportation services, NEC	4789	9	7.692
U.S. Postal Service	4311	3	2.564
Total		**117**	**100**

Table A3 - Distribution of conventional bonds per sub-sector (Company Parent Primary SIC) – initial classification

Company Parent Primary SIC	SIC 4 classification	Frequency	Frequency (%)
Air courier services	4513	4	0.810
Airports, flying fields, & services	4581	71	14.372
Commercial banks, NEC	6029	1	0.202
Deep sea foreign trans. of freight	4412	22	4.453
Freight transportation arrangement	4731	12	2.429
Heavy construction, NEC	1629	17	3.441
Inspection & fixed facilities	4785	167	33.806
Intercity & rural bus transportation	4131	12	2.429
Local and suburban transit	4111	25	5.061
Railroad equipment	3743	11	2.227
Railroads, line-haul operating	4011	132	26.721
Ship building and repairing	3731	6	1.215
Transportation services, NEC	4789	7	1.417
U.S. Postal Service	4311	7	1.417
Total		**494**	**100**

Table A4 - SIC-to-Adjusted Sub-Industry Reclassification

Initial SIC Classification	New SIC Classification
Air courier services	Freight Transportation Arrangement
Commercial banks, NEC	Transportation Services, NEC
General government, NEC	Airports, flying fields, & services
Heavy construction, NEC	Transportation Services, NEC
Inspection & fixed facilities	Railroads, Line-Haul Operating
Natural gas distribution	Local and suburban transit
Oil and gas field services, NEC	Deep sea foreign transportation of freight
Railroad equipment	Railroads, Line-Haul Operating
Real estate agents and managers	Local and Suburban Transit
Refuse systems	Transportation Services, NEC
Ship building and repairing	Deep Sea Foreign Transportation of Freight
U.S. Postal Service	Freight Transportation Arrangement
Intercity & rural bus transportation	Intercity & rural bus transportation

Table A5 - Descriptive statistics of new SIC classification

New SIC	Green Bond		Total
	0	1	
Airports, flying fields, & services	71	8	79
Deep sea foreign trans. of freight	28	7	35
Freight transportation arrangement	23	5	28
Intercity & rural bus transportation	12	1	13
Local and suburban transit	25	23	48
Railroads, line-haul operating	310	57	367
Transportation services, NEC	25	16	41
Total	494	117	611

9.3. Appendix 3: Sample selection of the matching analysis

To confirm the comparability between the treated and control groups, we conduct a descriptive analysis presented in **Table A6**.

Country of incorporation

The treated sample for this analysis contains 117 green bond deals issued by 58 firms scattered through 19 countries. The control sample consists of 494 conventional or social bond deals, corresponding to 116 firms and spans 16 countries. In terms of deal distribution within the treated sample, although China and Japan dominate in total volume, countries such as Norway, France, Switzerland, Italy, and Spain exhibit a higher proportion of green bond deals relative to their total issuance. In contrast, Japan, China, the UK, and the US show a stronger preference for conventional bonds, with green bond issuance making up a smaller share of their total activity.

When considering the entire sample of 611 deals (green and conventional), green bond deals represent 28.6% of the total. Focusing specifically on the subset of green deals, China emerges as the most prominent issuer, accounting for 19.7% of all green deals[26]. In contrast, France represents 10.3% of the total sample, but a higher proportion, 13.7%, within the green bond subset. Similarly, Norway comprises only 7.5% of the total sample, yet accounts for 12.8% of the green deals. Japan, although representing 25.2% of the total sample, is responsible for only 10.3% of the green bond deals, suggesting a lower relative emphasis

[26] Distribution of China green deals within the whole sample: $\frac{23+152}{117+494}$ = 28,6%; Distribution of China green deals in the green universe: $\frac{23}{117}$ = 19,7%. The procedure was the same for the remaining calculations.

on green bond issuance within its total activity.

Countries with a notable presence in either green or conventional bond segments include China, France, Norway and Japan, with the first three standing out in green bond issuance.

Sub-industry

According to **Table A6**, Local and suburban transit and Transportation services, NEC are the most representative sectors within the green deals while Airports, flying fields, & services and Intercity & rural bus transportation exhibit a higher proportion of conventional deals. The other classifications, including Railroads, line-haul operating do not present significant differences between the two types of deals.

Deal Value (in EUR)

Regarding the dispersion of the treated sample, the mean value is €454.505.630,09 but the median is €271.800.679,50 which denotes a positive asymmetry with right-skewed asymmetric distribution[27]. Moreover, it is possible to note the presence of a few large outliers, which **Graph A1** helps visualize. The interval of values range within [10.146.515,69; 3.541.860.362] as presented in **Table A6.**

Concerning the dispersion of the control sample, the mean value is €510.741.504,49 but the median, represented by the second quartile, is €252.109.966,20, which denotes a right-skewed asymmetric distribution, where some high values push the mean up[28]. Moreover, we can also point out that the maximum value, represented by the fourth quartile, is extremely high (€3.069.511.122), indicating the presence of important outliers, which is possible to observe in **Graph A2**. The high dispersion between quartiles also confirms the high dispersion of the sample and the presence of outliers. **Table A6** includes the interval of values which range within [19.075.232,72; 3.069.511.121,54], which is included in the interval of values of the treated group, confirming once more that the comparison between these two groups is viable.

Pricing Date (Issuance Date)

Regarding the issuance date, for the GTF, the issuance date of green bonds ranges between April 2015 and December 2022, however, 82,05% of the deals are concentrated

[27] As represented more clearly in **Graph A1**.
[28] As represented more clearly in **Graph A2**.

after January 2019 (included). Regarding the BTF, conventional bond issuance dates range between January, 2015, and December, 2022, with 71% of the deals being concentrated until December, 2018.

Such a temporal imbalance of the sample raises potential concerns on the comparability of the sample. To mitigate these concerns, we use year fixed effects in the regression analysis controls for time-specific macroeconomic conditions, ensuring that comparisons between green and conventional bond issuers are not biased by issuance timing (Flammer, 2021; Marques & Pinto, 2020).

Credit Rating

Concerning credit ratings, most deals (328) of a total of 611, have at least one credit rating assigned by Moody's Rating at the time of bond issuance. For the deals containing missing information, we reclassified them into the "Not Rated" category (283). If a tranche has two credit ratings, we computed the average. The rating is converted as follows: AAA=Aaa=1, AA+=Aa1=2, and so on until CCC+=17, with the "Not Rated" observations corresponding to the rating number 23, using the scale of Marques & Pinto (2020). Rating scales are inverse scales, so a lower numerical credit rating means better rating. **Table A6** summarizes our findings.

Among rated deals, the most common investment-grade rating is A+, with 94 deals, representing 15,4% of the total sample. This is followed by BBB+ with 45 deals (7,4%), and AA with 26 deals (4,3%). When disaggregating by bond type, green bonds are more concentrated in higher rating categories. For example, 17,1% of all green deals are rated AA, and 13,3% are rated A, whereas conventional bonds are more heavily represented in mid to lower investment-grade ratings. Specifically, 16,8% are rated A+ (83 out of 494 deals) while the 29,14% of the rated conventional bonds are predominantly distributed among other lower investment-grade ratings. Notably, 248 of the 494 conventional bonds (50.2%) are unrated, while only 35 of the 117 green bonds (29.9%) fall under the "Not Rated" category.

This suggests that green bond issuers in the sample are more likely to have higher or at least more transparent credit ratings compared to issuers of conventional bonds, potentially indicating different levels of market access, regulatory compliance, or investor expectations (Marques & Pinto, 2020).

Table A6 - Sample composition of the matching analysis (deal level)

		Number of observations (frequency (%))		
	Category/ Statistics	**Green Bond = 0**	**Green Bond = 1**	**Total**
Panel A	**Country of Incorporation**			
	Canada	13 (2,63%)	4 (3.42%)	17 (2.78%)
	China	152 (30.77%)	23 (19.66%)	175 (28.64%)
	Denmark	3 (0.61%)	1 (0.85%)	4 (0.65%)
	Finland	0 (0%)	1 (0.85%)	1 (0.16%)
	France	47 (9.51%)	16 (13.68%)	63 (10.31%)
	Germany	10 (2.02%)	2 (1.71%)	12 (1.96%)
	Hong Kong (China)	0 (0%)	4 (3.42%)	4 (0.65%)
	Italy	14 (2.83%)	7 (5.98%)	21 (3.44%)
	Japan	142 (28.74%)	12 (10.26%)	154 (25.20%)
	Mexico	10 (2.02%)	2 (1.71%)	12 (1.96%)
	Netherlands	1 (0.20%)	4 (3.42%)	5 (0.82%)
	Norway	31 (6.28%)	14 (11.97%)	45 (7.36%)
	Russian Federation	0 (0%)	1 (0.85%)	1 (0.16%)
	South Korea	2 (0.40%)	4 (3.42%)	6 (0.98%)
	Spain	9 (1.82%)	7 (5.98%)	16 (2.62%)
	Sweden	9 (1.82%)	1 (0.85%)	10 (1.64%)
	Switzerland	2 (0.40%)	9 (3.42%)	11 (1.80%)
	United Kingdom	14 (2.83%)	1 (0.85%)	15 (2.45%)
	United States	35 (7.09%)	4 (3.42%)	39 (6.38%)
Total		494	117	611
Panel B	**Company Parent Primary SIC**			
	Airports, flying fields, & services	71 (14.37%)	8 (6.84%)	79 (12.93%)
	Deep sea foreign trans. of freight	28 (5.67%)	7 (5.98%)	35 (5.73%)
	Freight transportation arrangement	23 (4.66%)	5 (4.27%)	28 (4.58%)
	Intercity & rural bus transportation	12 (2.43%)	1 (0.85%)	13 (2.13%)
	Local and suburban transit	25 (5.06%)	23 (19.66%)	48 (7.86%)
	Railroads, line-haul operating	310 (62.75%)	57 (48.72%)	367 (60.07%)
	Transportation services, NEC	25 (5.06%)	16 (13.68%)	41 (6.71%)
Total		494	117	611

Panel C	**TRBC Classification**			
	Transport Infrastructure	381 (77.13%)	65 (55.56%)	446 (73%)
	Freight & Logistics Services	76 (15.38%)	28 (23.93%)	104 (17.02%)
	Passenger Transportation Services	37 (7.49%)	24 (20.51%)	61 (9.98%)
	Total	494	117	611
Panel D	**Deal Value (EUR million)**			
	Min (Q0)	19 075, 23	10 146, 52	
	Q1	118 896, 35	128 527, 27	
	Median (Q2)	254 052, 13	271 800, 68	
	Mean	536 510, 20	454 505, 63	
	Q3	600 000, 00	551 267, 92	
	Max (Q4)	3 069 511, 12	3 541 860, 36	
Panel E	**Rating Level**			
	AAA	4 (0.81%)	2 (1.71%)	6 (0.98%)
	AA+	0 (0%)	6 (5.13%)	6 (0.98%)
	AA	6 (1.21%)	20 (17.09%)	26 (4.26%)
	AA-	9 (1.82%)	3 (2.56%)	12 (1.96%)
	A+	83 (16.80%)	11 (9.40%)	94 (15.38%)
	A	19 (3.85%)	12 (10.26%)	31 (5.07%)
	A-	23 (4.66%)	2 (1.71%)	25 (4.09%)
	BBB+	36 (7.29%)	9 (7.70%)	45 (7.36%)
	BBB	26 (5.26%)	9 (7.70%)	35 (5.73%)
	BBB-	14 (2.83%)	4 (3.42%)	18 (2.95%)
	BB+	6 (1.21%)	1 (0.85%)	7 (1.15%)
	BB	7 (1.42%)	3 (2.56%)	10 (1.64%)
	B+	1 (0.20%)	0 (0%)	1 (0.16%)
	B-	3 (0.61%)	0 (0%)	3 (0.49%)
	B	8 (1.62%)	0 (0%)	8 (1.31%)
	CCC+	1 (0.20%)	0 (0%)	1 (0.16%)
	Not Rated	248 (50.20%)	35 (29.91%)	283 (46.32%)
Total		494	117	611
Panel F	**Pricing Date**			
	2015	80 (19.19%)	1 (0.85%)	81 (13.26%)
	2016	75 (15.18%)	3 (2.56%)	78 (12.77%)
	2017	74 /14.98%)	8 (6.84%)	82 (13.42%)
	2018	72 (14.57%)	9 (7.69%)	81 (13.26%)
	2019	55 (11.13%)	20 (17.09%)	75 (12.27%)
	2020	56 (11.33%)	23 (19.66%)	79 (12.93%)
	2021	39 (7.89%)	31 (26.50%)	70 (11.46%)
	2022	43 (8.70%)	22 (18.80%)	65 (10.64%)
Total		494	117	611

Table A7 - Sample composition of the matching analysis (firm level)

		Number of observations (frequency (%))		
Variable	**Category/ Statistics**	**Green Bond = 0**	**Green Bond = 1**	**Total**
Panel A	**Country of Incorporation**			
	Canada	2 (1.72%)	1 (1.72%)	3 (1.72%)
	China	31 (26.72%)	11 (18.97%)	42 (24.14%)
	Denmark	3 (2.59%)	1 (1.72%)	4 (2.30%)
	Finland	0 (0%)	1 (1.72%)	1 (0.57%)
	France	10 (8.62%)	5 (8.62%)	15 (8.62%)
	Germany	4 (3.45%)	2 (3.45%)	6 (3.45%)
	Hong Kong (China)	0 (0%)	4 (6.90%)	4 (2.30%)
	Italy	7 (6.03%)	3 (5.17%)	10 (5.75%)
	Japan	21 (18.10%)	8 (13.80%)	29 (16.67%)
	Mexico	2 (1.72%)	1 (1.72%)	3 (1.72%)
	Netherlands	1 (0.86%)	3 (5.17%)	4 (2.30%)
	Norway	9 (7.76%)	4 (6.90%)	13 (7.47%)
	Russian Federation	0 (0%)	1 (1.72%)	1 (0.57%)
	South Korea	2 (1.72%)	4 (6.90%)	6 (3.45%)
	Spain	2 (1.72%)	3 (5.17%)	5 (2.87%)
	Sweden	2 (1.72%)	1 (1.72%)	3 (1.72%)
	Switzerland	2 (1.72%)	1 (1.72%)	3 (1.72%)
	United Kingdom	9 (7.76%)	1 (1.72%)	10 (5.75%)
	United States	9 (7.76%)	3 (5.17%)	12 (6.90%)
Total		116	58	174
Panel B	**Company Parent Primary SIC**			
	Airports, flying fields, & services	18 (15.52%)	5 (8.62%)	23 (13.22%)
	Deep sea foreign trans. of freight	11 (9.50%)	6 (10.34%)	17 (9.77%)
	Freight transportation arrangement	11 (9.50%)	5 (8.62%)	16 (9.20%)
	Intercity & rural bus transportation	5 (4.31%)	1 (1.72%)	6 (3.45%)
	Local and suburban transit	7 (6.03%)	9 (15.52%)	16 (9.20%)
	Railroads, line-haul operating	60 (51.72%)	24 (41.8%)	84 (48.28%)
	Transportation services, NEC	4 (3.45%)	8 (13.79%)	12 (6.90%)
Total		116	58	174
Panel C[29]	**Deal Value (EUR million)**			

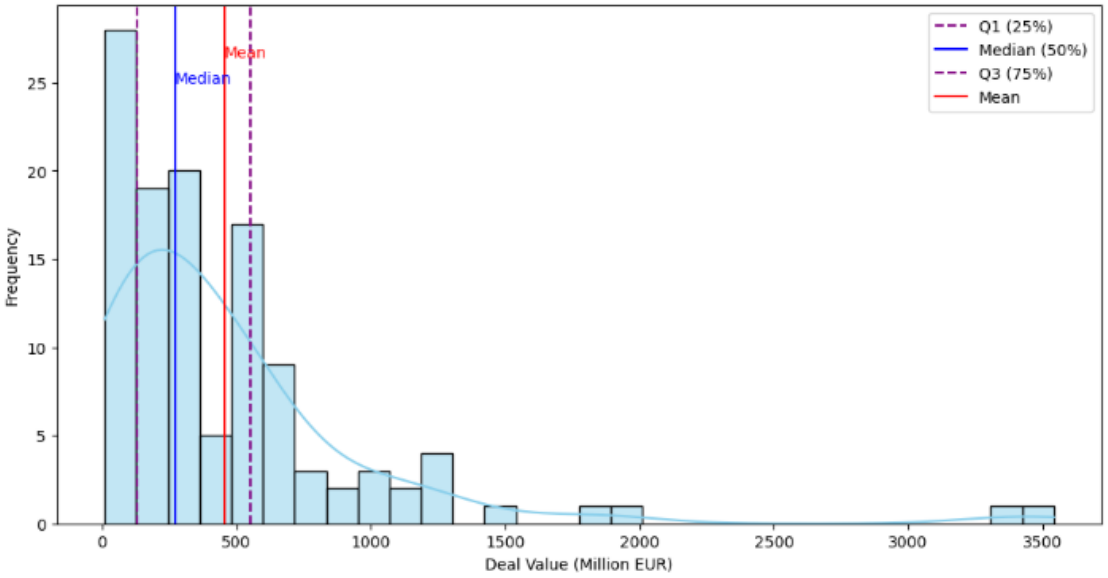
[29] The difference between the descriptive statistics at the deal-level is because, at the firm-level, if a firm issued

	Min (Q0)	29 352 914,99	19 737 588,76	
	Q1	82 335 182,22	134 230 932,33	
	Median (Q2)	175 314 523,22	315 736 539,40	
	Mean	349 223 683,08	483 120 496,02	
	Q3	497 500 000,00	537 500 000,00	
	Max (Q4)	3 000 000 000,00	3 541 860 362,16	
Panel D	**Rating Level**			
	AAA	4 (3.45%)	2 (3.45%)	6 (3.45%)
	AA+	0 (0%)	2 (3.45%)	2 (1.15%)
	AA	1 (0.86%)	8 (13.79%)	9 (5.17%)
	AA-	4 (3.45%)	1 (1.72%)	5 (2.87%)
	A+	11 (9.48%)	8 (13.79%)	19 (10.92%)
	A	4 (3.45%)	3 (5.17%)	7 (4.02%)
	A-	3 (2.59%)	1 (1.72%)	4 (2.30%)
	BBB+	9 (7.76%)	5 (8.62%)	14 (8.05%)
	BBB	8 (6.90%)	4 (6.90%)	12 (6.90%)
	BBB-	8 (6.90%)	4 (6.90%)	12 (6.90%)
	BB+	1 (0.86%)	0 (0%)	1 (0.57%)
	BB	1 (0.86%)	2 (3.45%)	3 (1.72%)
	BB-	1 (0.86%)	0 (0%)	1 (0.57%)
	B+	0 (0%)	0 (0%)	0 (0%)
	B-	2 (1.72%)	0 (0%)	2 (1.15%)
	B	1 (0.86%)	0 (0%)	1 (0.57%)
	CCC+	0 (0%)	0 (0%)	0 (0%)
	Not Rated	58 (50%)	18 (31.03%)	76 (43.68%)
Total		116	58	174
Panel E	**Pricing Date**			
	2015	44 (37.93%)	1 (1.72%)	45 (25.86%)
	2016	28 (24.13%	3 (5.17%)	31 (17.82%)
	2017	7 (6.03%)	5 (8.62%)	12 (6.90%)
	2018	13 (11.21%)	6 (10.34%)	19 (10.92%)
	2019	7 (6.03%)	5 (8.62%)	12 (6.90%)
	2020	6 (5.17%)	10 (17.24%)	16 (9.20%)
	2021	11 (9.48%)	17 (29.31%)	28 (16.09%)
	2022	(-)[30]	11 (18.97%)	11 (6.32%)
Total		116	58	174

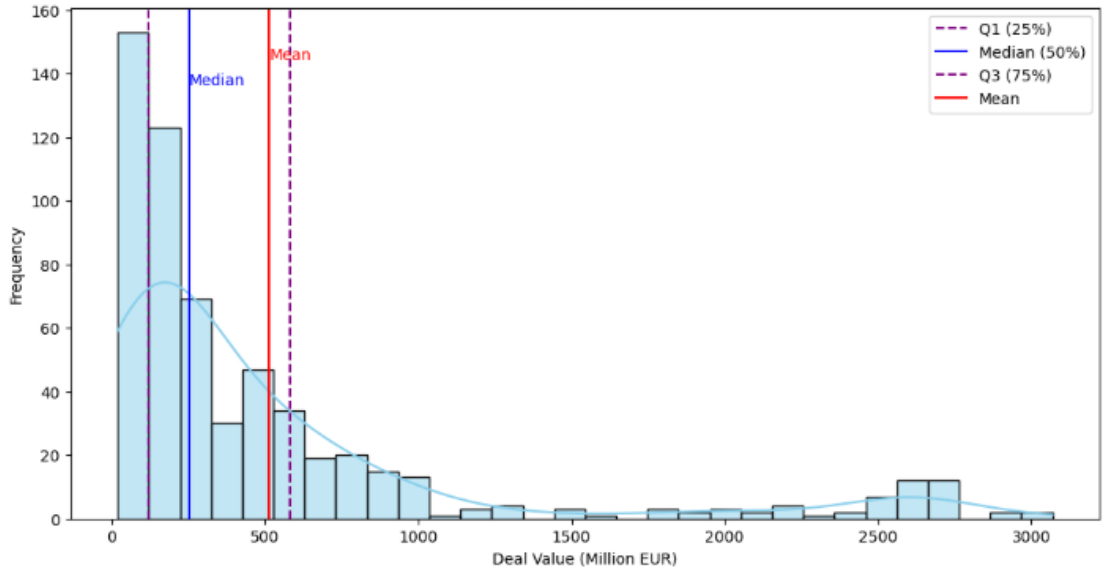
more than one bond in the same year, we consider its mean value.

[30] The difference between the descriptive statistics at the deal-level is because, at the firm-level, if a firm issued more than one bond in different years, we consider the first date of issuance.

Graph A1 - Deal Value Distribution for green bonds



Graph A2 - Deal Value Distribution for conventional bonds



9.4. Appendix 4: Supplementary Figures on High Carbon Intensity and High Climate Awareness at the firm-level

Table A8 - Distribution of high carbon intensity variable per sector

High Carbon Intensity	Industry classification - TRBC			Total
	Freight & Logistics Services	Passenger Transportation Services	Transport Infrastructure	
0	0	0	1177	1177
1	495	242	0	737
Total	495	242	1177	1914

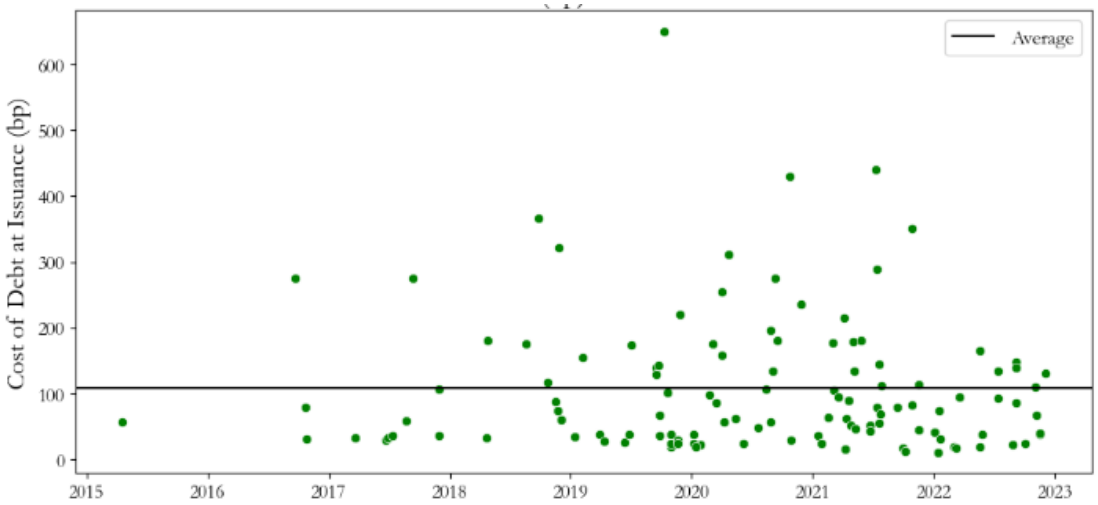
Table A9 - Distribution of High Climate Awareness per country

High Climate Awareness	Company Nationality																		
	Canada	China	Denmark	Finland	France	Germany	Hong Kong (China)	Italy	Japan	Mexico	Netherlands	Norway	Russian	South Korea	Spain	Sweden	Switzerland	United Kingdom	United States	Total
0	33	462	0	11	0	0	44	0	319	33	44	0	11	66	0	33	0	0	132	1188
1	0	0	44	0	165	66	0	110	0	0	0	143	0	0	55	0	33	110	0	726
Total	33	462	44	11	165	66	44	110	319	33	44	143	11	66	55	33	33	110	132	1914

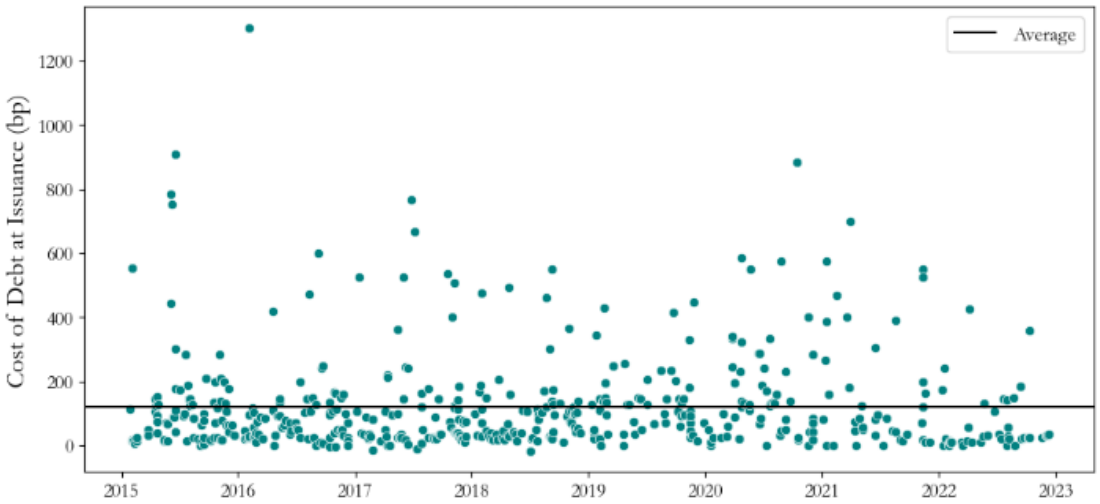
9.5. Appendix 5: Supplementary Figures on credit spread

Regarding the descriptive statistics of green and conventional bonds, **Graph A3** and **Graph A4** are useful to corroborate and better visualize this information, having an overview of the relationship between the mean and the issued yields throughout the years.

Graph A3 - Dispersion plot of credit spread (bp) for green bonds



Graph A4 – Dispersion plot of credit spread (bp) for conventional bonds



9.6. Appendix 6: Preliminary Statistical Tests at the deal level

As referred in section 4.2 our original regression (equation 9.6.1) suffered some modifications that will be delve into more specifically in this section[31]:

[31] The variable Maturity refers to the Weighted Tranche Years to Maturity; Tranches are the number of tranches; Rank Number is a numerical variable of seniority ranking in which 1 corresponds to Senior Secured, 2 to Senior Unsecured and 3 to Subordinated Unsecured. The remaining variables are already defined in section 3.

$$\text{Credit Spread}_{d,t} = \beta_0 + \beta_1 \text{Green Bond}_{d,t} + \beta_2 \text{Banks}_{d,t} + \beta_3 \text{Callable}_{d,t} + \beta_4 \text{Deal Value}_{d,t} + \beta_5 \text{Currency Risk}_{d,t} + \beta_6 \text{Rating Number}_{d,t} + \beta_7 \text{Maturity}_{d,t} + \beta_8 \text{Perpetual}_{d,t} + \beta_9 \text{Tranches}_{d,t} + \beta_{10} \text{Rank Number}_{d,t} + Year_t + Nationality_n + Subsector_j + \varepsilon_{dt} \quad (9.6.1)$$

Table A10 – Credit Spread: initial regression results (at the deal level)

	Credit Spread
Green Bond	-15.479
	(12.683)
Banks	-1.027
	(0.968)
Callable	67.009***
	(18.904)
Deal Value	-16.780**
	(6.842)
Currency Risk	38.023***
	(14.375)
Rating Number	2.138***
	(0.626)
Maturity	-0.695
	(0.606)
Perpetual	117.341*
	(66.278)
Tranches	2.907
	(6.143)
Rank Number	-57.391*
	(33.876)
Constant	508.721***
Nationality fixed effects	Yes
Year fixed effects	Yes
Sub-industry fixed effects	Yes
R^2	0.551

Notes: ***, ** and * indicate that the reported coefficients are significantly different from zero at the 1%, 5% and 10% levels, respectively. The statistics reported in parentheses are based on standard errors.

Then we proceed to compute the preliminary statistical tests.

Multicollinearity

The purpose of testing for multicollinearity is to determine if any independent variables are excessively correlated with each other. To inquire about the presence of multicollinearity, we use the Variance Inflation Factor (VIF) statistics and used the average VIF above 5 (VIF>5) to confirm the presence of multicollinearity issues. The results are presented in **Table A11**.

Table A11 - First VIF results

Variable	**VIF**	**1/VIF**
Deal Value	104.21	0.01
Rank Number	79.13	0.013
Maturity	16.44	0.061
Perpetual	12.60	0.079
Tranches	6.80	0.147
Rating Number	4.90	0.204
Banks	2.44	0.410
Callable	2.29	0.436
Green Bond	1.40	0.716
Currency Risk	1.29	0.778
Mean VIF	**23.15**	

Not all VIF values are well below 5, which is the common rule-of-thumb threshold indicating multicollinearity problems. However, since the logarithmic function of deal value and the variable currency risk were statistically significant at the 1% level and their sign was the expected one according to referred literature, we opted for not removing them from the model. Moreover, since our variable of interest was Green Bond, we also have attention to its coefficient variation when accounting for multicollinearity problems.

Given that, after excluding the variables Rank Number, Maturity and Tranches (which were not statistically significant), and running the VIF test again, the results were the following:

Table A12 - Second VIF results

Variable	VIF	1/VIF
Deal Value	7.53	0.133
Rating Number	4.66	0.215
Banks	2.28	0.439
Callable	2.04	0.490
Green Bond	1.38	0.726
Perpetual	1.35	0.742
Currency Risk	1.27	0.787
Mean VIF	**2.93**	

Although the Deal Value still have VIF>5, the mean VIF of the overall variables is 2.93, so we decided to keep the model like that.

Specification Test - Ramsey RESET

To assess if there are omitted relevant variables in the model provided, we perform the specification test, more precisely the Ramsey test. When variables are omitted, variations in the dependent variable may be inaccurately attributed to the included explanatory variables leading to biased and inefficient estimation. Therefore, additional variables should be included in the model to obtain a more accurate result.

The Ramsey test involves adding higher-order terms of predicted values and testing their global significance to capture potential non-linear relationships. If they are statistically significant, it suggests that the original model might be misspecified.

H_0: model is well specified (has no omitted variables bias)

H_1: model is not well specified (suffers from omitted variables bias)

Based on a 5% level of significance, the observed p_value (0.5409) is higher than the critical p-value (0.05), so we do not reject the null hypothesis that the model is well specified. This can be also interpreted as the additional variables are statistically significant to explain the dependent variable.

Heteroskedasticity - Breusch–Pagan/Cook–Weisberg test for heteroskedasticity

To check whether a regression model is characterized by heteroscedasticity, we chose to develop the Breusch–Pagan/Cook–Weisberg test for heteroskedasticity.

H_0: presence of homoscedasticity

H_1: presence of heteroscedasticity (variance of the errors or disturbance terms is not constant)

Based on a level of significance of 5%, the observed p-value of 0 is lower than the critical p-value of 0.05. As a result, we reject the null hypothesis that there is homoscedasticity the original model, concluding that there is evidence of heteroskedasticity.

In the presence of heteroskedasticity, the estimators are centric, linear, and consistent, but they are no longer efficient. This means that they are "no longer the estimators of minimal variance in the class of centric and linear estimators". Furthermore, they loss the validity of statistical inference.

Hence, it is necessary to correct the heteroscedasticity. For that, we use the OLS + White estimator procedure (with robust standard errors) using the option vce(cluster AnalyticsDeal) to estimate the regression with Statistics robust to heteroskedasticity. This indicates that the coefficients are robust to heteroscedasticity, meaning they are calculated in a way that accounts for potential heteroscedasticity in the residuals. Although this procedure does not eliminate the heteroscedasticity problem, "it restores the validity of the statistic inference in large samples", allowing the accommodation of the presence of heteroscedasticity.

Autocorrelation

In order to check for the presence of first-order autocorrelation on the estimation residuals of my panel regression model (serial correlation AR(1)), we perform the Durbin-Watson or Wooldridge-style test.

This result strongly indicates the presence of first-order positive serial correlation (AR(1)) in the residuals of our main model. This means that the error terms are not independent, so it is necessary to account for correction methods. We opt for the Newey-West (HAC - Heteroskedasticity and Autocorrelation Consistent), accounting for clustered standard errors).

Endogeneity

The purpose of testing endogeneity is to determine whether the independent variables are correlated with the error term. According to the classical assumptions, the OLS estimators are known as BLUE estimators, which stands for Best Linear Unbiased Estimator, under the condition that the independent variables are not correlated with the error term. Instead of using the lagged values of which variable to test for endogeneity we use variables

of our dataset that were not present in the regression to test for endogeneity.

When testing the endogeneity of the suspected variables using variables of our dataset that were not present in the regression as its instruments, we encounter multiple problems, namely, weak instruments and some invalid ones because of collinearities detected between the chosen instruments and the endogenous variables being tested.

The reason for not using lagged variables as instruments relies on the fact that our regression in not based on a panel structure but rather cross-sectional. Each of those 611 observations identifies a single Analytics Deal, which is unique and do not vary within our time period (2015-2022).

However, given the problems in using our existing variables as instruments, we decide to create lagged values for the temporal sample of our analysis but instead it to be within Analytics deals, given the limitations explained, we generate lagged versions of your variables using the company nationality and pricing year as our panel structure.

For that, we decide to test the dummy Green Bond, since reverse causality is a well-known concern, mentioned by numerous authors. Companies expecting lower credit spreads may self-select into issuing green bonds. The results showed that its lagged value is a strong instrument but there is no evidence that Green Bond is endogenous.

Also, since some of our deals (although not in most representations) are in a foreign currency, firms may choose to issue in a foreign currency (incurring currency risk) strategically, based on expectations of better pricing in foreign markets. Its lagged value was considered strong and there is also no evidence of endogeneity.

9.7. Appendix 7: Preliminary Statistical Tests at the firm-level

We repeated the procedure before for section 6.2.2. The preliminary regression is given by the equation (9.7.1) and the results are displayed in **Table A13**.

$$\begin{aligned} Credit\ Spread_{i,t} &= \beta_0 + \beta_1 Green\ Firm_{i,t} + \beta_2 ROA_{i,t} + \beta_2 Size_{i,t} \\ &+ \beta_3 Leverage_{i,t} + \beta_4 Current\ Ratio_{i,t} + \beta_5 Firm\ Age_{i,t} \\ &+ Year_{\mathrm{t}} + Nationality_n + Subsector_j + \varepsilon_{i,t} \end{aligned} \tag{9.7.1}$$

Table A13 - Credit Spread: initial regression results (at the firm level)

	Credit Spread
Green Firm	-27.007
	(25.637)
ROA	-2.173
	(2.564)
Size	-16.480**
	(6.445)
Leverage	54.160
	(49.418)
Current Ratio	3.027
	(3.093)
Firm Age	0.454
	(0.308)
Constant	352.539***
	(116.286)
Nationality fixed effects	Yes
Year fixed effects	Yes
Sub-industry fixed effects	Yes
Observations	334
R^2	0.488

Notes: ***, ** and * indicate that the reported coefficients are significantly different from zero at the 1%, 5% and 10% levels, respectively. The statistics reported in parentheses are based on standard errors.

Multicollinearity

To inquire about the presence of multicollinearity, we use the Variance Inflation Factor (VIF) statistics and used the average VIF above 5 (VIF>5) to confirm the presence of multicollinearity issues.

Table A14 - Second VIF results

Variable	**VIF**	**1/VIF**
Size	8.13	0.123
Leverage	4.96	0.202
Firm Age	2.50	0.400
ROA	1.39	0.719
Current Ratio	1.37	0.727
Green Firm	1.30	0.770
Mean VIF	**3.27**	

Although the first variable still have VIF>5, which is the common rule-of-thumb threshold indicating multicollinearity problems, the mean VIF of the overall variables is 3.27, and the variable is statistically significant to explain our output, so we decide to keep the model like that.

Specification Test - Ramsey RESET

To assess if there are omitted relevant variables in the model provided, we perform the specification test, more precisely the Ramsey test. The Ramsey test involves adding higher-order terms of predicted values and testing their global significance to capture potential non-linear relationships. If they are statistically significant, it suggests that the original model might be misspecified.

H_0: model is well specified (has no omitted variables bias)

H_1: model is not well specified (suffers from omitted variables bias)

Based on a 5% level of significance, the observed p_value (0.1730) is higher than the critical p_value (0.05), so we do not reject the null hypothesis that the model is well specified. This can be also interpreted as the additional variables are statistically significant to explain the dependent variable.

Heteroskedasticity - Breusch–Pagan/Cook–Weisberg test for heteroskedasticity

To check whether a regression model is characterized by heteroscedasticity, we choose to develop the Breusch–Pagan/Cook–Weisberg test for heteroskedasticity.

H_0: presence of homoscedasticity

H_1: presence of heteroscedasticity (variance of the errors or disturbance terms is not constant)

Based on a level of significance of 5%, the observed p-value of 0 is lower than the critical p-value of 0.05. As a result, we reject the null hypothesis that there is homoscedasticity the original model, concluding that there is evidence of heteroskedasticity.

In the presence of heteroskedasticity, the estimators are centric, linear, and consistent, but they are no longer efficient. This means that they are "no longer the estimators of minimal variance in the class of centric and linear estimators". Furthermore, they loss the validity of statistical inference.

Hence, it is necessary to correct the heteroscedasticity. For that, we use the OLS + White estimator procedure (with robust standard errors) using the option vce(cluster firm) to estimate the regression with Statistics robust to heteroskedasticity. This indicates that the

coefficients are robust to heteroscedasticity, meaning they are calculated in a way that accounts for potential heteroscedasticity in the residuals. Although this procedure does not eliminate the heteroscedasticity problem, "it restores the validity of the statistic inference in large samples", allowing the accommodation of the presence of heteroscedasticity.

Autocorrelation

In order to check for the presence of first-order autocorrelation on the estimation residuals of my panel regression model (serial correlation AR(1)), we perform the Wooldridge test for autocorrelation in panel data.

Since the observed p-value (0.0339) is lower than the critical p_value of 5%, it indicates the presence of first-order positive serial correlation (AR(1)) in the residuals of our main model. This means that the error terms are not independent, so it is necessary to account for correction methods. We opted for the Newey-West (HAC - Heteroskedasticity and Autocorrelation Consistent), accounting for clustered standard errors and for lag all variables, except for Green Firm. After repeating the process, we conclude in favor of no first-order correlation.

Endogeneity

The purpose of testing endogeneity is to determine whether the independent variables are correlated with the error term. When testing the endogeneity of the suspected variables using variables of our dataset, we used its lagged values as instruments.

We test all variable in our regression, and they all tested negative for being endogenous. Some relevant aspects to mention are that we decided to test the dummy Green Bond, since reverse causality is a well-known concern, mentioned by numerous authors. Companies expecting lower credit spreads may self-select into issuing green bonds. The results showed that its lagged value is a strong instrument but there is no evidence that Green Bond is endogenous. Moreover, Size was one of our main concerns since there might be a case of reverse causality, where the decision to issue a green bond (or signal green credentials) affects firm size over time. For instance, green bond issuance could improve access to capital and lead to growth in firm size, making the direction of causality ambiguous.

After contemplating all the statistical tests, the final regression used in our main analysis is presented in section 6.2.2.

9.8. Appendix 8: Reasons for the incompatibility of the staggered difference-in-differences method in our dataset

Our initial dataset included 1,914 firm-year observations, organized for each company from 2013 to 2022. However, exploratory analysis revealed that the credit spread (bps) variable was missing in 1,511 of these cases. After including only observations for the period between 2015 to 2022 (as explained in section 9.3) with no missing values for our variable of interest, we ended up with a total of 403 firm-year observations without missing credit spread values. Specifically, we observed that many of the treated firms (GTF) had outcome data only in a single year - the year of bond issuance - with no valid data before or after treatment. This high rate of missingness stems largely from the fact that many firms in the sample issued only one or two bonds, and frequently in non-consecutive years, resulting in significant temporal gaps and the conditions mentioned were largely unmet. This made the dynamic event study design unviable, as the remaining observations could not support the required before/after comparison.

Additionally, while the control group (BTF) comprised 1,276 firm-year observations, we found that only 313 observations had non-missing outcome data, and the treated group (GTF) had only 90 observations with non-missing outcome data. Crucially, even though the control firms were present across all years in the panel (2015 - 2022), many of them lacked outcome data in years that aligned with treated firms' bond issuances. While the overall number of 403 firm-years observations may seem sufficient, it does not imply that individual firms meet the conditions required for a dynamic event study, namely, having outcome data in both pre- and post-treatment periods.

To illustrate, we provide the distribution of green and conventional firms with non-missing credit spread for 3 consecutive years in **Table A15**, which clearly shows the sparse nature of the data[32].This restriction is essential because the DiD framework relies on within-firm temporal variation to credibly estimate causal effects. In the absence of consecutive-year data, lagged variables become undefined, which jeopardizes core assumptions such as parallel trends and temporal consistency (Callaway & Sant'Anna, 2021).

[32] The choice of using three consecutive years as a criterion is based on the need to gather information from the year prior to the bond issuance, the year of the issuance itself, and the year following the issuance. Additionally, for companies that have issued multiple bonds, we have determined that the year of the first bond issuance will serve as the reference point for the treatment period for each company and as our coefficient of interest.

Table A15 - Distribution of unique firms observations with non-missing credit spread information in 3 consecutive years from 2015 to 2022

Green Bond	Freq.	Percent	Cum.
0	39	90.70	90.70
1	4	9.30	100.00
Total	43	100.00	

This table shows the aggregate pool of treated firms generated a certain number of firm-year observations with non-missing credit spread data occurring before and after the treatment year. It is possible to observe that only 43 firms in total had sufficient information for the required comparison. Though the number of firms in each group is small to ensure the robustness of our analysis, we would still need to verify whether those firms issued bonds within the same range of years across each group to make the comparison valid.

Within this set of 43 unique firms, each company may contribute more than one valid sequence of three consecutive years with available credit spread data, as demonstrated in the **Table A16**. The presence of multiple sequences per firm reflects the longitudinal structure of the dataset, where firms with sustained reporting can appear in overlapping time windows - for instance, a firm with data from 2016 to 2019 would contribute to both the "2016–2017–2018" and "2017–2018–2019" sequences. This feature increases the richness of the panel but also introduces potential dependence across observations that share the same firm.

Notably, only four of the identified sequences include both green bond issuers and conventional bond issuers. These sequences represent the only windows in which direct comparisons between treated and control groups are feasible within the same time frame.

As such, while the overall number of valid sequences is relatively high, the number of comparable groups for matched analysis remains limited to these four periods, which may constrain the statistical power and generalizability of any findings derived from matched comparisons.

Table A16 - Distribution of Firms with Valid Sequences of Three Consecutive Years of Credit Spread Data, by Bond Type

seq	**Green Bond**		**Total**
	0	1	
2015-2016-2017	13	0	13
2016-2017-2018	17	0	17
2017-2018-2019	14	2	16
2018-2019-2020	10	3	13
2019-2020-2021	7	4	11
2020-2021-2022	9	1	10
Total	**70**	**10**	**80**

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