# Deconstruction of ESG Impacts on US Corporate Bond Pricing: The Cost of Capital Benefits Across Industry Sectors

**Article** *in* Journal of Management in Engineering · January 2024

DOI: 10.1061/JMENEA.MEENG-5521



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# Deconstruction of ESG Impacts on US Corporate Bond Pricing: The Cost of Capital Benefits Across Industry Sectors

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**Abstract:** The growing interest in the financial materiality of Environmental, Social, and Governance (ESG) ratings has prompted recent investigations into their risk pricing impact in the corporate bond market. The specific implications for the Architecture, Engineering, and Construction (AEC) industry have not been explored, as prior work has primarily focused on broad-based ESG integration. To fill this gap, our study employed an interpretable machine learning technique using a sample universe of U.S. corporate bonds spanning from 2010 to 2021 to estimate the impact of ESG ratings on corporate bond issuance spreads. The results revealed an average ESG benefit of 10 basis points across all sectors. However, it is important to note that the effects of ESG ratings on bond pricing demonstrate variation across sectors and individual ESG constituent ratings. Significantly, our findings show that social and governance ratings emerge as the primary drivers influencing bond issuance costs, whereas the impact of environmental scores is comparatively less significant. Within AEC-related industries, empirical data on the influence of ESG ratings indicate discounted pricing by the market is particularly channeled through environmental and governance scores. These findings emphasize the value-added impact of enhanced ESG performance on the cost of debt financing, presenting a financially material opportunity for operational and management decision-making. By adopting sustainable strategies to improve ESG performance, organizations in the AEC industry can potentially achieve lower costs of debt when issuing bonds to secure financing for construction projects. The managerial implications extend to policymakers, corporate managers, and creditors, as they all stand to benefit from the financial implications of ESG performance. **DOI: 10.1061/JMENEA.MEENG-5521.** 



## Introduction

Sustainability risk disclosures and mitigation efforts in corporate, municipal, and sovereign contexts are widely recognized as Environmental, Social, and Governance (ESG) or Corporate Social Responsibility (CSR) matters. The integration of sustainability metrics with financial materiality, which examines the influence of these sustainability factors on a company's profitability, cost of financing, and long-term value generation, has gained substantial attention in the past decade. Particularly driven by the UN Sustainable Development Goals (SDGs) call to action and investor demand, the number of companies that measure, manage, and disclose sustainability risks and opportunities has experienced exponential growth. The term ESG emerged after a 2004 report (UN Environment Programme-Finance Initiative 2004), while CSR has a much longer history in academia and industry. The term ESG is derived from the concept of "Sustainability," which gained prominence following the establishment of CSR. As sustainability standards evolved and became more standardized, ESG emerged as a framework with financial implications. Unlike CSR, which primarily emphasizes social responsibility, ESG encompasses a broader spectrum of considerations, including environmental, social, and governance aspects (Gillan et al. 2021). The private sector has been using "Sustainability" interchangeably with ESG for years, but there is a growing preference for ESG terminology due to its stronger emphasis on stakeholder value from a financial perspective.

Discussions around the ESG/CSR topic are often organized around various aspects of corporate management. For example, one stream of literature is focused on establishing links between ESG/CSR reporting and firm structure, including leadership and ownership efforts (Dyck et al. 2022; Cronqvist and Yu 2017; Jian and Lee 2015), or firm management characteristics such as board composition and executive compensation (Boubakri et al. 2019; Kim et al. 2019). Another line of inquiry emphasizes the relationship between ESG/CSR and firm risk and financial performance (Fatemi et al. 2018; Chen et al. 2018; Polbennikov et al. 2016; Eccles et al. 2014). There is evidence indicating that considering ESG/CSR factors leads to improved corporate performance or risk profiles (Amiraslani et al. 2022; Apergis et al. 2022; Sharfman and Fernando 2008), supported by both qualitative and quantitative assessments. However, other studies suggest that there is no significant overperformance or underperformance when ESG factors are taken into account in bond investments (Gehricke et al. 2023; Larcker and Watts 2020). Whether the integration of ESG brings financial benefits or increases the cost of borrowing is not clear given the limited research focus on the corporate bond market, relative to equities pricing.

Non-financial corporate disclosures, exemplified by CSR and ESG reporting, play a pivotal role in augmenting transparency and social reputation (Aguilera-Caracuel and Guerrero-Villegas 2018). The primary aim is to foster awareness of environmental and social

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Note. This manuscript was submitted on February 17, 2023; approved on August 10, 2023; published online on October 10, 2023. Discussion period open until March 10, 2024; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Management in Engineering***, © ASCE, ISSN 0742-597X.

practices of the firm, effectively fulfilling the informational requirements of stakeholders. However, unlike in other regulatory environments such as Europe, non-financial disclosures continue to be voluntary in the US, notwithstanding their pertinence in catering to the informational needs of internal and external stakeholders. Conventional accounting systems have been recognized for their inadequacy in meeting stakeholders' information needs, primarily due to their predominant focus on financial data, thus limiting transparency in operations (Dando and Swift 2003). In contrast, social and environmental information proves invaluable to both financial stakeholders, who seek to enhance profitability (Serafeim 2020; Eccles et al. 2014) and reduce capital costs (Sharfman and Fernando 2008), and non-financial stakeholders, encompassing employees, customers, and the broader community. However, research findings indicate a lack of fulfilment in meeting stakeholders' information needs regarding ESG management within the construction industry (Hadro et al. 2022). Companies operating within this sector tend to selectively disclose favorable impacts on the environment and the local community, underscoring the imperative for comprehensive improvement in addressing stakeholders' concerns.

Although non-financial disclosure is essential for meeting stakeholders' needs, there is a lack of comprehensive sector-level research, particularly in the Architecture, Engineering, and Construction (AEC) industry. Additionally, engagement with ESG practices within this sector remains limited. According to a recent report, only 72% of companies in this sector disclose ESG information in their annual reports, placing it as the third-lowest among all 15 industry sectors (KPMG 2020). Owners and developers often struggle with the integration of an ESG framework, and management decisions have been limited despite positive financial incentives (Guo et al. 2020; Yan et al. 2019; Xiong et al. 2016). The AEC industry plays a crucial role in the economy, with its progress closely tied to a nation's economic advancement (Daszyńska-Zygadło et al. 2022). The development of infrastructure necessitates substantial financial investments that surpass the capabilities of government funding alone (Lam et al. 2011). To bridge this gap, capital market instruments such as sustainability-linked bonds, green bonds, and social impact bonds (Alonso-Conde and Rojo-Suárez 2020; Warner 2013) have emerged, leveraging social and environmental benefits and injecting resources into infrastructure projects. The utilization of project bonds within the debt market presents an effective financing option for sizable infrastructure projects, as they address the challenges posed by economies of scale and facilitate private investments (Gatti 2013; Scannella 2012). Pricing benefits of debt at the project finance scale are of utmost importance to the AEC industry and its public partners.

The aim of this study is to utilize machine learning tools to evaluate the financial materiality of ESG performance within the corporate bond market for the AEC industry, in comparison to the broader sector spectrum. Understanding financial benefits and improved performance is an essential step toward unlocking the predictive power of ESG data for corporate management decisions. The relationship between ESG and financial performance has primarily been investigated using regression and other statistical methods (Apergis et al. 2022; Jang et al. 2020; Slimane et al. 2019; Polbennikov et al. 2016). However, machine learning methods that go beyond correlation analysis or model-based predictions are being proposed to advance the premise of ESG reporting and to develop compliance mechanisms in the Task Force on Climate-related Financial Disclosures (TCFD) regulation. The current paper explores the heterogeneous effects that exist across sectors and ESG pillars and how they influence corporate bond financial performance across sectors, with a specific emphasis on the AEC industry.

## Literature Review

### Stakeholder Theory

There has been a longstanding debate on whether companies should prioritize short-term financial goals or maximize the total firm interests. This debate centers around the conflicting viewpoints of shareholder theory (Friedman 1970) and stakeholder theory (Freeman 1984) regarding the fundamental purpose of companies. However, recently there has been a notable shift toward a more sustainable approach, driven by the introduction of the ESG concept, which encompasses both the financial goals of the company's legitimate owners and the well-being of the broader network of impacted parties. The Business Roundtable made an announcement on August 19, 2019, introducing a new statement in alignment with the stakeholder theory (Kay 2020). This revised definition broadens the scope of a corporation's purpose, recognizing the growing emphasis on addressing social concerns. It encompasses not only the direct shareholders but also emphasizes the importance of considering the well-being of employees, communities, suppliers, environment, and customers, as they all constitute stakeholders of a corporation.

According to Donaldson and Preston (1995), companies that prioritize the interests of all stakeholders are more likely to achieve greater probability and growth. Additionally, companies that establish trusting relationships with stakeholders will not only mitigate the considerable costs associated with opportunistic behavior but also enjoy a competitive advantage over those that overlook these principles, based on the instrumental stakeholder theory (Jones 1995). By proactively recognizing and addressing significant ESG factors, companies can attain superior long-term performance by bolstering their risk management capabilities, cultivating stronger stakeholder relationships, establishing a robust business reputation, and achieving stronger financial performance, as evidenced in prior studies (Eccles and Serafeim 2013; Sharfman and Fernando 2008). From a risk mitigation perspective, ESG can be regarded as a strategy to enhance stakeholder relationships by mitigating the probability of negative events, such as legal actions stemming from environmental violations, employee strikes, and reputational deterioration (Gonçalves et al. 2022). Moreover, it serves as a protective measure for shareholders against the excessive expenses associated with severe financial distress during a financial crisis (Godfrey et al. 2009). Stakeholder theory forms the fundamental basis for our study, which seeks to investigate the relationship between ESG performance and bond issuance costs.

### ESG in Fixed Income Assets and the Pricing Benefits

With the demand for ESG data transparency increasing due to TCFD, the Sustainable Finance Disclosure Regulation (SFDR), US Security and Exchange Commission, and US Treasury actions, research is focused on exploring the financial materiality of ESG factors. The question asked is whether asset performance reflects any ESG-related organizational behaviors. A review of 2,200 individual studies on the financial effects of ESG criteria showed, on average, a neutral/mixed relationship between the ESG/CSR criteria reported or used in ratings and corporate financial performance. More importantly, 56% of studies report positive relationships, indicating that ESG considerations improve the financial outlook and metrics of the firm (Friede et al. 2015).

While a few studies focus on the fixed income market, most of the research on the relationship between ESG/CSR and financial indicators is related to equities, leaving a research need. Responsible investment approaches consider both stocks and bonds in their portfolios and apply ESG/CSR policy mandates to both equity and debt investments, for example through integration in creditworthiness and allocation strategies (Slimane et al. 2019). Research has suggested that good CSR is rewarded through lower corporate bond credit spreads based on regression analysis (Hsu and Chen 2015; Oikonomou et al. 2014). The relationship between ESG ratings and corporate bond performance (Desclée et al. 2016; Polbennikov et al. 2016) showed that bonds with high ESG ratings outperformed lower-rated bonds when controlling for various risk factors. Conversely, (Amiraslani et al. 2019) found no relationship between CSR and bond spreads between 2005 and 2013. However, during the financial crisis of 2008–2009, high CSR companies were able to raise debt at lower spreads. Although most studies showed a positive relationship between ESG/CSR and debt performance, there is no conclusive impact of nonfinancial disclosure due to differences in methodologies, datasets, and time frames.

The impact of ESG factors on corporate bond performance has not been explicitly studied, resulting in considerable uncertainty about this relationship. To provide a reference point, Giese et al. (2021) conducted a systematic and comprehensive analysis of ESG effects in the equity markets, and proposed that ESG effects were transferred to their financial performance through selected channels, such as business activities that boost cash flow, risk mitigation strategies, lower levels of systematic risk, and costs of capital. They also uncovered sectoral differences in environmental (E), social (S), and governance (G) performance, with the G pillar demonstrating the strongest link to share price performance. The difference was further influenced by key metrics within the E, S, and G pillars. For example, corporate governance (key issue under the G pillar) and health and safety (key issue under the S pillar) showed the most significant financial relevance. These channel, sectoral and ESG metric differences are referred to as heterogeneity effects.

Heterogeneity effects also pertain to corporate bonds, whereby "the materiality of ESG factors tends to be dependent upon sector, region, timescale and leverage." (Kohut and Beeching 2013). On the environmental level, the cost of debt may rise by 64 basis points (bps) for debt issuers who engage in environmental misconduct (Bauer and Hann 2010). Within the social pillar, a study of over 2,000 bonds (Bauer et al. 2009) showed that firms with robust employee relations tend to have a lower cost of debt financing. The authors argued that strong human capital practices improve a firm's capability to generate stable cash flows, thus affecting the cost of debt financing resulting from credit risk mitigation. Similarly, Oikonomous et al. (2014) found that good corporate social behavior was rewarded by a lower cost of debt, whereas corporate social wrongdoings were punished by higher bond credit spreads based on a two-dimensional panel regression. As a comparison, Li et al. (2020) showed that social responsibility is a less important predictor of bond default rates in the Chinese bond market. Lastly, empirical results provided evidence on the association between good corporate governance and bond yields, whereby stable boards result in bonds with higher credit ratings and lower spreads (Bhojraj and Sengupta 2003; Bradley et al. 2008). According to a recent study by Apergis et al. (2022), all pillars of ESG have a negative and significant impact on the cost of debt, while decomposition of the ESG score into environmental, social, and governance factors may increase the statistical significance of their impact.

Industry sector effects have been observed as well. Evidence that bond prices are discounted based on costs associated with environmental contamination was based on a study scope of 48 firms and 244 firm-year observations in the pulp and paper and chemical industries (Schneider 2011). Using regression analysis, Polbennikov et al. (2016) observed that ESG-weighted corporate bond indices performed in the same fashion as their benchmark because underperformance in the utility sector was offset by overperformance in the financial and industrial sectors. Yang et al. (2021) showed that in the Chinese bond market, ESG disclosures of high pollution and energy consumption companies lower the credit spreads of their corporate bonds. Baldi and Pandimiglio (2022) showed that greenwashing risk is higher in the financial sector. Hence, different dimensions of ESG may be particularly relevant to certain industries because those industries are sensitive to bondholder and media scrutiny pertaining to sector specific ESG metrics.

### *AEC Industry: Its Relevance and ESG Considerations*

According to Allied Market Research (2020), the global AEC market generated $7.18 billion in 2020 and is expected to grow and reach $15.84 billion by the year 2028. The role of the AEC sector in infrastructure development is critical to enhancing the well-being of citizens and has substantial derivative impacts on the surrounding environment and the local community. Infrastructure projects require substantial investments in terms of finances, time, and resources. While these projects yield beneficial outputs such as durable products that lead to community enhancement and economic growth, they also have the potential to cause environmental damage, raise health concerns, or cause demographic inequities (Kamardeen and Hasan 2022). As reported by the U.S. Green Building Council, the AEC sector is responsible for 40% of the energy-based carbon emissions in the US (Verdinez 2018). In addition to its significant environmental impact, this sector has faced ongoing scrutiny due to unethical practices, such as corruption and fraudulent practices, which can lead to building collapses and work-related accidents (Owusu and Chan 2019). The sector's importance to the economy, coupled with its significant environmental and local community impact, necessitates a comprehensive understanding of the financial materiality associated with ESG considerations in this sector.

The demand for capital to finance the AEC sector is substantial. Historically, government funding has been the primary source for financing large infrastructure projects. However, relying solely on government financing has become impractical and unaffordable. According to a World Bank report (World Bank 2022), the global surplus of savings presents an opportunity to meet the investment demand in infrastructure and support the achievement of the SDGs and the transition toward sustainable energy. In this context, AEC companies are leveraging capital market financing strategies, particularly through the use of private activity bonds under public-private partnership (PPP) contracts, or project bonds (Delhi and Mahalingam 2020; Zahed et al. 2018). Bonds offer a flexible structure and enable diversification of financing sources, making them a viable solution for AEC companies engaged in infrastructure projects (Lam et al. 2011; Gatti 2013). The recent financial crisis has raised concerns about bank loans, which were traditionally considered low-risk instruments (Yousaf and Goodell 2023) and, hence, corporate bonds provide avenues for accessing capital and reallocating resources toward sustainable initiatives, where the adoption of sustainable practices may yield financial advantages (Alonso-Conde and Rojo-Suárez 2020).

Research on the financial impact of ESG factors in the AEC industry has been limited, with existing literature primarily focusing on emerging markets (Chang et al. 2016; Ho et al. 2023; Yan et al. 2019). For instance, several empirical studies (Deng and Cheng 2019; Wang et al. 2022; Xiong et al. 2016) have identified a positive correlation between ESG indices and stock market performance in the Chinese construction industry. In contrast, Wang et al. (2022) found that the relationship between ESG disclosure and stock financial performance is negligible. A few studies have focused on certain measures within ESG coverage such as the governance pillar. For example, Khan et al. (2020) observed that strong stakeholder interaction might improve project governance, hence enhance the performance of public infrastructure projects. Despite the fact that bonds have long been used to finance construction projects in developed countries, this is the first systematic research to investigate the financial impact of ESG performance in the U.S. fixed income market while comparing industry sectors and separate pillar effects between the AEC industry and other sectors.

### Machine Learning and ESG

Machine learning (ML), an application of artificial intelligence (AI), is playing an increasingly significant role in understanding market sentiment and guiding the structuring and interpretation of sustainable finance instruments and ESG/CSR reporting (Kumar et al. 2022). Machine learning algorithms have been used in the financial markets for high frequency trading and to detect signals such as economic fluctuations and interest rate movements (McGowan 2010). Because of the challenges of unstructured ESG data and non-standard reporting schemes, ML applications have not been widely adopted in the sustainable reporting field. However, ML offers intriguing opportunities along multiple lines of inquiry such as detecting and predicting patterns in corporate governance diversity (Erfani et al. 2023; Hickey et al. 2022), inclusion (Jafari et al. 2020), and misconduct (Wang et al. 2018b). Natural language processing (NLP) enables the automatic extraction of information relevant to ESG metrics from 10-K reports filed by public companies. Sentiment analysis, a subfield of NLP, which works by assigning positive or negative point values, has been used to examine trends or public perceptions of corporate ESG performance (Zeidan 2022; Xu et al. 2021). Increasingly, ML is used to impute missing values for incomplete ESG reporting. Algorithms such as random forest, nearest-neighbor imputation, and matrix completion can be used to impute ESG metrics from known metrics and data similarity between companies (Kotsantonis and Serafeim 2019). Since ESG has been recognized as a non-traditional reporting measurement or leading indicator that could offer insights into future financial performance or price movements, the integration of ML has been explored in various studies such as time series forecasting and modeling of portfolio risks. Various publications (Derrien et al. 2022; Capelli et al. 2021) have utilized these approaches to investigate the financial materiality of ESG metrics and to estimate the impact of ESG factors using ratings and disclosures. Studies in this area are critical for institutional investors and policymakers to determine which issues should be considered and how much of an impact they may have when incorporating them into the investment decision-making process (Chollet and Sandwidi 2018; Fatemi et al. 2018).

The current paper approaches the link between ESG criteria and bond performance, through a machine learning technique that allows for matching corporate bonds based on multiple characteristics and conducting comparison studies with regression results, with a breakdown to specific industry sectors, such as the AEC industry. By conducting a granular analysis across sectors and considering sector-specific dynamics, the paper aims to enhance our understanding of the heterogeneity effect of ESG financial materiality, thereby providing valuable insights into the nuanced relationship between ESG criteria and bond performance in the AEC industry versus broader sectors.

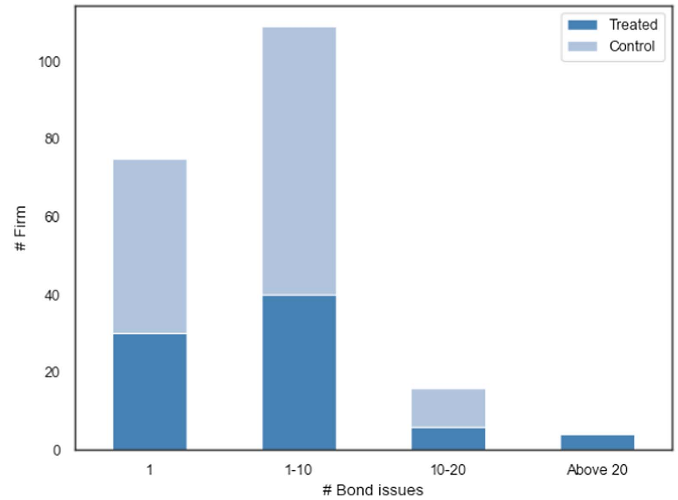


**Fig. 1.** Distribution of the number of bond issues across firms.

## Research Design and Methodology

### Data, Samples, and Measures

**Coverage**

This study examines US corporate bond issuances that are listed on Bloomberg, encompassing the time period from 2010 to 2021. This timeframe was selected to capture the increase in adoption and mainstreaming of ESG ratings in the market. We exclude bonds that are callable, puttable, convertible, sinkable, or extendable as they may interfere with the matching algorithms in the model. The universe comprised 4,697 corporate bonds with uses of proceeds including general corporate finance, green/social bonds, or project finance, from issuers across 10 Bloomberg Industry Classification Standard (BICS) industry sectors. These sectors include communications, consumer discretionary, consumer staples, energy, financials, health care, industrials, materials, technology, and utilities. The corporate bonds were identified using Committee on Uniform Securities Identification Procedures (CUSIP) and cross-linked to issuing firms with available ESG data using tickers and firm names, resulting in a final curated dataset comprising 799 U.S. bonds derived from 204 corporations. The distribution of the number of bond issues across firms can be seen in Fig. 1, and it is worth noting that this distribution is relatively balanced between the treated and control groups. The process of data curation is consistent with prior studies (Gehricke et al. 2023; Yang et al. 2021; Jang et al. 2020; Eccles et al. 2014), as illustrated in Fig. 2.

**Independent Variable**

We chose to utilize the ESG ratings provided by MSCI Inc. as a proxy for environmental, social, and corporate governance scores. MSCI is the leading provider of ESG data to investors, with widely used ratings given their credibility. With global coverage across sectors and regions, MSCI offers a comprehensive view of ESG performance. Their assessment methodology is robust, encompassing qualitative and quantitative indicators, while facilitating meaningful comparisons with prior research (Bahra and Thukral 2020; Polbennikov et al. 2016; Serafeim 2020). The ratings are based on corporate exposure to industry-material risks in the scope of ESG, and their capability to manage those risks. The ratings range from AAA to CCC and comprise seven grades in total. MSCI ESG ratings are based on industry specific key issues (e.g., carbon emissions, water stress, health & safety, supply chain labor standards,

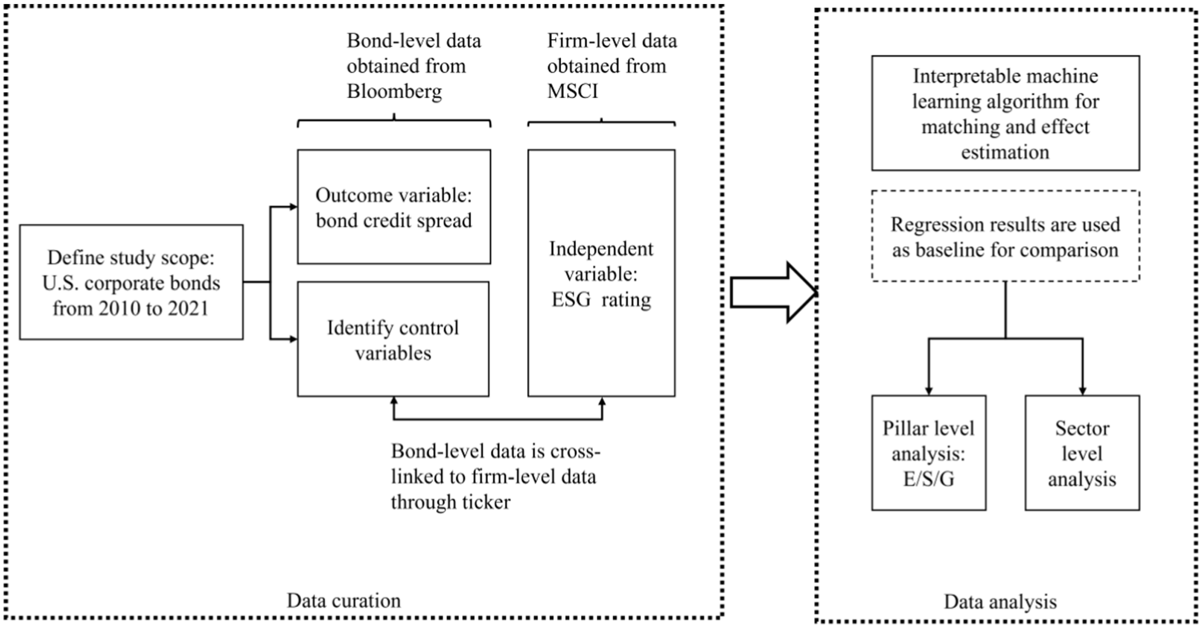


**Fig. 2.** Financial data flow and processing.

corporate governance, corruption & instability, etc.), selected based on the likelihood that those risk factors can influence corporate performance metrics (Giese et al. 2021). Based on the published methodology (MSCI 2023), key issues impacting each sector are then used to calculate the E, S, and G pillar scores based on pre-defined weighting parameters which are different between industry sectors. The pillar scores are then aggregated to an overall ESG score at the corporate level. Ratings data for this study were obtained through ESG Direct and used to define two test cohorts. Bonds from companies with ESG ratings of A, AA, and AAA are categorized as leaders (treated group), while debt issuances from companies ranging from BBB to CCC are laggards (control group) for the binary input of the treatment variable into the causal machine learning model.

### Outcome Variable

Corporate bond credit spread is the dependent variable in this study. By definition, the credit spread of a given bond at a certain time point is the difference between the bond yield and the yield of a Treasury bond that is identical to the corporate bond in all characteristics such as coupon rate, term to maturity, and payment schedule excluding credit ratings. We selected the credit spread data in the issuance market for the study of the impact of ESG on the issuance price of corporate bonds. The data is obtained from Bloomberg.

### Company Classification

The AEC industry relies significantly on labor to build public or private infrastructure that serves as the foundation for many economic sectors. However, the way AEC firms are categorized differs from the typical capital market categorization frameworks, such as the Global Industry Classification Standard (GICS), BICS, or North American Industry Classification System (NAICS). GICS, NAICS, and BICS classify organizations based on their primary income sources, such as banking, energy, and the materials sector, whereas the AEC industry is classified based on manufacturing and operating processes rather than revenue streams. As a result, we manually classified bond issuers in our sample universe as AEC or non-AEC, with the AEC cluster encompassing firms with a significant construction workforce or construction projects. Among the top ten US construction corporations, only AECOM and Fluor Corp. have been assigned ESG ratings by MSCI (A and BB, respectively) and issued bonds in the 2010 to 2021 period. These are callable bonds which typically have a lower price than a straight bond due to their issuer-friendly feature of allowing early redemption. As a result of their incomparability, these bonds are not in our sample universe. Hence, we defined the broader sector of AEC-related companies to include industrial companies such as Deere & Co. and Caterpillar Inc. that manufacture construction equipment; energy and utilities companies that involve a significant amount of construction projects, such as Duke Energy Corp.; and chemical companies that manufacture construction materials, such as 3M Co. and Cleveland-Cliffs Inc. This broadening of the AEC is consistent with the GICS, a close relative of BICS, which lists construction-relevant industries mainly as subsectors under Materials and Industrials.

### Control Variables

A set of explanatory variables was included in the models, chosen based on previous literature discussing the effect of sustainable metrics on bond performance (Dridi and Boughrara 2021; Larcker and Watts 2020; Gianfrate and Peri 2019). The following variables were included: issue date (label: *issuedate*), coupon rate (label: *cpn*), term to maturity (label: *Term-to-Maturity*), credit rating (label: *bbgcomposite*), and Bloomberg Industry Classification Standard (BICS) industry sector (labels: *bicslevel1_consumerdiscretionary, bicslevel1_consumerstaples, bicslevel1_energy, bicslevel1_financials, bicslevel1_healthcare, bicslevel1_communications, bicslevel1_industrials, bicslevel1_materials, bicslevel1_technology* and *bicslevel1_utilities*). Issue dates and term to maturity of bonds are rounded to the nearest integer, and coupon rates are rounded to one basis point. The credit rating data used in this study was based on Bloomberg Composite credit ratings, which define categorical ratings from AAA (best-in-class) to D (worst-in-class) as numeric values ranging from 2 (worst) to 23 (best). In the case that no credit rating information was available, a numeric value of 0 was assigned. Tables 1 and 2 provide descriptions of the variables along with the corresponding statistics. Table 3 summarizes the distribution of bonds by industry sector, as well as the total bonds in the treated (AAA, AA, and A) and untreated (BBB to CCC) categories used.



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**Table 1.** Descriptive statistics and variable description

| Variable | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|
| | | Bond specific | | |
| Coupon (%) | 3.655 | 1.621 | 0.000 | 12.000 |
| Issue date (year) | 2015 | 3.278 | 2010 | 2021 |
| Term-to-maturity (year) | 12.001 | 8.731 | 1 | 100 |
| Credit rating | 16.111 | 3.765 | 0.000 | 23.000 |
| Spread at issuance (bps) | 149.127 | 117.370 | 15.000 | 1,170.000 |
| | | ESG related | | |
| ESG_Rating (binary) | 0.460 | 0.499 | 0.000 | 1.000 |
| Weighted_avg_ESG | 4.795 | 0.835 | 2.500 | 6.900 |
| E score | 6.374 | 2.451 | 0.000 | 10.000 |
| S score | 4.529 | 1.380 | 1.000 | 10.000 |
| G score | 4.719 | 1.145 | 1.400 | 7.400 |

Note: Coupon, issue date, term-to-maturity, and credit rating are control variables of interest. Spread at issuance is the outcome variable in this study, expressed in basis points (bps). The ESG_Rating was utilized as the treatment variable in the machine learning model. The weighted average ESG scores, obtained from MSCI, are numerical values ranging from 0 to 10.

### *Methods*

A high-dimensional ML matching algorithm for discrete variables, referred to as Fast Large-scale Almost Matching Exactly (FLAME) (Liu et al. 2018; Wang et al. 2021), was applied to estimate the average treatment effect (ATE) of ESG ratings on bond credit spreads. ATE quantifies the differences in average outcomes between the treated and control groups. By comparing the differences in outcomes between these two groups, the ATE estimates provide valuable insights into the effectiveness of the treatment and its impact on the evaluated outcome. FLAME compares samples from the treated and control groups that are nearly identical in their characteristics. It matches samples based on important covariates and learns the matching distance from the training set. Because of their simplicity and interpretability, matching methods are widely used in studies on treatment effects. As opposed to FLAME, more traditional matching methods such as propensity score matching (PSM) (Rosenbaum and Rubin 1983), optimal matching (Rosenbaum 2017), and coarsened exact matching (Iacus et al. 2012) match pairs based on a predefined distance, which may be dominated by unimportant or non-significant covariates.

**Table 3.** Distribution of bonds by industry sector

| Sector | Full sample # total | Sample for ML matching: # Untreated (ESG ratings: BBB to CCC) | Sample for ML matching: # Treated (ESG rating: AAA, AA, A) |
|---|---|---|---|
| Financials | 256 | 136 | 120 |
| Consumer discretionary | 64 | 54 | 10 |
| Utilities | 41 | 12 | 29 |
| Industrials | 124 | 41 | 83 |
| Health care | 72 | 57 | 15 |
| Energy | 24 | 23 | 1 |
| Communications | 53 | 35 | 18 |
| Consumer staples | 92 | 35 | 57 |
| Technology | 58 | 25 | 33 |
| Materials | 15 | 13 | 2 |

Furthermore, matching pairs based on methods such as PSM may have widely differing covariates despite being in the same group, which is one of the major flaws of the one-dimensional matching method (King and Nielsen 2019). High dimensional matching, on the other hand, may produce an insufficient number of matches, because of the restrictions in the algorithm. The FLAME algorithm, an almost exact matching method, combines the strengths of one- and high-dimensional tools and yields highly interpretable matching results. It computes the optimal distance by learning on a training set, thus reducing model specification bias. The premise is that based on these optimizations, it outperforms regression, propensity score matching, and other high-dimensional matching methods by not imposing a pre-defined model form and instead matching on important covariates nonparametrically, and by leveraging a hold-on training set to learn an interpretable distance metric for matching (Wang et al. 2021).

The FLAME algorithm initiates estimates by building near-exact matches on all covariates between the treated and untreated universes of bonds, and then iteratively removes variables while still maintaining interpretable high-quality matches and balance between the treatment and control groups. FLAME ranks the significance of variables and eliminates the least significant ones at each iteration. When there are no more unmatched treated bonds, the iterations come to an end. This approach combines the straightforwardness and interpretability of matching, a technique frequently

**Table 2.** Variable description

| Variable | Description |
|---|---|
| | Bond specific |
| Coupon (%) | The coupon rate is presented as a percentage of the bond's face value. |
| Issue date (year) | The bond's initial issuance date refers to the date when it is first introduced. |
| Term-to-maturity (year) | The term-to-maturity of a bond refers to the remaining time until the bond reaches its maturity date, at which point the principal amount is repaid to the bondholder. |
| Credit rating | The bond rating obtained from the Bloomberg terminal was transformed into a numerical scale for analytical purposes |
| Spread at issuance (bps) | Spread refers to the yield difference between a corporate bond and a benchmark bond with the same maturity. |
| | ESG-related |
| Weighted_avg_ESG* | The weighted average ESG score, obtained directly from MSCI, signifies the relative management of material ESG risks by companies in comparison to sector peers. The scores range from 10 (best) to 0 (worst). |
| ESG_Rating (binary) | The ESG rating obtained from MSCI, which range from AAA to CCC, are transformed into binary form for matching input. "A" categories are assigned a value of 1, while "B" and "C" categories are assigned a value of 0. |
| E score | The E score from MSCI refers to the environmental score assigned to companies based on their environmental performance |
| S score | The S score from MSCI refers to the social score assigned to companies based on their social performance |
| G score | The G score from MSCI refers to the governance score assigned to companies based on their governance performance |

Note: A binary variable labeled "ESG_Rating" was created based on the MSCI ESG ratings, comprising seven levels ranging from AAA to CCC. The ESG_Rating was utilized as the treatment variable in the machine learning model. *The weighted average ESG scores, obtained from MSCI, are numerical values ranging from 0 to 10. These scores, labeled "Weighted_avg_ESG," were sourced from MSCI but were not utilized for analysis in this study.

used in causal inference, with the high predicted accuracy of black-box machine learning models. The prediction error criterion is used to eliminate irrelevant covariates. The algorithm examines the balancing condition in each iteration to achieve the goal of maximizing the balancing factor. A similar procedure was applied when investigating the various impacts of E/S/G pillars and across industry sectors.

Since regression analysis has been employed as the most common technique in the ESG literature, it was used to study the time effect and ensure the robustness of our ML results and subsequent discussion.

## Results and Discussion

### Time Effects and Correlation Estimation

Table 4 presents the temporal impact of ESG ratings on corporate credit spreads from 2010 to 2021, assessed through bivariate linear regression. The estimated coefficient for the difference in credit spreads between the treated group (ESG ratings above BBB) and the control group (ESG ratings BBB and below) across all years is 45.5 bps. During the first five years, the ESG impact on credit spreads was insignificant. After 2015, the ESG discount effect was statistically significant and increased to a maximum of 126.9 bps. The evolution of pricing benefits can be attributed to the growing trend among companies to disclose more ESG-related information, to further corporate transparency in operations. This shift in disclosure practices has not only led to a significant increase in ESG-themed corporate bonds but also facilitated the sustained momentum of outperformance relative to unrated bonds since 2016 (Eisenegger 2021; Agarwal and Ouaknine 2019). Moreover, this observation is in line with a study conducted by Partridge and Medda (2020), which noted the emergence of pricing benefits associated with green bonds during the same time period. In 2020 and 2021, the discount was still evident but not statistically significant. The time component (i.e., issue dates) serves as a control variable in the machine learning analyses to eliminate temporal bias.

**Table 4.** Time effect of ESG ratings on bond spreads

| # Observations = 799 | Estimate | Std. error | T-stats |
|---|---|---|---|
| ESG premium | −45.448*** | 8.179 | −5.557 |
| ESG premium (Year 2010) | −30.140 | 20.640 | −1.461 |
| ESG premium (Year 2011) | −8.648 | 22.080 | −0.392 |
| ESG premium (Year 2012) | −34.860 | 23.170 | −1.505 |
| ESG premium (Year 2013) | −29.550 | 13.417 | −2.202 |
| ESG premium (Year 2014) | −17.330 | 15.300 | −1.132 |
| ESG premium (Year 2015) | −35.400 | 20.690 | −1.711 |
| ESG premium (Year 2016) | −90.580*** | 28.370 | −3.193 |
| ESG premium (Year 2017) | −126.97*** | 25.460 | −4.987 |
| ESG premium (Year 2018) | −74.31** | 26.030 | −2.855 |
| ESG premium (Year 2019) | −52.15** | 17.660 | −2.952 |
| ESG premium (Year 2020) | −46.570 | 51.370 | −0.907 |
| ESG premium (Year 2021) | −27.510 | 18.620 | −1.478 |
| ESG premium + control variables | −10.430* | 4.650 | −2.243 |
| ESG premium + control variables + credit rating | −6.360 | 4.705 | −1.352 |

Note: This table reports estimates of ESG premium at the corporate bond level. The independent variable is ESG ratings. Coupon, issue date, term to maturity, and credit rating are control variables of interest. '***' 0.001 '**' 0.01 '*' 0.05 denote p-values less than 0.01, 0.05, and 0.10, respectively.

The overall decadal average discount did not account for control variables that may influence bond performance. When issue date, term to maturity, and coupon rate are used as control variables, the estimated ESG discount decreased to 10.4 bps at the 5% significance level. When credit rating was included as an additional control variable, the discount decreased further to 6.4 bps and was not statistically significant. Both regression models produced an R-squared greater than 0.7. These results indicate that issue date alone does not account for the differences in credit spread, but the quality of the bond as well as other characteristics (especially credit rating) are significant predictors for discounted pricing. These results are consistent with the observations by Slimane et al. (2019).

To examine the relationship between ESG rating and bond credit spreads, a correlation analysis was conducted between the independent variables (ESG rating, E, S, and G scores) and the control variables used in this study. The results, presented in Table 5, indicate that issue date, coupon rate, and term to maturity exhibit weak correlations (coefficients below 0.2) with all three ESG pillars. However, credit rating shows a moderate correlation with social rating, with a significant positive coefficient of 0.29. Existing literature has indicated that credit agencies incorporate ESG information into their credit ratings (Slimane et al. 2019). In line with this, the correlation analysis conducted in this study reveals a significant relationship between credit scores and social ratings, providing valuable insights into the potential pathway for integrating ESG factors into credit assessments. It should be noted that bond characteristics, including issue date, coupon rate, term to maturity, and credit rating, exhibit moderate interrelationships. Therefore, caution is advised when examining the influence of ESG ratings on credit ratings, taking into account the potential confounding effects of these bond characteristics.

To account for the influence of confounding variables on the correlation between ESG performance and credit spreads of corporate bonds, partial correlation coefficients were computed (Table 6). This approach is adopted to address the potential distortion in the bivariate correlation coefficient when another bond characteristic is numerically related to both variables of interest. To calculate the

**Table 5.** Correlation estimates between explanatory variables

| Control variables | Issue date | Coupon | Term-to-maturity | Credit rating | E score | S score | G score | ESG rating |
|---|---|---|---|---|---|---|---|---|
| Issue date | 1.00 | — | — | — | — | — | — | — |
| Coupon | −0.57* | 1.00 | — | — | — | — | — | — |
| Term-to-maturity | −0.40* | 0.43* | 1.00 | — | — | — | — | — |
| Credit rating | 0.08* | −0.33* | 0.14* | 1.00 | — | — | — | — |
| *Ind. variables*: | | | | | | | | |
| E score | −0.10* | 0.02 | 0.10* | 0.15* | 1.00 | — | — | — |
| S score | 0.07* | −0.17* | −0.01 | 0.29* | 0.09* | 1.00 | — | — |
| G score | −0.08* | 0.00 | 0.06 | −0.05 | −0.19* | 0.13* | 1.00 | — |
| ESG rating | 0.01* | −0.18* | −0.01 | 0.26* | 0.17* | 0.56* | 0.44* | 1.00 |

Note: '*' denotes p-values less than 0.05 significance level.

**Table 6.** Partial correlations of ESG ratings on bond spreads on condition of a set of control variables

| Category | 1 | 2 | 3 | 4 | (5) | (6) |
|---|---|---|---|---|---|---|
| First-order partial correlation | | | | | | |
| 1. $r_{x,y\|I}$ | −0.297*** | — | — | — | — | — |
| 2. $r_{x,y\|C}$ | — | −0.192*** | — | — | — | — |
| 3. $r_{x,y\|M}$ | — | — | −0.300*** | — | — | — |
| 4. $r_{x,y\|B}$ | — | — | — | −0.147*** | — | — |
| Second-order partial correlation | | | | | | |
| 1. $r_{x,y\|I,C}$ | −0.137*** | — | — | — | — | — |
| 2. $r_{x,y\|I,M}$ | — | −0.299*** | — | — | — | — |
| 3. $r_{x,y\|I,B}$ | — | — | −0.146*** | — | — | — |
| 4. $r_{x,y\|C,M}$ | — | — | — | −0.145*** | — | — |
| 5. $r_{x,y\|C,B}$ | — | — | — | — | −0.088* | — |
| 6. $r_{x,y\|M,B}$ | — | — | — | — | — | −0.146 * ** |
| Third-order partial correlation | | | | | | |
| 1. $r_{x,y\|I,C,M}$ | −0.102** | — | — | — | — | — |
| 2. $r_{x,y\|I,C,B}$ | — | −0.062 | — | — | — | — |
| 3. $r_{x,y\|I,M,B}$ | — | — | −0.146*** | — | — | — |
| 4. $r_{x,y\|C,M,B}$ | — | — | — | −0.075* | — | — |
| Fourth-order partial correlation | | | | | | |
| 1. $r_{x,y\|I,C,M,B}$ | −0.052 | — | — | — | — | — |

Note: The bar in the notation separates the correlated variables from the controlled for variables. For example, correlating ESG ratings ($x$) against credit spreads ($y$) while controlling for issue dates is written as $r_{xy|I}$. The controlling variables issue dates, coupon rates, term-to-maturity, and Bloomberg composite ratings are abbreviated as $I$, $C$, $N$, and $B$, respectively, in the notation of correlation coefficients. The partial correction between x and y is −0.295. '***' 0.001 '**' 0.01 '*' 0.05 denote p-values less than 0.01, 0.05, and 0.10, respectively.

partial correlation coefficient, the independent and dependent variables were individually regressed on the set of control variables. The partial correlation coefficient is then obtained by regressing the residuals.

The initial correlation between ESG rating and credit spread was −0.295 at a 0.001 significance level. The estimation results of the partial correlation where we tested the relationships between ESG ratings and credit spreads while controlling for issue dates ($r_{x,y|I}$), coupon rates ($r_{x,y|C}$), term-to-maturity ($r_{x,y|M}$), and credit ratings ($r_{x,y|B}$) are −0.297, −0.192, −0.300, and −0.147, respectively. None of the control variables by themselves can explain the negative relationship between ESG ratings and credit spreads. However, the correlation estimate increased most when controlling for credit rating, $r_{x,y|B}$, by approximately half. This suggests that credit ratings explain a significant portion of the financial materiality in ESG ratings, which may correspond to the increased awareness of ESG among credit rating agencies.

The second-order partial correlation results revealed that the relationship between ESG ratings and credit spreads conditioning on the combination of coupon rates and credit ratings, $r_{x,y|C,B}$ increased by 70% (from −0.295 to −0.088), indicating that most of the impact of ESG ratings on corporate bond pricing is accounted for in the credit ratings and coupon rates of corporate bonds. These partial correlation results, based on bond issues between 2010 and 2021, further validate previous empirical studies capturing the timeframes from 2007 to 2015, where ESG was shown to exhibit a more limited correlation to credit ratings of between −10% and 10% (Polbennikov et al. 2016). Note that the smaller correlation may be due to the time period considered in this study, which preceded the years when significant effects of ESG ratings on yield spreads were observed as shown in Table 4.

The adjusted R-squared of the regression model that includes issue dates, coupon rates, term-to-maturity, and credit ratings is 0.714. The high R-squared value demonstrates the regression model's goodness of fit. As a result, a combination of issue dates, coupon rates, term-to-maturity, and credit ratings can approximate the relationship between ESG ratings and credit spreads and be used for predictive analysis.

### ATEs on Credit Spreads

This section explores the relative importance of selected control variables and estimates the ATE of ESG ratings on credit spreads across all sectors. To accomplish this, the FLAME algorithm, a machine learning technique for matching, is utilized. By considering all bond characteristics alongside the industry sector, the algorithm pairs bonds from the treated group (ESG leaders) with those from the control group (ESG laggards) in order to precisely quantify the impact of ESG rating on credit spreads. Importantly, the findings demonstrate robustness, as they remain unaffected by the selection of group size for training and matching sets.

The importance of control variables in the FLAME matching process of bonds across all industry sectors is shown in Fig. 3. In iteration 1, there are 237 matches, corresponding to 55 matched groups, and all covariates are used for matching. Between iterations 2 and 11, the least important covariate was eliminated at each iteration until all treated samples were matched. The earlier the covariates are eliminated, the less important they are to the outcome variable. The findings revealed that industry sectors are least predictive of bond credit spreads because they were eliminated first among other control variables. In descending order of importance,

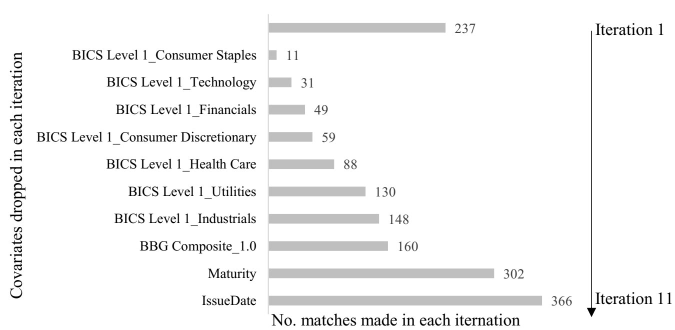


**Fig. 3.** The relative importance of selected control variables based on FLAME.

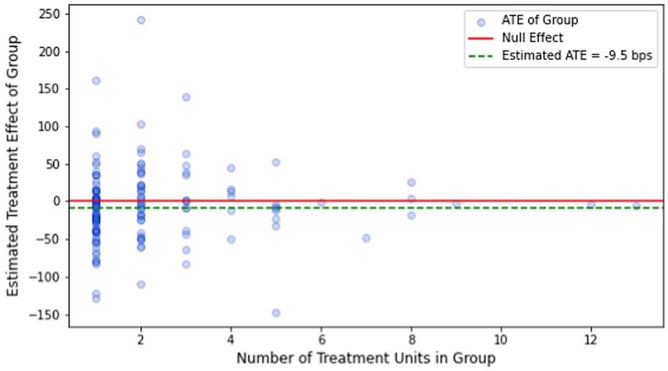


**Fig. 4.** Scatter plots of treatment effect estimation against the size of the matched group based on FLAME.

**Table 7.** Correlation estimates between E, S, and G pillar scores and the overall ESG ratings

| Variable | E score | S score | G score | ESG_Rating |
|---|---|---|---|---|
| E score | 1 | — | — | — |
| S score | 0.09** | 1 | — | — |
| G score | −0.19*** | 0.13*** | 1 | — |
| ESG_Rating | 0.17*** | 0.56*** | 0.44*** | 1 |

Note: This table reports correlation estimates of E, S, G pillar scores and the EGS rating scores. '***' 0.001 '**' 0.01 '*' 0.05 denote p-values less than 0.01, 0.05, and 0.10, respectively.

the remaining parameters are the coupon rate, issue date, term to maturity, and credit rating.

After examining the significance of control variables, the bonds are matched based on these important variables. The analysis reveals an estimated treatment effect of −9.5 bps between bonds issued by ESG leaders and bonds issued by ESG laggards, as depicted in Fig. 4. The sample is split into 80% (n = 640) for training purposes, while the full sample (n = 799) is employed for matching. The results demonstrate the presence of heterogeneity in the conditional treatment effects of ESG on credit spreads. This heterogeneity is most pronounced in matched groups characterized by smaller sizes. However, the calculation of treatment effects becomes challenging in small-sized matched groups, leading to less accurate results. The heterogeneity effect is discussed in depth in the sections "Impacts of Individual E, S and G Pillars, Industry Sector Effects" and "Effects in AEC-Related Industries."

The estimated ESG impact on bond credit spread aligns with the findings of Li et al. (forthcoming), which utilized the same bond universe and a statistical inference model (PSM), reported a 14 bps ESG discount effect on credit spreads. Using regression analysis, Polbennikov et al. (2016) found a decrease of 2.8 bps in spread per standard deviation increase in ESG score from 2007 to 2015, while Slimane et al. (2019) estimated that the cost of capital difference is 31 bps between the top and bottom performers on ESG ratings using bonds issued between 2010 and 2019. The higher discount value for bonds in the latter study is consistent with the temporal ESG effect shown earlier in Table 4.

## *Impacts of Individual E, S, and G Pillars*

The information content of the environmental (E), social (S), and governance (G) pillars differs, impacting investment decision-making. For example, Polbennikov et al. (2016) observed that governance is the largest contributor to bond spreads. Building upon this understanding, this section focuses on assessing the financial significance of individual pillar scores and their impact on credit spreads.

In Table 7, we present the correlation analysis of the individual pillars. The findings reveal that the average cross-pillar correlations among the E, S, and G pillars are statistically significant; however, they exhibit relatively low magnitudes. E pillar scores are inversely related to G pillar scores, whereas E and S, as well as S and G scores are positively related. The negative correlation observed between the E and G scores indicates that the market price in certain dimensions of sustainable metrics for corporations and their debt issuance, while it underemphasizes others. This finding aligns with a previous study (Dell'Atti et al. 2017), which demonstrated that the three pillars of ESG exhibit distinct correlations and have varying impacts on a company's reputation. On the contrary, Rajesh and Rajendran (2020) demonstrated a positive correlation between E and G based on Thomson-Reuters ESG scores for companies spanning the period from 2014 to 2018. The divergence in findings can potentially be attributed to the variances in measurement, scope, and weighting methods among different ESG rating providers (Berg et al. 2022). The last row of the table shows that S and G scores contribute significantly to overall ESG ratings in the corporate bond universe assessed here, with correlation coefficients of 0.56 and 0.44, respectively. ESG ratings, on the other hand, are less influenced by E scores within the bond universe. The correlations between E, S, and G pillars show that decomposing ESG ratings to the pillar level is critical to understanding the impact of ESG on credit spreads.

The regression results regarding the discount effects of the E, S, and G pillars are shown in Table 8. When controlling for bond characteristics such as term-to-maturity, issue data, coupon rate, and credit rating, the G scores have the most substantial impact on credit spreads, with a coefficient of −5.6 bps at a significance level of 0.01, as demonstrated in model 4. These findings align with the results reported by Polbennikov et al. (2016). Model 5 shows the regression coefficients when all three pillar scores are included as independent variables in a single model. In the absence of control for bond-related characteristics, the S pillar emerges as the most significant contributor, with a coefficient of −15.0 bps at a significance level of 0.001. These findings indicate that while the S effect on credit spreads appears to be strong, it is primarily influenced by bond-related characteristics rather than having a direct impact. In other words, the S effect is intricately intertwined with the underlying bond attributes, suggesting that the observed relationship between the S-pillar and credit spreads is mediated by these characteristics. Our findings suggest that investors in the bond issuance market demonstrate a willingness to accept lower payments for bonds that have higher S/G ratings. This indicates that social and governance considerations such as carbon emissions and tax transparency are favored by sustainability-oriented investors in the bond market, who are willing to trade off returns to mitigate associated risks. However, despite the presence of a superior E rating, our study shows that there is no corresponding reduction in issuance costs within the corporate bond market of our study universe. This is contrary to research showing that the market values carbon disclosures in the context of share price returns (Bolton and Kacperczyk 2019). Apergis et al. (2022), using regression models and bonds issued by the S&P 500 between 2010 and 2019, showed that the S pillar has the strongest effect on bond yields when controlling for bond characteristics such as term to maturity, subordination, and issue size. The divergent outcomes observed may be attributed to differences in the bond universes examined and the sets of control variables employed in the models.

To enhance our comprehension of the effects of individual ESG pillars, we employed the FLAME algorithm to estimate the separate

**Table 8.** Ordinary least squares (OLS) regression analysis of the ESG rating, E pillar score, S pillar score, and G pillar score effects on bond credit spreads (n = 799)

| Variable | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| ESG score (bps) | −6.360 | — | — | — | — |
| E score (bps) | — | 0.243 | — | — | 0.243 |
| S score (bps) | — | — | −1.263 | — | −14.975*** |
| G score (bps) | — | — | — | −5.593** | −6.904 |
| Issue date | 12.125*** | 12.103*** | 12.080*** | 11.884*** | — |
| Coupon rate | 71.179*** | 71.350*** | 71.265*** | 70.872*** | — |
| Term-to-maturity | −2.375*** | −2.383*** | −2.382*** | −2.324*** | — |
| Credit rating | −2.870*** | −3.087*** | −2.943*** | 3.213*** | — |
| Adjusted R-squared | 0.707 | 0.706 | 0.706 | 0.709 | 0.0363 |

Note: *** 0.001 ** 0.01 * 0.05 denote p-values less than 0.01, 0.05, and 0.10, respectively.



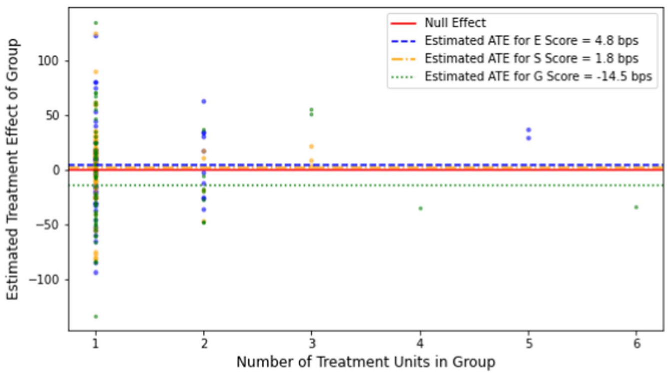


**Fig. 5.** Scatter plots of treatment effect estimation against the size of the matched group for E, S, and G pillar scores.

**Table 9.** Effects of ESG ratings on credit spreads by clustered industry sectors using OLS regression

| Sector clusters | # Obs. | Estimate | Std. error | t value | Pr(> \|t\|) |
|---|---|---|---|---|---|
| Cluster 1: finance | 256 | −19.246*** | 6.953 | −2.768 | 0.006 |
| Cluster 2: engineering | 204 | −14.503* | 6.236 | −2.326 | 0.021 |
| Cluster 3: ICT | 111 | −5.051 | 11.020 | −0.458 | 0.648 |
| Cluster 4: consumer | 228 | 24.520* | 10.720 | 2.289 | 0.023 |

Note: This table reports estimates of ESG premium on corporate bond level with control variables being term-to-maturity, coupon rate, credit rating and issue date. '***' 0.001 '**' 0.01 '*' 0.05 denote p-values less than 0.01, 0.05, and 0.10, respectively. The clustering of industries is based on the similarity of their business lines (LOB). The financial sector is represented in the first cluster. The energy, utilities, industrials, and materials sectors comprise the second cluster. The third cluster includes the sectors of information and communication technology (ICT). The consumer discretionary, consumer staples, and health care sectors comprise the fourth cluster.

impacts of each pillar, as depicted in Fig. 5. The training phase of our analysis involved utilizing 80% of the sample, equivalent to a total of 640 observations. The full sample of 799 observations was employed for the matching process. ATE estimates for E, S, and G scores are estimated to be 4.8 bps, 1.8 bps, and −14.5 bps, respectively. When controlling for important variables, the discount effect of G scores is the strongest among the ESG pillars. However, it is noteworthy that the average effect of E scores is positive, while the impact of S scores is found to be negligible in terms of their effect on credit spreads. Moreover, the presence of extreme values within larger-sized groups contributes to influencing the overall effect on credit spreads. The variations observed among the ESG pillars account for the overall moderate effect of ESG on spreads, as they exhibit differences in both the magnitude and direction of their impact on the outcome. Because the results of causal machine learning are not dependent on predefined matching distances as is the case in propensity score matching or on embedded selection bias from regression analysis, it is thought to have less model specification error (Wang et al. 2021). Polbennikov et al. (2016) also stated that the overall ESG discount of 2.8 bps in their study is primarily driven by the governance score, which contributes 4.3 bps to the overall effect. In contrast, the estimates for the environmental and social scores fall below, with respective values of 2.1 bps and 2.0 bps. In contrast, Jang et al. (2020) showed that environmental score effects dominated the discount effect of ESG scores, and the regression coefficients for social and governance have opposite effects.

### *Industry Sector Effects*

ESG ratings comprise different underlying metrics that are tailored to each industry sector, as the materiality of environmental, social, and governance risk factors varies across sectors (Giese et al. 2021). For instance, under the E pillar, MSCI has identified carbon emissions, biodiversity for land use, and toxic emissions as critical risk factors specific to the energy industry. Conversely, these environmental factors hold less relevance for the financial industry. Thus, breaking down ESG analysis at the industry sector level allows for sector-specific insights.

To approximate this sector-specific effect, we categorized the ten industry sectors represented in our bond universe into four subsectors based on their business nature. This classification was implemented to accommodate the limited sample size within each individual sector. The grouping of industry sectors into sub-sectors was guided by the similarity in their core operations and intended to augment the sample size within each sub-sector. For example, the energy, utilities, industrials, and materials sectors were grouped together due to their shared dependence on energy, natural resources, and extractive processes. Consequently, these sectors are anticipated to face similar types of environmental risks.

When the bonds are aggregated into industry sector groups, the effect of ESG scores on bond performance varies by sector type, as does the statistical significance level. Among all industries, the financial sector (Cluster 1, as shown in Table 9) has the largest count of corporate bonds. In this industry, a statistically significant negative relationship between ESG ratings and credit spreads is observed, with a credit spread of −19.2 bps and a significance level of 0.001. The observed negative relationship between higher ESG ratings and lower credit spreads within the financial industry indicates a potential association with the sector's heightened impact on ESG factors. It has been suggested that the implementation of restricted regulations in the financial sector following the 2008–2009

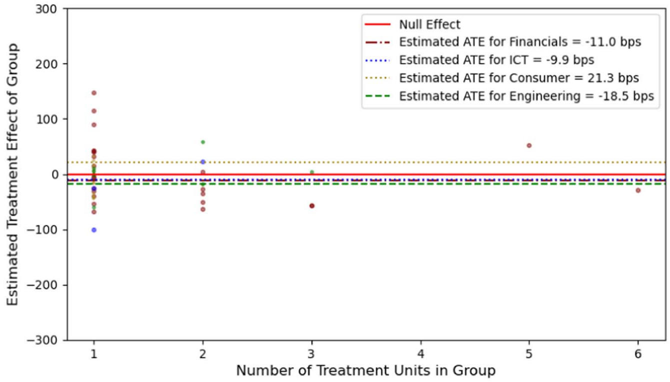


**Fig. 6.** Scatter plots of treatment effect estimation against the size of the matched group for the financial, ICT, consumer, and engineering sectors.

financial crisis, such as the Dodd-Frank Act, has influenced market perceptions of bond valuations (Li et al. 2016). Moreover, Crespi and Migliavacci (2020) argue that the upward momentum of financial institution ESG ratings is highly correlated with social and economic development impacts. Similarly, the engineering cluster also exhibits a discount effect of ESG ratings on credit spreads, with an estimated value of −14.5 bps and a significance level of 0.05. This implies that higher ESG ratings within the engineering cluster are linked to reduced credit spreads, which aligns with the findings of Gehricke et al. (2023). In contrast, the consumer cluster demonstrates a positive ESG effect on credit spreads. No statistically significant effect of ESG ratings on credit spreads is observed in the information and communication technology (ICT) cluster. These sectoral differences in the relationship between ESG scores and credit spreads have the potential to influence and dilute the overall effect of ESG on corporate bond performance.

Fig. 6 shows the ATE estimates for different industry clusters, obtained through the utilization of the FLAME algorithm. The results reveal that the impacts in clusters 1 to 4, representing the financial, energy-related, ICT, and consumer groups, respectively, are −11.0, −18.5, −9.9, and 21.3 bps. These results confirm the sector-specific nature of ESG impact on credit spreads. The magnitude of ATE is comparable between the financial and ICT sectors. The impact of ESG ratings on credit spreads, however, is more pronounced in the engineering sector. In contrast, the consumer sector demonstrates a positive effect on credit. The results of the causal machine learning analysis are consistent with the ranking of effects based on regression, except for the engineering cluster. However, the estimated ATE values tend to be lower in the FLAME approach. This discrepancy can be attributed to the matching effect with the control group, which tends to be more restrictive using the FLAME algorithm. While regression analysis suffers from selection bias due to non-randomized experiments (Angrist and Pischke 2008), the FLAME matching model matches pairs between ESG leaders and laggards in each industry based on important variables defined by the learning set, making the results more comparable (Gupta et al. 2021; Wang et al. 2021).

### *Effects in AEC-Related Industries*

The transition toward carbon-neutrality and sustainable practices entails substantial investments to access new markets, acquire resources, and enhance operational efficiency in the construction industry (Soares and Pereira 2022). Hence, the financial implications of ESG in the AEC industry may differ from those in other sectors.

**Table 10.** Effects of ESG ratings on credit spreads in AEC/non-AEC sectors from OLS regression

| Variable | # Bond ober. | Estimate | Std. error | t value | Pr(> \|t\|) |
|---|---|---|---|---|---|
| Cluster 1: AEC-related | 186 | — | — | — | — |
| ESG score | — | −13.471* | 6.102 | −2.208 | 0.0285 |
| E score | — | −5.480* | 2.139 | −2.562 | 0.0112 |
| S score | — | 8.466*** | 1.875 | 4.514 | $1.15 \times 10^{-05}$ |
| G score | — | −7.584* | 3.257 | −2.328 | 0.0210 |
| Cluster 2: non-AEC | 613 | — | — | — | — |
| ESG score | — | 4.332 | 5.041 | 0.859 | 0.390 |
| E score | — | −0.623 | 0.986 | −0.631 | 0.528 |
| S score | — | 1.920 | 2.090 | 0.919 | 0.359 |
| G score | — | −1.230 | 2.060 | −0.595 | 0.552 |

Note: Estimates of ESG premium at the corporate bond level are provided with control variables being term-to-maturity, coupon rate, credit rating, and issue date. '***' 0.001 '**' 0.01 '*' 0.05 denote p-values less than 0.01, 0.05, and 0.10, respectively.

Given the dearth of bond issues for construction companies such as AECOM, Arcadis, Jacobs, or Stantec, the companies were grouped into AEC-related and non-AEC groups based on whether the company was involved in a significant portion of planning and operation of construction projects.

Based on the regression results presented in Table 10, the AEC-related industry exhibits comparable ESG benefits to the broader engineering cluster. Bonds in the AEC sector display an average pricing discount of 13.5 bps for companies with leading ESG scores. The analysis reveals that the E and G pillars dominate the potential cost benefits of bond issuance, emphasizing the importance of environmental and governance considerations in this sector. The lower bond issuance prices observed can be attributed to management practices related to these specific issues, which are recognized by investors who are more willing to invest in these bonds. This finding aligns with the study conducted by Guo et al. (2020), which demonstrated that strong environmental performance of firms can contribute to their financial performance up to a certain threshold. However, their study did not investigate the financial implications of governance scores. On the other hand, the S score has an opposite effect on bond credit spreads. This suggests that social metrics, such as ensuring comfort and health for building occupants and implementing effective construction labor management policies, are viewed as a risk by the market, and may result in higher costs for firms to address concerns. The samples in the non-AEC group reveal an insignificant positive relationship between ESG ratings and bond issuance prices, which may be attributed to varied effects across the remaining industries, as illustrated in the section "Industry Sector Effects."

In Fig. 7, the results obtained using the FLAME technique are depicted, revealing that the ATE estimates are −12.7 bps in the AEC sector and 3.5 bps in the non-AEC sector. The pricing benefit observed in the AEC sector can be attributed to the growing recognition of ESG considerations. This recognition is primarily driven by the increasing prevalence of mandates and incentives that promote the adoption of environmentally sustainable practices in construction operations, particularly concerning carbon and particulate emissions (Wang et al. 2018a). Moreover, previous research has shown that the adoption of green construction practices by firms leads to improved corporate image and financial profitability (Shurrab et al. 2019). The lack of significant results in the non-AEC sector can be attributed to the diluting effects stemming from various sectors.

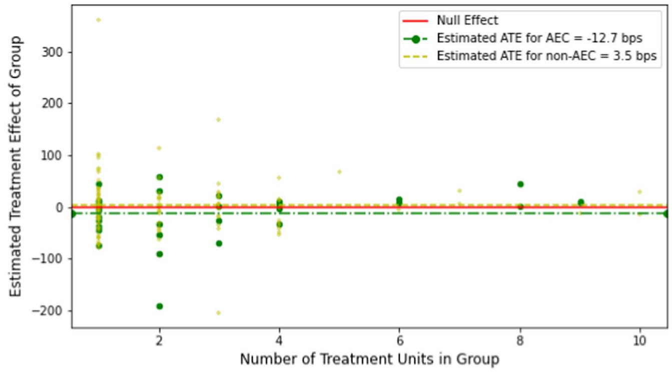


**Fig. 7.** Scatter plots of treatment effect estimation against the size of the matched group for AEC and non-AEC sectors.

This is evident from the contrasting pricing observed in the financial and consumer sectors. Fig. 7 shows the diverse influence of ESG on individual corporate bonds, as well as the presence of outliers. Large matching groups tend to have larger estimating errors and can thus be discarded. In Fig. 7, small matching groups showed comparatively concentrated effects, indicating that the ATE estimates are adequately qualified. Moreover, the findings highlight that the impact of ESG on bond pricing in this sector differs from that observed in other industry sectors. These results are in line with the findings obtained from the regression analysis.

## Conclusions

This study employs an empirical analysis of corporate bonds issued between 2011 and 2021 to investigate the impact of ESG ratings on corporate bond performance in the AEC industry, taking into account various bond-related metrics and comparisons to other sectors. Our results indicated that, while the variables are not independent, there is substantial heterogeneity in how ESG ratings are transferred to credit spreads, similar to what is observed in equities (Giese et al. 2019, 2021). The interdependence of individual ESG scores gives rise to intricate and interconnected effects. Specifically, while the governance pillar exerts the greatest influence on credit spreads when considered individually, the social pillar emerges as the most significant contributor when all three pillars are jointly included in the model. Furthermore, the industry sector plays a pivotal role, with the financial and engineering industry clusters showing the most pronounced ESG benefits in terms of debt financing costs. Notably, the AEC-related industry demonstrates comparable ESG benefits to other sectors within the engineering domain, mainly driven by environmental and governance pillars, as evidenced by both regression analysis and machine learning methodologies.

This study contributes to the existing ESG and corporate bond risk literature in multiple ways. First, this is the first study on the relationship between ESG performance and bond cost of issuance in the US, with specific emphasis on the AEC industry. The AEC sector's considerable need for capital investment and reliance on natural resources render the ESG cost benefit paradigm exceptionally promising for investors and practitioners alike. Second, unlike previous studies, our analysis examined the relationship between ESG performance and the cost of issuance for corporate bonds, and explored the impact of sectoral and individual pillars. Our findings revealed the presence of heterogeneous effects of the ESG premium in the bond market. Thus, caution must be exercised when attributing cost reduction benefits to ESG performance only, given sectoral differences and the effects of individual ESG pillars. Third, we employed an interpretable machine learning technique to assess the financial significance of ESG factors. This enabled us to identify the financially material variables for matching and to estimate the impact of ESG on bond performance based on the matched bond sets. ML matching tools possess significant advantages over regression-type tools utilized in previous studies (Gehricke et al. 2023; Apergis et al. 2022; Jang et al. 2020; Slimane et al. 2019; Polbennikov et al. 2016) for exploring ESG materiality, as they avoid making assumptions about sample distribution and effectively eliminate model specification errors. Indeed, our results showed that ML constrains the bond pricing benefit relative to regression analysis.

### *Implications*

This study has several important academic and practical implications. First, it incorporates the fundamental concepts of ESG and stakeholder theory into the evaluation of sustainable metrics in the corporate bond issuance market. The technical approach can identify relevant factors that can ultimately translate into cost of capital benefits, as measured using bond spreads. Second, the cost reduction benefits associated with ESG performance in the bond issuance market serve as a market signal, allowing companies with superior ESG performance to issue bonds at a lower price. Consequently, companies, particularly those in AEC-related industries, should proactively implement ESG measures, including effective governance policies, community engagement, and environmental mitigation to reduce their bond issuance expenses. From a risk management perspective, prioritizing environmental concerns like carbon emissions, water stress, biodiversity, and waste management, as well as governance metrics such as board diversity, business ethics, and tax transparency, can lead to significant cost reductions by mitigating the risks of environmental violations and legal disputes. Third, cross-sector comparison empirically shows the financial impact of risk mitigation across industries, and industry-specific differences on the impact of ESG pillars. Specifically, companies in the AEC sector have an opportunity to tailor their strategies to address industry-specific challenges and capitalize on the recognized value of Environmental and Governance performance indicators. Lastly, policymakers have an opportunity to leverage the ESG premium into sustainability incentives by strategically shifting stakeholders' attention from passive non-financial disclosure to proactive utilization of such reporting toward ESG leadership. Through the implementation of tax policies, incentives for alternative energy consumption and a focus on green and social bonds, policymakers can further encourage the development of ESG initiatives and foster the growth of sustainable business operations.

### *Limitations and Opportunities for Future Research*

The main limitation of the study is related to the size of the bond universe utilized, resulting from the availability of bond spreads at issuance and ESG ratings. This could potentially impact the matching of leading and laggard bond issues and the resulting credit yield outcomes, despite the flexibility of the FLAME algorithm in handling small datasets. Furthermore, the reliance on ESG ratings exclusively from MSCI, without incorporating a broader range of rating providers, may introduce biases in the findings. Additionally, we acknowledge that this study did not consider firm-level variables and other market determinants that may impact bond performance, such as liquidity or federal interest rates. These factors have the potential to influence the ESG premium and subsequently affect the study's outcomes. For example, Li et al. (forthcoming) explored the effect of bond liquidity in the secondary markets and noticed that leading ESG bonds were more actively traded than laggards, though the implications on credit spread were not explicitly quantified. Incorporating these factors into future research will contribute to a more nuanced understanding of the relationship between ESG factors and corporate bond performance. Furthermore, comparisons across industry sectors should be approached with caution, as each sector identifies specific ESG factors as material using proprietary models from commercial providers (MSCI 2023). The results exhibit a heterogeneous pattern and encompass a wide range of indicators related to ESG risks, opportunities, and subtopics. Ratings agencies generally assess ESG risks on a case-by-case basis, taking sector-specific considerations into account in order to establish ratings. However, ESG indicators such as carbon emissions, renewable energy, climate adaptation, community relations, and independent board composition, are commonly applicable across a wide range of engineering sectors including the AEC industry.

## Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

## Acknowledgments

The authors acknowledge funding from the Center for Digital Asset Finance at the University of Michigan for Dan Li. We gratefully acknowledge Neha Gupta, Vittorio Orlandi, and Dr. Cynthia Rudin from the Almost Matching Exactly Lab at Duke University for their contributions and feedback on the results and discussions. Any mistakes or oversights in this study remain the responsibility of the authors.

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