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Empirical evidence of ESG premium in the U.S. corporate bond market: a propensity score matching approach

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ABSTRACT

This study aims to explore the connection between ESG scores and corporate bond performance, particularly credit spreads, by adopting a propensity score matching (PSM) approach, enabling a balanced comparison between a control group and one exposed to the ESG treatment effect. The results indicate that bonds issued between 2010 and 2020 by MSCI-rated ESG leaders across all industry sectors are priced at an average lower credit spread of 14.3 basis points (bps) relative to laggards, in the primary market. This credit spread difference persists in the secondary market and increases further when bonds of financial issuers are separated from non-financial sectors. In contrast, the impact of ESG disclosure on bond credit spread results is negligible. The willingness of investors to accept a discount on the credit spreads of a bond issued by highly rated companies offers potential incentives for broader adoption of ESG performance assessment.

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ESG; sustainability; bond markets; propensity score matching; corporate responsible

1. Introduction

Launched in 2006, the UN Principles for Responsible Investment (PRI) are dedicated to promoting sustainable investment through the adoption and incorporation of environmental, social, and governance (ESG) factors. One area that has witnessed substantial growth in ESG integration is the U.S. corporate bond market, which has been used as a securitized debt instrument facilitating sustainable practices and climate transition investment. Given the longer maturities of corporate bonds, investors are exposed to variations in ESG risks of issuers over extended periods. Hence, there is a need to understand how sustainability indicators such as ESG scores are associated with corporate bond rates. While past literature has been limited in scope and mainly focused on regression analysis to understand the relationship between sustainability indicators and bond rates, this paper aims to provide a comprehensive examination via matching to understand whether there is a premium for ESG performance and disclosure in the primary market, the secondary market, and the impact of industry sector on these pricing benefits.

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The Business Roundtable (BRT) in recent years revised the purpose of a corporation to align with stakeholder theory, where firms serve all stakeholders – including employees, end-users, communities, and the environment. Stakeholder theory argues that a firm that takes care of all its stakeholders generates higher long-term value (Freeman 1994; Parmar et al. 2010). Environmental, social, and governance (ESG) metrics are presented as a nuanced assessment and measurement of a firm's risks and performance with consideration of its stakeholders (Hörisch and Schaltegger 2019; Kay et al. 2020). Thus, research has shown that firms with stronger ESG performance may have a better financial outlook and reduced risk of default, as well as fewer occurrences of unsuspected negative events affecting revenue (Sharfman and Fernando 2008; Henisz and McGlinch 2019).

Previous empirical studies have attempted to measure the financial implications of sustainable indicators such as ESG scores, corporate social responsibility (CSR) and green indicators, with mixed findings on the relationship between ESG and bond rates. Polbennikov et al. (2016) and Jang et al. (2020) found that bonds with higher ESG ratings slightly outperformed those with lower ratings. In contrast, Gehricke, Ruan, and Zhang (2023) and Amiraslani et al. (2022) found no significant cost reduction or relationship between ESG performance and bond spreads, except during the 2008–2009 financial crisis, when companies with better E&S performance had lower credit spreads. Their findings differ from the assumption that the governance aspect of ESG is correlated with bond spreads.

This study builds upon prior research by considering the ESG premium net of credit rating, and by taking liquidity and sectoral differences between treated and control bond populations into account. A negative relationship between ESG performance and credit spreads in both primary and secondary markets was found in our study, which is consistent with previous literature (Polbennikov et al. 2016; Jang et al. 2020; Li, Zhou, and Xiong 2020; Apergis, Poufinas, and Antonopoulos 2022) and theoretical assumptions. The negative trend was consistent across different matching algorithms. However, the impact of ESG disclosures on credit spreads is negligible in both the primary and secondary markets, possibly due to the lack of mandatory regulation in the US, and concerns about greenwashing (Lyon and Montgomery 2015). Gehricke, Ruan, and Zhang (2023) concluded that integrating ESG performance scores or disclosure scores does not result in under- or over-performance of bond investments, which is in line with our findings regarding ESG disclosure but not ESG performance scores. When comparing financial and non-financial issuers, the impact of ESG performance is more pronounced for bonds issued by financial firms, an effect that has not been documented in prior literature. All PSM results in this study showed comparable or higher statistical significance than ordinary least squares (OLS) regression analysis.

This paper contributes to the ESG and corporate bond literature in several ways. Firstly, unlike previous studies that focused on regression analysis (Polbennikov et al. 2016; Jang et al. 2020; Gehricke, Ruan, and Zhang 2023), our research employed a matching approach to reduce selection bias and avoid functional form misspecification (Shipman, Swanquist, and Whited 2017). The mixed **results** of previous bond premium estimates are in part due to the statistical tools employed or the selection of the bond universe for analysis. The non-parametric nature of PSM allows for the avoidance of any assumptions about the underlying data distribution and serves to address selection bias by balancing the distribution of confounding variables between treatment and control groups, an issue not considered in regression methods (Shipman, Swanquist, and Whited 2017). In the green bond market, Gianfrate and Peri (2019) used a propensity score matching approach to study 121 European green bonds issued between 2013 and 2017, finding that green bonds are more financially advantageous than their vanilla counterparts. Huang et al. (2022) found that firms tend to enhance the transparency of their ESG disclosures following natural disasters, as demonstrated through PSM analysis. To the best of our knowledge, this is the first study in the ESG and corporate bond literature that utilizes a PSM-based technique which effectively ensures optimal overlapping of variables between the treated and control groups, thereby satisfying the balancing criterion. Our findings reveal that the effects are equal or more significant compared to the regression results based on the same sample. Secondly, we analysed the effects of ESG disclosures and ESG performance on bond credit spreads to determine any distinctions in the impacts of information transparency and ESG-related performance. Our results indicate that better ESG performance can lead to significant ESG premium in credit spreads, especially in the financial sector. The effects of ESG disclosures, however, were negligible, pointing to the need for actual ESG-relevant actions rather than simply disclosing. Finally, we explored the impact of ESG in both primary and secondary markets. The effects in the primary market demonstrate the influence of ESG on credit spreads during the initial bond issuance. Meanwhile, the secondary market results provide evidence of the credit risks associated with ESG after the bonds have been traded. By conducting liquidity tests on leading and lagging ESG-rated bonds, it appears that higher liquidity in the treated bond universe may influence the substantial ESG premium observed in the secondary market.

2. Literature review and hypotheses

2.1. Theoretical background

The United Nations PRI recognizes that ESG factors affect investment analyses, decision-making, ownership policies and practices. Policy guidelines and regulatory requirements have increasingly asked for ESG risk disclosures and more comprehensive considerations that align with ESG issues in investment decisions. Pressure from stakeholders, including firm shareholders, has advocated that ESG considerations can provide a holistic view on risk and increase corporate value (Cornell and Shapiro 2021; Flammer, Toffel, and Viswanathan 2021). Stakeholder theory forms the basis of such advocacy as it suggests that firms should actively acknowledge the interests and welfare of all stakeholders, including employees, customers, the environment, and the community (Freeman 1994; Hörisch and Schaltegger 2019). Over the years, there has been growing recognition that companies that identify and address material ESG factors, such as reducing their environmental impact, promoting social justice, and maintaining good governance practices, tend to perform better over the long term (Eccles and Serafeim 2013; Serafeim 2020). Companies that prioritize ESG factors are also seen as fulfilling their broader social responsibilities to society and the environment from a **stakeholder** theory perspective (Driscoll and Starik 2004). Better firm governance structures, which can be measured as lower ESG risks, promote stakeholder interests and enable access to credit from financial institutions at a relatively lower interest rate (Jizi et al. 2014; Zhu 2014; Loumioti and Serafeim 2022). These perspectives therefore form the theoretical framework for the ESG and corporate bond relationship, on which we **based** our hypotheses and the interpretation of results in this study.

2.2. ESG scores and corporate bond rates

Amid the increasing global attention on ESG disclosure and risk management, researchers have turned their focus to the impact of ESG factors on financial performance. A key question on financial materiality of ESG in the bond market is the relation to credit spread or yield-to-maturity (YTM). Most previous literature on the effects of ESG in fixed income markets has shown that there is a positive association between ESG scores and corporate bond financial performance. For example, Polbennikov et al. (2016) found that corporate bonds with higher composite ESG ratings have slightly lower spreads relative to low ESG-rated issuers based on regression analysis. When using total return as the outcome variable, Jang et al. (2020) noted that high ESG scores lower the cost of debt financing based on regression analysis. Bahra and Thukral (2020) observed that MSCI ESG scores enhance the investment returns of corporate bonds but cautioned that the scores may already be incorporated in credit ratings, and thus no additional pricing benefit should be expected.

Literature regarding primary and secondary markets showed varying relationships between ESG factors and bond credit spreads. For example, several studies (Partridge and Medda 2018; Amiraslani et al. 2022) suggest that the economic impact of ESG benefits or green indicators on bond performance is relatively subdued in the primary market as opposed to the secondary market. Due to secondary market prices reflecting market demand, the presence of a premium in the secondary market could affect primary market prices. According to Zerbib (2019), the secondary market structure may enhance green bond issuance while providing a primary yield slightly lower than the observed bond curve. Within the context of this study, there could be evidence of a premium effect in the secondary market even if corporate issuers do not see ESG as providing a cost benefit as long as the market views ESG as a mechanism for mitigating risk.

Past literature on the relationship between ESG ratings and bond spreads revealed that this link is more prominent in certain sectors (Polbennikov et al. 2016; Li and Adriaens 2024). Additionally, Aevoae et al. (2023) found evidence indicating that a high ESG score has a positive effect on the extent to which banks contribute to system-wide distress. They also identified improved corporate governance as a valuable tool for promoting financial stability. The presence of regulations in the financial sector, such as the Dodd-Frank Act, may have a considerable impact on market views of bond valuations (Li, Liu, and Siganos 2016). As such, the bond market's reaction to ESG information when issuing bonds in highly regulated financial companies may differ from that of less regulated non-financial companies.

We propose the following hypotheses to investigate the relationship between ESG scores and corporate bond financial performance:

H1: Strong ESG performance can lead to a reduced bond credit spread.

The first hypothesis gives rise to three sub-hypotheses, which can be formulated as follows:

H1.1: A negative relationship exists between ESG performance scores and bond credit spreads.

H1.2: The impact of ESG performance scores is more pronounced in the secondary market.

H1.3: The impact of ESG performance scores is more pronounced in financial firms.

2.3. ESG disclosure and corporate bond rates

In contrast to the prior work on the yield impact of ESG ratings, the literature on ESG disclosure, which measures the level of completeness of public disclosures but not corporate performance on ESG metrics, is more ambiguous (Qiu, Shaukat, and Tharyan 2016; Yu, Guo, and Van Luu 2018; Fatemi, Glaum, and Kaiser 2018). A few studies showed that companies with higher levels of ESG disclosure benefit from a lower cost of debt financing (Raimo et al. 2021), reduced credit spread (Yang et al. 2021) and lower bond default rates (Li, Zhou, and Xiong 2020). This set of studies assumed that organizations with superior ESG performance typically disclose more information regarding their sustainable practices, inferring that higher levels of ESG disclosure could lead to reduced credit spread or lower costs of debt financing. However, the studies are centred on the European and Asian bond markets with less focus on U.S. exchanges.

On the other hand, Qiu, Shaukat, and Tharyan (2016) did not find a relationship between environmental and social disclosure and corporate financial performance. Their study suggested that companies with greater economic resources tend to provide more comprehensive disclosures, independent of the presence of positive economic incentives. The findings from Fatemi, Glaum, and Kaiser (2018) even suggested that ESG disclosure has an overall negative impact on firm value, as investors may perceive disclosures as an overinvestment in ESG activities. Therefore, further examination of the connection between ESG disclosure and corporate bond rates is necessary. As a result, we present Hypothesis 2 to investigate the impact of ESG disclosure in primary and secondary markets, financial and nonfinancial firms:

H2: A higher level of ESG disclosure leads to a lower bond credit spread.

This can be broken down into the following sub-hypotheses:

H2.1: There is a negative relationship between ESG disclosure scores and bond credit spreads.

H2.2: The impact of ESG disclosure scores on credit spreads is more pronounced in the secondary market.

H2.3: The impact of ESG disclosure scores is more pronounced in financial firms.

3. Data and methods

3.1. Bond characteristics and selection of bond treatment

Treatment variables: In this study, two treatment variables were considered, ESG performance score and ESG disclosure score. While multiple ratings are available, we selected MSCI ESG ratings in our study due to their broad adoption and coverage. The objective of the study was to assess the differences in the effect of ESG performance and disclosure scores on credit spreads, and the benefit of using PSM analyses to uncover credit spreads rather than evaluate the impact of different rating processes on ESG premia. MSCI rates companies according to corporate exposure to, and management of, ESG risks and opportunities, based on corporate disclosures and other public information. The proprietary ratings calculate ESG risks based on the breakdown of a company's line of business, while considering the extent to which a company develops strategies to manage risks. Corporate ratings range from AAA (best in class) to CCC (worst in class), based on a combination of data analytics and expert opinion-based proprietary weighting scales for ESG factors considered material to an industry sector.

ESG disclosure scores, obtained from Bloomberg, are derived from corporate annual self-reporting and are quantified based on completeness. Companies that do not disclose ESG reporting have a score of '0'. The scores range from 0.1 to 100, where 0.1 indicates that the disclosure of ESG data is at the minimum level and 100 indicates full disclosure for every data point that Bloomberg collects. The scores measure the relative percent completeness of public disclosures, and do not assess corporate performance on any specific ESG metric. Hence, disclosure is a recognition of transparency about ESG risks, but not of how these risks are managed or alleviated. The correlation between ESG performance and disclosure scores is weak (correlation coefficient is approximately −0.05). The correlations between ESG performance, ESG disclosure scores and other bond-related explanatory variables are included in Table 1.

Outcome variable: Credit spread is the outcome variable used to study the ESG impact after the removal of macroeconomic market conditions. The credit spread data relative to the benchmark (a Treasury-note benchmark with the same term-to-maturity) is captured using the Bloomberg Fixed Income Search function. Spread was used instead of yield because it has been argued to improve the ability to isolate the effect of ESG on the price of a new bond from its secondary market price. The rationale is that spread is relative to the benchmark and thus already accounts for the impact of systemic risks and allows for assessing the impact of additional information relative to the returns of government bonds (Elton et al. 1999).

Table 1. Correlations of attributes on the sample set.

	ESG performance score	ESG disclosure score	Credit rating	Maturity	Coupon	Issue date
ESG performance score	1.000					
ESG disclosure score	−0.054 (0.289)	1.000				
Credit rating	0.3225* (0.000)	0.012 (0.811)	1.000			
Maturity	−0.001 (0.981)	0.014 (0.786)	0.055 (0.286)	1.000		
Coupon	−0.2455* (0.000)	0.083 (0.104)	−0.5737* (0.000)	0.2575* (0.000)	1.000	
Issue date	0.089 (0.082)	−0.038 (0.460)	0.035 (0.490)	−0.2314* (0.000)	−0.3040* (0.000)	1.000

Notes: *p*-values correspond to correlation coefficients are marked in parenthesis, and the * indicate significance level at 5%.

Coverage. The coverage includes issuers across all industry sectors (based on BICS, Bloomberg Industry Classification System) for the period from 2010 to 2020. These sectors include consumer discretionary, consumer staples, energy, financials, health care, industrials, materials, communications, technology and utilities. All corporate bonds were cross-referenced against corporate ESG data availability to curate the final dataset of companies with ESG performance and disclosure data. The sample size was then reduced to 747 observations in the primary market and 1773 observations in the secondary market where credit spread data were available and the sample for ESG performance and disclosure scores overlapped.

Confounding variables. Information about bond issues and issuer characteristics is from Bloomberg. We analyzed the following variables in the study of the impact of ESG on corporate bond credit spreads: issue date (data label: issuedate), coupon (data label: cpn), maturity date (data label: maturity), credit rating (data label: bbgcomposite) and industry sector (data labels: bicslevel1_consumerdiscretionary, bicslevel1_consumerstaples, bicslevel1_energy, bicslevel1_financials, bicslevel1_healthcare, bicslevel1_industrials, bicslevel1_materials, bicslevel1_technology, bicslevel1_communications and bicslevel1_utilities). Issue dates of bonds and maturity dates are rounded to a year, and coupon rates are rounded to one basis point. The credit rating approach for this

Table 2. Summary statistics and variable description.

Panel A: summary statistics

Variable	Mean	Std. Dev.	Min	Max
Coupon (%)	3.831	1.501	0	12
Issue Date (year)	2015.078	3.0340	2010	2020
Maturity (year)	2029.131	9.178	2020	2111
Spread at Issuance (bps)	155.880	117.130	20	1170
Credit rating	0.884	0.320	0	1

Panel B: variable description

Dependent variable	
Credit spread	A credit spread is the difference in yield between a corporate bond and a benchmark bond of the same maturity. It is measured in basis point in this study.
Independent variables	
ESG performance score (+)	MSCI-rated ESG performance scores (ranging from AAA to CCC) assess performance in relation to certain ESG aspects. For PSM analysis, they are converted to binary form (all 'A' categories: 1, all 'B' and 'C' categories: 0).
ESG disclosure score (+)	ESG disclosure scores from Bloomberg measure the level of transparency for various ESG factors. They were transformed into binary format to facilitate the PSM analysis. Specifically, a value of 1 was assigned to companies that disclosed their ESG scores, while a value of 0 was assigned to those that did not.
Control variables	
Coupon (−)	The coupon rate is expressed as a percentage of the bond's face value, rounded to nearest integer number.
Issue Date (−)	The issue date of a bond is the date on which the bond is first issued and the date on which the bond's terms and conditions, such as the coupon rate and maturity date, become effective. It is measured in year in this study.
Maturity (+)	The maturity time for a non-callable/non-putable bond is the date on which the bond reaches the end of its term and the principal amount of the bond is repaid to the bondholder, measured in years.
Credit rating (+)	The bond rating, obtain from Bloomberg terminal, was converted to a numerical scale (investment grades: 1, high-yield grades:0).

Notes: Panel A provides a summary of the variables' statistics, while Panel B includes a description of each variable and its expected effect on the outcome variable based on existing literature.

Table 3. Distribution of bond samples by industry sector

	Bonds in the primary market	Bonds in the secondary market
Financials	249	725
Industrials	105	332
Consumer staples	85	89
Health care	67	71
Consumer discretionary	61	76
Technology	57	59
Communications	50	58
Utilities	35	318
Energy	23	31
Materials	15	14
Total	747	1773

Notes: This collection of bonds represents a sample that discloses both ESG performance scores and ESG disclosure scores.

study was based on a binary conversion of the data, where investment grade bonds (BBB- or better) are assigned one (1) and high-yield grades (lower than BBB-) are assigned zero (0). Tables 2 and 3 present the characteristics of corporate bond universe used in the study, and the distribution of treated and untreated groups by industry sector, respectively.

We chose the set of confounding variables based on the availability of bond related data and related empirical literature in the ESG and green bond fields (Gianfrate and Peri 2019; Larcker and Watts 2020).

3.2. Liquidity tests

Common liquidity measurements include volume-based proxies such as the Index of Martin, price-based proxies such as Amihud's illiquidity measure, and trading frequency proxies such as the Zero Trading Days (Jain and Singla 2018). While it was not possible to directly obtain the above-mentioned measures due to the time-stamped nature of the PSM samples, we conducted two liquidity tests on the studied bonds in the secondary market, based on liquidity data from Bloomberg. The first test is the bid-ask spread for the treated and untreated groups. A bid-ask spread is defined as the discrepancy in price of what a buyer is willing to purchase an asset for (bid price) and what a seller is willing to accept (ask price). The more liquid an asset, the lower its spread (Gwilym, Trevino, and Thomas 2002). The second test is the proprietary Bloomberg Liquidity Assessment (LQA) score which compares securities based on their relative liquidity on three dimensions: time, volume and cost. This normalized score measures the expected average liquidation cost for a range of data points as a reference of trading volumes, assuming a one-day liquidation time horizon. The LQA score provides a more holistic view of liquidity based on indicators selected by Bloomberg using machine learning techniques (Boermans, Frost, and Bisschop 2016). As the score increases, so does the asset's liquidity.

3.3. Statistical methodology and assumptions

To address the question of whether ESG premia exists in the corporate bond market, we should compare the rates of bonds with superior ESG scores to those of their counterparts. To conduct this comparison, we use PSM techniques to assess the extent to which bond rates differ due to two distinct 'treatments': bonds issued by companies that are ESG leaders and bonds issued by companies with an ESG disclosure score. Bonds issued by the leading performance group or those with an ESG disclosure score represent the treated group. Bonds issued by ESG laggards or those without an ESG disclosure score on the issuers' level were used as the control group. The rationale is to compare whether both the level of ESG performance and the extent of ESG information disclosure contribute to superior bond rates.

A key question in treatment effect analysis is whether the differences in outcomes between the two groups can be directly attributed to the treatment. Randomized Control Trials (RCTs) are regarded as the gold standard for establishing this causal relationship. However, it is not possible to randomly assign a treatment (ESG performance or disclosure) to the corporate bond universe being analyzed. Whether a company discloses ESG information and how well the company manages its ESG risks is not random, as there is clearly a trend towards ESG adoption in corporate disclosures and financial investment considerations. Since it is not possible to observe a true countereffect, the counterfactual outcome must be estimated by 'mimicking' randomization. Propensity score analysis is a non-parametric technique that balances pretreatment covariates in which data are not assumed to be based on prescribed distributions and aims to quantify causal effect inference from observational data (Rosenbaum and Rubin 1983). In this research, the PSM method estimates the average treatment effect on the treated sample (ATT). The treatment effect represents the average effect of ESG metrics on the bond credit spreads in the treated groups and is not diluted by the control group.

Key assumptions of propensity score analysis about the unconfoundedness include the conditional independence assumption and the common support condition (Rosenbaum and Rubin 1983). Assume that each unit i has a treatment condition z_i, response r_i and a set of covariables vectors X_i. A propensity score of a unit i, $e(X_i)$, is the probability of receiving treatment, conditioned on the covariables vector X_i, as illustrated in equations (1) and (2) (Pan and Haiyan 2012).

$$(r_{1i}, r_{0i}) \perp z_i | X_i \tag{1}$$

$$0 < e(X_i) < 1 \tag{2}$$

The conditional independence assumption (CIA) states a condition that treatment assignment z_i and response r_i are conditionally independent given the common support assumption and assumes sufficient overlap in the covariates of treated and control populations to find adequate matching pairs between the treated and control group (Rosenbaum and Rubin 1983). The authors further state that ignorability on X_i implies the ignorability on $e(X_i)$. Thus, in the case that a unit from the treated group and a unit from the control group have the same propensity score, it indicates that the two matched units will essentially have the same value of the covariate vector, in probability. As a result, analyses on the matched data tend to produce unbiased estimates of the treatment effects.

The common support condition is implemented as a specification test in this study and is also checked through visual inspection. The conditional independence assumption can be defended if (1) the covariates jointly determine the outcomes and there are rarely unobserved confounders, and (2) there is a high degree of post-matching balance across the covariates (Thoemmes and Kim 2011; Rosenbaum and Rubin 1983). The steps to calculate the ATT are comprised of the following: (1) selection of covariates; (2) estimation and implementation of the propensity score in the sample; (3) determination of the covariate balance between both sample pools after propensity score implementation; (4) evaluation of differences between matched and unmatched issues after propensity score matching.

The propensity score was estimated using multivariable logistic regression, where the treatment is the dependent variable, and the confounder set is selected as independent variables. The regression coefficients are employed to estimate the propensity score for each bond, taking into account the combination of confounding variables that reflect the bond's unique covariate pattern. The estimated propensity score is then applied to address confounding issues by matching the treated and untreated bond universes with the same estimated propensity score, since the assumption is that treated and untreated samples have similar propensity scores and hence similar covariate patterns. Radius matching and kernel matching techniques were used to match treated and untreated bonds based on the estimated propensity scores.

Radius matching, as proposed by Rubin and Rosenbaum (1985), was applied in this study with three different distances, 0.005, 0.2 and 0.4. For kernel matching, two bandwidths are tested, 0.03 and 0.15 (Dridi and Boughrara 2021a, 2021b). By using different matching algorithms, the validity of the results can be cross-checked and helps to build a more robust set of outcomes.

An assessment of the balancing properties between both bond groups is required to ensure the quality of the ATT estimates. Rosenbaum and Rubin (1985) suggest using the mean Standardized Difference Bias (SDB) which measures the average distance in the distribution of the variables between treated and untreated samples. The merit of SDB is that it is not influenced by sample size. We consider an SDB of 20% as a threshold for balancing assessment (Rosenbaum and Rubin 1985) and we also apply the visual inspection of the density distribution plots of propensity scores (Dridi and Boughrara 2021a, 2021b).

4. Results and discussion

The results of the propensity score estimation and bond matching based on MSCI-rated ESG performance scores in the primary market are shown first. We then perform the same analysis of credit spread estimates in the secondary market, and measure liquidity for the treated and control groups. Then, the impact of the Bloomberg ESG disclosure score on credit spreads in the primary and secondary markets is explored. Last, we present the results on the sub-groups by splitting the sample into bonds issued by financial and non-financial companies.

4.1. Impact of MSCI-rated ESG performance scores on credit spreads in the primary market

Assessment of the capacity of propensity score matching to uncover differences in credit spreads between bonds with similar financial characteristics except for their ESG performance requires multiple steps. For treatment effect estimation, ESG ratings were split between 'A' and 'BBB' because the sample size is suitable in the control and treated groups, and issuers rated above A are designated as 'leaders' in the MSCI methodology as they are above the industry sector's average. The analysis to estimate the ATT was initiated by obtaining the propensity scores for all variables in each bond universe (treated and control). A binary model was used based on multivariable logistic regression (Table 4).

The results indicate that a bond is more likely to be labeled as treated (A to AAA rated) if the issuer belongs to the utilities sector. On the contrary, bonds issued by the consumer discretionary or health care sector are less likely to be in the treated group. We also observed that, overall, the treated bond universe exhibited a higher credit rating, a lower coupon rate, and shorter time to maturity (Table 4). Finally, bonds issued more recently are associated with a higher probability of being in the treated group within the range of the study time horizon. This is consistent with market history which has shown improvements in ESG ratings since 2016 (Gianfrate and Peri 2019).

Since it is important to check whether the matching process results in a balanced distribution of the relevant covariates in the control and treated groups, our analysis used a SDB threshold of 20%. Based on this criterion, confounders including issue date, credit rating, sector dummy variables such as consumer discretionary, consumer staples, energy, financials, health care, industrials, technology, utilities were selected as the set of variables to compare treated and untreated groups. If after matching, the SDB of selected variables is below the threshold, this indicates that the matching process based on propensity scores allows for comparing the treated and control populations based on this subset of variables (Figure 1). Visual inspection of the density distribution plots (Figure 2) further supports the quality of matching results (Dridi and Boughrara 2021a, 2021b). This condition is defined as the highest level of similarity between the treated and control populations. The balancing criteria indicate that the industry sector of corporate bond issuers plays a crucial role in assessing how leading and lagging ESG performance scores affect credit spreads.

The balancing condition was tested based on the premise that bonds with the same propensity score have, probabilistically, the same distribution of observable variables

Table 4. Estimated propensity scores on MSCI ESG performance scores based on Logit model.

Treatment effect: ESG performance scores	Coefficient	Std. err.
cpn	−0.068	0.090
maturity	−0.017	0.011
issuedate	0.088*	0.035
bbgcomposite	1.447***	0.387
bicslevel1_consumerdiscretionary	−1.028**	0.484
Bicsleve1_consumerstaples	0.572	0.397
bicslevel1_financials	0.196	0.348
bicslevel1_healthcare	−1.061**	0.440
bicslevel1_industrials	−0.024	0.526
bicslevel1_technology	−0.216	0.638
bicslevel1_utilities	1.742***	0.540
Constant	−175.379**	75.353
Log likelihood	−440.686	
Blocks number	6	
Common support	[.0168, .9133]	
Pseudo R^2	0.144	
Observations	747	

Notes: Pseudo R^2 is the McFadden's Pseudo R^2. Common support is the region where the propensity score distributions of treated and untreated units interfere. Blocks number is the optimal number of blocks to ensure that the PS mean is equal for treated and untreated groups in each block. (***) (**) (*) indicate significance level at (1%) (5%) (10%) respectively.

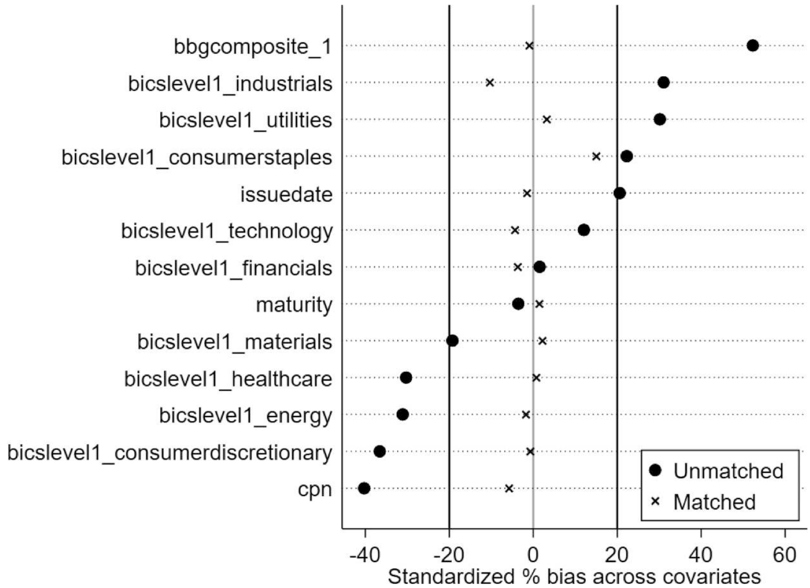

Figure 1. SDB on the unmatched and matched units for the MSCI-rated ESG performance scores in the primary market.

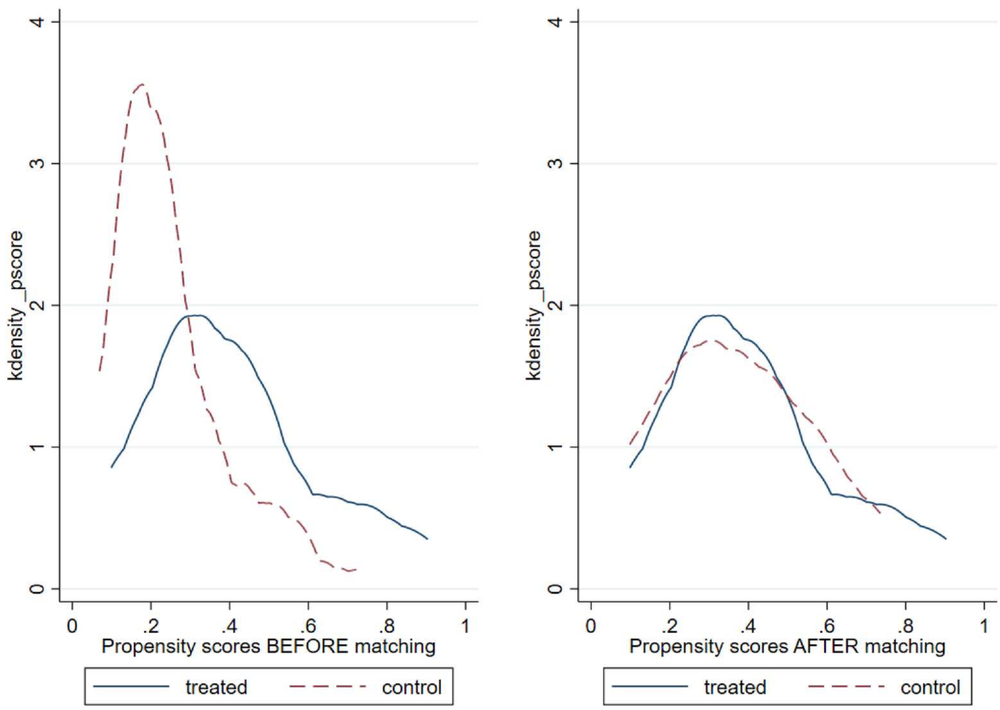

Figure 2. The density distribution plots of the treated and control groups on ESG performance scores in the primary market for the common support specification test.

(Table 5). Based on the p-values, we cannot reject the null hypothesis that the means between treated and control groups are equal. Note that the percentage bias was reduced by ten out of thirteen of the variables, where percentage bias is the difference in means divided by the total sample standard deviation. In addition, Rubin's B is lower than 25% and Rubin's R is in the range of 0.5–2 within matched groups. Hence, the tests demonstrate that the balancing condition is satisfied using these confounders.

To assess the treatment effect in the study cohort, bond matching was performed by identifying an untreated sample with a similar logit propensity score to the treated sample. As described earlier, kernel matching and radius matching were used to identify bond pairs with similar characteristics. Due to the smaller size of untreated samples relative to the treated universe, matching with replacement was selected, i.e. the same untreated bond can be used to compare with the treated bonds.

Table 6 presents the results of the average treatment effect on the treated (ATT) estimates of ESG performance scores on credit spreads, along with a comparable analysis of the effects obtained through PSM, OLS regression, and entropy balancing (EB). Overall, the ATT of ESG performance scores ranged from −5.8 bps (kernel matching, bandwidth of 0.03) to −30.5 bps (radius matching with radius of 0.4) with an average premium of 14.3 bps. These results validate Hypothesis 1.1, indicating that robust ESG performance results in a lower bond credit spread. The coefficients obtained from radius matching with calipers of 0.2 and 0.4, as well as kernel matching with a bandwidth of 0.15, are statistically significant, and the average magnitude of credit spread differences is greater than the estimates obtained from EB and OLS regression conducted on the same sample (Panel B, Table 6). While regression techniques consider the entire sample for effect estimation, the effects obtained through PSM are estimated on control and treated groups with comparable bond characteristics based on propensity scores (Shipman, Swanquist, and Whited 2017). In addition, EB has gained popularity in recent years due to its ease of implementation and ability to achieve enhanced covariate balancing between treated and control groups (Hainmueller 2012; Hainmueller and Xu 2013). However, our PSM model results remain effective as the balancing assessments and common support checks are upheld. In comparison to previous literature, Polbennikov et al. (2016) reported a negative impact of 2.8 bps on credit spread for each standard deviation increase in ESG score during the period from 2007 to 2015, which corresponds to the first half decade of our bond universe when the investor demand for ESG or green tagged bonds was emerging. Jang et al. (2020) found that a one-point increase in the ESG scores results in a 0.543% (54.3 bps) decrease of bond returns in Korean corporate bonds from 2010 to 2015, suggesting that a higher ESG performance score is related to a lower bond return, and hence a higher issuance price and a lower cost of debt. The ESG premium analysis using regression by Polbennikov et al. (2016) and Jang et al. (2020), however, was heavily influenced by sample selection bias since the treated group of corporate bonds in their studies differed from the control group across a range of bond related factors.

4.2. Impact of MSCI-rated ESG performance scores on credit spreads in the secondary market

The credit spreads of corporate bonds issued by highly rated ESG companies, and those from the control group are compared in the secondary market. To carry out the analysis,

Table 5. Balancing condition for all variables after matching on the matched and unmatched groups.

Variable	Unmatched (U) Matched (M)	Mean		% Bias	% Reduction Bias	*t*-test		
		Treated	Control			*t*	$p > t$	
issuedate	U	2015.400	2014.800	26.5		2.810	0.005	
	M	2015.400	2015.500	−10.1	92.6	−0.190	0.846	
cpn	U	3.510	4.101	−40.3		−5.46	0.000	
	M	3.510	3.595	−5.8	85.6	−0.79	0.428	
bbgcomposite	U	0.967	0.807	52.3		6.920	0.000	
	M	0.967	0.970	−1.0	98.2	0.230	0.825	
maturity	U	2029	2029.3	−3.6		−0.49	0.627	
	M	2029	2027.9	11.2	−215.9	1.46	0.145	
bicslevel1_consumerdiscretionary	U	0.041	0.177	−44.5		−4.340	0.000	
	M	0.041	0.046	−1.7	96.2	−0.250	0.805	
bicslevel1_consumerstaples	U	0.191	0.034	51.0		4.810	0.000	
	M	0.191	0.175	5.0	90.1	0.390	0.695	
bicslevel1_financials	U	0.337	0.330	1.5		0.21	0.836	
	M	0.337	0.354	−3.7	−144.6	−0.48	0.630	
bicslevel1_healthcare	U	0.036	0.149	−39.5		−3.850	0.000	
	M	0.036	0.027	3.0	92.4	0.480	0.631	
bicslevel1_industrials	U	0.253	0.137	29.4		2.800	0.005	
	M	0.253	0.316	−16.2	44.9	−1.390	0.166	
bicslevel1_technology	U	0.094	0.062	12.1		1.66	0.098	
	M	0.094	0.130	−13.5	−12.1	−1.50	0.135	
bicslevel1_materials	U	0.006	0.032	−19.3		−2.55	0.011	
	M	0.006	0.004	1.4	92.5	0.37	0.715	
bicslevel1_energy	U	0.003	0.054	−31.1		−4.08	0.000	
	M	0.003	0.009	−3.6	88.6	−1.00	0.317	
bicslevel1_utilities	U	0.036	0.023	7.8		0.740	0.457	
	M	0.036	0.033	2.0	74.0	0.190	0.853	
Sample	Ps R^2	LR chi^2	$p >$ chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.139	143.35	0	25.5	30.2	92.5*	0.55*	33
Matched	0.008	7.43	0.879	4.0	2.2	20.9	1.09	0

*If variance ratio outside [0.75; 1.33] for U and [0.75; 1.33] for M. Variables dropped are due to collinearity.
*If B > 25%, *R* outside [0.5; 2].

Table 6. Estimated ATT values for MSCI-rated ESG performance scores in the primary market.

Panel A: detailed results obtained through the process of PSM

	Radius			Kernel	
	Caliper: .005	Caliper:.2	Caliper:.4	Bandwidth (.03)	Bandwidth (.15)
ATT (bps)	−8.350	−16.934**	−30.532***	−5.763	−9.917*
Std. Err.	11.775	9.458	8.683	10.751	7.033
# Treated sample	303	341	341	336	329
# Untreated sample	406	406	406	406	307

Panel B: comparison of the effects derived from PSM and OLS regression

	Coefficient	Std. err	*p*-value
PSM	−14.299**	9.540	0.044
OLS regression	−5.298	7.597	0.486
Entropy balancing	−6.507	5.630	0.248

Notes: In panel A, the ATT and Std. Err. figures are expressed in basis points (bps). Columns refer to the different matching methods including radius matching (calipers = 0.005, 0.2 and 0.4) and kernel matching (bandwidth = 0.03 and 0.15). ATT is the average treatment effect on the treated sample. #Treated and untreated is the number of treated and untreated units on common support, respectively. (***) (**) (*) indicate significance level at (1%) (5%) (10%) respectively. In all estimations, a common support condition of the treated and control units is satisfied in order to ensure better comparability of matched units. Panel B presents the average effects obtained through PSM, OLS regression and entropy balancing using the same set of control variables. The balance constraints for entropy balancing are set as the first moment.

the spread at a specific date (4/18/2021) was used. Since these data are market based, they are likely strongly affected by the liquidity of the bonds. A liquidity analysis was conducted on the corporate bonds in the secondary market due to the impact on bond credit spreads.

Among bid-ask spread data, 321 bond observations come from MSCI-rated ESG leaders, and 620 come from ESG laggards. The bid-ask spread was calculated as ask minus bid divided by the average bid and ask price (midpoint) on an annual basis. The ratio of the bid-ask spread between the treated and control groups is 0.49 (Table 7), indicating that the bonds that have leading company-level ESG performance are more liquid (smaller spread) in the secondary market. This finding needs to be considered in the interpretation of the credit spread difference as a positive premium for the treated group (higher liquidity, lower spread) may be an overestimate relative to the control group.

Table 8 shows that the ratio of LQA score between the treated and control groups is 1.50, indicating that the treated group is more liquid than the control group (Table 8), thus supporting the bid-ask spread test. A similar phenomenon has been observed for stocks where ESG-leading companies are more liquid given that ESG-leading companies provide investors with comfort during economic downturns and liquidity shortages (Luo 2022). Other studies have also shown that market liquidity improves as firms increase their level of sustainable disclosure, and that consideration of ESG issues could improve trades (Pan 2020; Egginton and McBrayer 2019). Hence, the ATT values in

Table 7. Bid-ask spread on the treated (leaders) and control (laggards) samples in the secondary market.

ESG rating	Count	Mean	Std	Min	25%	50%	75%	Max
0 [laggards]	620	9.10E-03	8.60E-03	0.00E+00	3.28E-03	6.46E-03	1.26E-02	8.79E-02
1 [leaders]	321	4.49E-03	4.07E-03	0.00E+00	2.02E-03	3.41E-03	5.91E-03	3.65E-02

Table 8. Bloomberg LQA score between the treated (leaders) and control (laggards) groups in the secondary market.

ESG rating	Count	Mean	Std	Min	25%	50%	75%	Max
0 [laggards]	541	39.275	30.069	1.000	8.000	34.000	64.000	98.000
1 [leaders]	340	58.824	23.937	2.000	38.750	62.000	79.250	98.000

the secondary market also capture the liquidity difference between the treated group and the control group and should be interpreted with caution.

Following the same procedure as in the primary market, we use a logistic regression to assess the propensity score in the secondary market and match bond populations by identifying an untreated sample with a similar logit propensity score to the treated sample. As before, radius and kernel matching were used to identify matching candidates. Using the same confounders and SDB threshold tests (Figure 3), the ATT values associated with the ESG performance scores in the secondary market are presented in Table 9. The ATT of high ESG ratings (AAA to A) ranged from −12.7 bps (radius matching within a caliper of 0.005) to −49.5 bps (radius matching within a caliper of 0.4) with an average effect of −28.0 bps. These results are consistent with those obtained from primary market analysis but the discount for each matching method is larger and all estimates are statistically significant. These findings provide support for Hypothesis 1.2. To validate the results, we performed robustness tests on our sample (Panel B of Table 9) using OLS regression and EB, which yielded identical results in terms of statistical significance level, thus supporting both outcomes. ESG premium estimates derived from the primary market (issuance market) represent the issuer's perspective, whereas secondary market (trading market) statistics reflect investors' perceptions of how much ESG premium they are willing to accept. The impact of the ESG performance scores in the

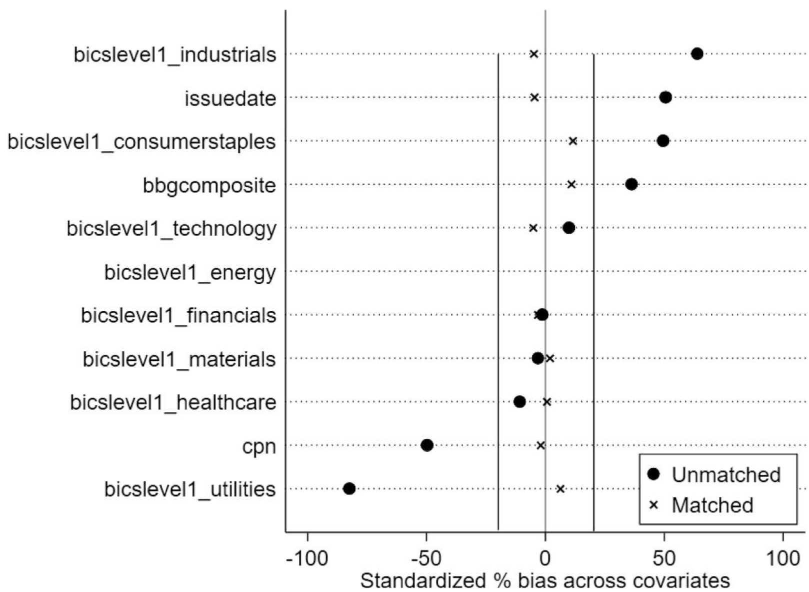

Figure 3. SDB on the unmatched and matched units for the ESG performance scores in the secondary market.

Table 9. Estimated ATT values for MSCI-rated ESG performance scores in the secondary market.

Panel A: detailed results obtained through the process of PSM

	Radius			Kernel	
	Caliper: .005	Caliper:.2	Caliper:.4	Bandwidth (.03)	Bandwidth (.15)
ATT (bps)	−12.674**	−33.863***	−49.476***	−17.368***	−26.535***
Std. Err.	6.759	4.942	4.402	6.025	5.320
# Treated sample	418	442	442	442	418
# Untreated sample	1329	1329	1329	1329	1329

Panel B: comparison of the effects derived from PSM and OLS regression

	Coefficient	Std. err	*p*-value
PSM	−27.983***	5.489	<0.001
OLS regression	−32.827***	4.481	0.000
Entropy balancing	−28.488***	3.715	0.000

Notes: In panel A, the ATT and Std. Err. figures are expressed in basis points (bps). Columns refer to the different matching methods including radius matching (calipers = 0.005, 0.2 and 0.4) and kernel matching (bandwidth = 0.03 and 0.15). ATT is the average treatment effect on the treated sample. #Treated and untreated is the number of treated and untreated units on common support, respectively. (***) (**) (*) indicate significance level at (1%) (5%) (10%) respectively. In all estimations, a common support condition of the treated and control units is satisfied in order to ensure better comparability of matched units. Panel B presents the average effects obtained through PSM, OLS regression and entropy balancing using the same set of control variables. The balance constraints for entropy balancing are set as the first moment.

secondary market indicates that the market is willing to accept a lower credit spread for a bond issued by a company with leading ESG performance, thereby shifting the pressure onto the spread during issuance. An alternative explanation is that bonds issued by ESG leaders are more liquid than those of ESG laggards, and hence the spread discount reflects this difference. In their study using 4000 corporate bonds, Chen, Lesmond, and Wei (2007) demonstrated that more illiquid bonds earn higher credit spreads, while improvements in liquidity result in a significant reduction in credit spreads, even after correction for bond-specific and macroeconomic variables. However, a PSM-based greenium analysis for municipal and corporate bonds (Gianfrate and Peri 2019) did not address the issue of liquidity bias embedded in bond spreads, nor did the authors discuss the potential implications for data interpretation.

4.3. Comparison of ESG disclosure influences on credit spreads

The impact of Bloomberg ESG disclosure scores on bond spreads and the existence of a credit spread premium in the primary and secondary markets are explored in this section. If a leading ESG performance score confers a premium, would the extent of data disclosure have a similar effect, given that data has been made transparent but actual ESG performance is not accounted for? The data presented here is based on whether the company discloses ESG metrics, rather than the actual degree of disclosure. Corporate disclosure is used as the treatment effect, whereby bonds issued by ESG disclosing companies are in the treated group, and those issued by non-disclosing companies are in the control group. The confounder set used for this analysis was the same as before (coupon rate, maturity date, issue date, credit rating, and selected industry sectors). A new SDB analysis was required because that the universe of corporate bond issuers that disclose ESG data is different from that which comprises the ESG rated leaders.

Following the same process, the propensity score was estimated to sort bond observations (Appendix A). The set of confounders that met the SDB requirement comprises

Table 10. Estimated ATT values for ESG disclosure scores in the primary market.

Panel A: detailed results obtained through the process of PSM

	Radius			Kernel	
	Caliper: .005	Caliper:.2	Caliper:.4	Bandwidth (.03)	Bandwidth (.15)
ATT (bps)	−9.884	−4.366	−7.078	−7.078	−6.108
Std. Err.	9.779	7.134	9.757	7.385	7.336
# Treated sample	268	273	273	273	273
# Untreated sample	385	385	385	385	385

Panel B: comparison of the effects derived from PSM and OLS regression

	Coefficient	Std. err	*p*-value
PSM	−6.903	8.278	0.179
OLS regression	−1.908	4.876	0.696
Entropy balancing	2.993	6.507	0.646

Notes: In panel A, the ATT and Std. Err. figures are expressed in basis points (bps). Columns refer to the different matching methods including radius matching (calipers = 0.005, 0.2 and 0.4) and kernel matching (bandwidth = 0.03 and 0.15). ATT is the average treatment effect on the treated sample. #Treated and untreated is the number of treated and untreated units on common support, respectively. (***) (**) (*) indicate significance level at (1%) (5%) (10%) respectively. In all estimations, a common support condition of the treated and control units is satisfied in order to ensure better comparability of matched units. Panel B presents the average effects obtained through PSM, OLS regression and entropy balancing using the same set of control variables. The balance constraints for entropy balancing are set as the first moment.

issue date, coupon credit rating, and industry sectors (except consumer discretionary). The ATT results for bond yields in the primary market and secondary market are shown in Tables 10 and 11. In the primary market (Table 10), ATT values range from −4.4 bps (radius of 0.2) to −9.9 bps (radius of 0.005), with an average value of −6.9 bps. However, the ATT results in the primary market are not statistically significant. Panel B presents the discount effects obtained from PSM, EB, and OLS regression. The estimates from EB and OLS are relatively small in magnitude and exhibit larger *p*-values, indicating lower statistical significance. These findings fail to support Hypothesis 2.1, as

Table 11. Estimated ATT values for ESG disclosure scores in the secondary market.

Panel A: detailed results obtained through the process of PSM

	Radius			Kernel	
	Caliper: .005	Caliper:.2	Caliper:.4	Bandwidth (.03)	Bandwidth (.15)
ATT (bps)	−2.975	1.308	.901	−10.178*	−6.604
Std. Err.	5.274	5.414	5.218	5.770	5.507
# Treated sample	573	588	589	588	588
# Untreated sample	1184	1184	1184	1184	1184

Panel B: comparison of the effects derived from PSM and OLS regression

	Coefficient	Std. err	*p*-value
PSM	−3.510	5.437	0.369
OLS regression	0.556	3.992	0.889
Entropy balancing	1.523	4.453	0.732

Notes: In panel A, the ATT and Std. Err. figures are expressed in basis points (bps). Columns refer to the different matching methods including radius matching (calipers = 0.005, 0.2 and 0.4) and kernel matching (bandwidth = 0.03 and 0.15). ATT is the average treatment effect on the treated sample. #Treated and untreated is the number of treated and untreated units on common support, respectively. (***) (**) (*) indicate significance level at (1%) (5%) (10%) respectively. In all estimations, a common support condition of the treated and control units is satisfied in order to ensure better comparability of matched units. Panel B presents the average effects obtained through PSM, OLS regression and entropy balancing using the same set of control variables. The balance constraints for entropy balancing are set as the first moment.

there is no indication of a statistically significant negative relationship between disclosure scores and credit spreads.

The disparities in the effects of disclosing ESG risks and rated ESG performance indicate that, during the study period, the disclosure of sustainable performance metrics is less important determinant for the issuance costs of corporate bonds. This conclusion is consistent with the findings of Gehricke, Ruan, and Zhang (2023) that ESG considerations in bond portfolios do not result in excess or underperformance. Our results are in contradiction to the findings of Yang et al. (2021) who observed a 0.35% (35 bps) reduction in credit spread for each unit of increase in ESG disclosure score in China's bond market using regression analysis. However, this study did not employ comparable groups.

In the secondary market (Table 11), the ATT estimations indicate no apparent trend, rejecting Hypothesis 2.2. In addition, we conducted EB and OLS regression analysis to examine the effects of ESG disclosure as shown in Panel B and found that the impact was negligible with a relatively large p-value compared to the results obtained through PSM. The liquidity tests of disclosing and non-disclosing populations are shown in Appendix C. Both the LQA scores and the bid-ask spread ratio indicate that the treated group (disclosed ESG) is more liquid than the control group (no disclosure). Although a positive impact of disclosure on bond spreads would be expected given that companies with superior ESG performance typically disclose more information regarding their sustainable practices, our results show that disclosure does not lead to reductions in credit spreads. According to Lyon and Montgomery (2015), companies may even face financial risks if investors perceive their disclosure as greenwashing. Lindquist et al. (2022) demonstrated that ESG disclosures may not adequately address information asymmetry, as firms can tailor their disclosures strategically to align with their economic interests.

4.4. Credit spread differences by issuer industry sector

Given the high occurrence of financial bonds in our sample, we sought to understand whether the results of credit spread differences are influenced by the sector of issuer. We separated the full sample into financial and non-financial issuers to investigate the impacts on credit spreads (Tables 12 and 13).

The results indicate that the impact of ESG performance scores on credit spreads is more pronounced for bonds issued by financial institutions (Table 12), both in the primary and secondary markets, providing evidence in support of Hypothesis 1.3. The treatment effect estimates for bonds issued by financial institutions with leading ESG performance scores range from −30.4 to −51.6 bps (all statistically significant) in the primary market, suggesting the impact of ESG rating scores on credit spreads is dominated by bonds from financial issuers. The secondary market effects are similar to those of the primary market. In contrast, the estimates for non-financial issuers are inconclusive and lack statistical significance.

The impact of ESG disclosure scores for bonds issued by financial and non-financial institutions is shown in Table 13. In the primary market, the results for the disclosure scores are positive but not statistically meaningful, while the results in the secondary market are unstable. Whether this indicates that investors do not appear to prioritize the level of ESG information disclosure when evaluating a financial company's credit

Table 12. Estimated ATT values for ESG performance scores for bonds issued by financial and non-financial institutions.

	Market	# of Treated and untreated samples	Radius Caliper: .005	Radius Caliper:.2	Radius Caliper:.4	Kernel Bandwidth (.03)	Kernel Bandwidth (.15)
Financial institutions	Primary	111/134	−39.035***	−30.423***	−51.616***	−37.266***	−38.236***
	Secondary	141/580	−43.948***	−46.421***	−55.481***	−33.231***	−40.008***
Non-financial institutions	Primary	149/283	8.649	1.084	−8.189	10.511	9.081
	Secondary	297/749	−7.418	−29.823***	−49.352***	−12.505*	−20.638***

Notes: The ATT values are expressed in basis points (bps). Columns refer to the different matching methods including radius matching (calipers = 0.005, 0.2 and 0.4) and kernel matching (bandwidth = 0.03 and 0.15). ATT is the average treatment effect on the treated sample. #Treated and untreated is the number of treated and untreated units on common support, respectively. (***) (**) (*) indicate significance level at (1%) (5%) (10%) respectively. In all estimations, a common support condition of the treated and control units is satisfied in order to ensure better comparability of matched units.

Table 13. Estimated ATT values for ESG disclosure scores for bonds issued by financial and non-financial institutions.

	Market	# of Treated and untreated samples	Radius Caliper: .005	Radius Caliper:.2	Radius Caliper:.4	Kernel Bandwidth (.03)	Kernel Bandwidth (.15)
Financial institutions	Primary	138/109	1.104	9.909	9.909	2.958	9.151
	Secondary	212/463	7.8779	−2.516	−8.476	13.166	9.685
Non-financial institutions	Primary	176/322	2.061	−13.812	−4.4228	−3.1140	−22.158*
	Secondary	327/721	10.238	8.2685	12.986*	6.652	6.707

Notes: The ATT values are expressed in basis points (bps). Columns refer to the different matching methods including radius matching (calipers = 0.005, 0.2 and 0.4) and kernel matching (bandwidth = 0.03 and 0.15). ATT is the average treatment effect on the treated sample. #Treated and untreated is the number of treated and untreated units on common support, respectively. (***) (**) (*) indicate significance level at (1%) (5%) (10%) respectively. In all estimations, a common support condition of the treated and control units is satisfied in order to ensure better comparability of matched units.

risks, or whether other reasons account for this observation, requires further study. Bonds from non-financial issuers (with ESG disclosure) show inconclusive effects in the primary and secondary markets. Based on these findings, we must reject Hypothesis 2.3.

5. Conclusion

This study contributes to the literature on the impact of ESG data on corporate bond performance and, specifically, credit spreads. Based on our findings, it can be concluded that the ESG premia in the bond market are associated with the performance of ESG activities, rather than with the level of transparency. Even after adjusting for credit risks, the ESG premia persists and could potentially be more prominent in a liquid market. Results were obtained by using a non-parametric causal inference model, propensity score matching, whose main advantage is to overcome some caveats of the regression analysis such as the 'functional form misspecification' (Shipman, Swanquist, and Whited 2017). The results from PSM, using different matching algorithms, indicate that there is a negative relationship between ESG performance and spread at issuance and in the secondary market. This is consistent with previous literature (Polbennikov et al. 2016; Jang et al. 2020; Li, Zhou, and Xiong 2020; Apergis, Poufinas, and Antonopoulos 2022). Similar trends in ATT based on different matching algorithms also provide more credibility to the PSM-based analysis. For ESG disclosure, the impact was statistically insignificant in both primary and secondary markets. This distinct effect between performance and disclosure was not observed by Gehricke, Ruan, and Zhang (2023), who demonstrated that regardless of the specific ESG indicator utilized (i.e. ESG performance or disclosure), neither overperformance nor underperformance occur at the bond portfolio level. Our work further saw a significant sector effect from financial services issuers, whose leading ESG rated bonds commanded a much higher credit spread than the cross-sectoral universe (30–51 bps vs 14 bps).

To assess the robustness of our findings, we also conducted EB and OLS regression analyses corresponding to their matching counterparts. In the primary market, only PSM showed significance in credit spread reduction. In the secondary market, however, all three methods suggest that leaders in ESG performance are associated with lower credit spreads. Additionally, the PSM results demonstrate equal or greater statistical significance compared to those obtained from entropy balancing or regression analyses.

5.1. Research limitations

The authors recognize that this study has several limitations. First, while the use of PSM sought to overcome the limitations of regression analysis by accounting for confounders in the treated and control populations, the PSM approach is dependent on the confounder selection process (King and Nielsen 2019). Additionally, matching processes often restrict the analysis to a subset of observations, and the process of comparing a treatment group with a control group on one dimension potentially results in the loss of important information during the matching process. Multi-dimensional statistical inference tools could be explored to address this limitation (Li and Adriaens 2024). Second, statistical inference does not prove causality between ESG performance or disclosure and credit spread. Further analysis of causal relationships would necessitate the inclusion of valid instrumental variables (Baiocchi, Cheng, and Small 2014). While the focus of the paper was on applying PSM to measuring ESG benefits on bond credit spreads, the third limitation is that a single source of ESG disclosures (Bloomberg) and performance scores (MSCI) was used. Given the divergence in scope, methods of analysis and weightings used by different ESG rating providers, results may differ. A comparison of multiple datasets would serve to further prove the robustness of the results obtained in this study, as would a broader comparison of bonds from US-listed (Ari and Feifei 2020) versus cross-listed companies. The initial results did not show a clear trend, but a broader comparison of regional effects may present a productive avenue for further study. In addition, although robustness tests using EB are consistent with the PSM method for ESG performance scores in the secondary market, and for ESG disclosure in both the primary and secondary markets, the results do not align for ESG performance in the primary market. This suggests that the lower credit spread may be analytical method-dependent in the primary market, and generalizing this phenomenon to other contexts should be met with caution.

The implications of this work for other regional corporate bond markets are speculative, in part due to the low correlations between ESG providers overall, and the difference in correlation between the governance ratings in, for example, the US and the EU. For example, according to Research Affiliates, a smart beta and asset allocator, the correlation in governance scores between providers in the US is 0.38, while it is 0.55 in the EU. Furthermore, Abdul Razak, Ibrahim, and Ng (2023) and Stellner, Klein, and Zwergel (2015) found that country-level ESG performance has a moderating effect on the relationship between ESG performance and credit spreads. Hence, the impact of ESG performance on credit spreads is amplified in countries with superior levels of sustainability.

5.2. Practical implications

From an financing standpoint, the ESG premia in the bond market can be seen as a market signal reflecting the increasing relevance of environmental, social, and governance issues for investors. This can incentivize firms to improve their ESG performance and ratings, as doing so can reduce their borrowing costs and increase access to financing. Based on our findings, the ESG premia are linked to ESG performance, rather than to the level of transparency. To achieve cost benefits linked to improved ESG performance, corporations must disclose publicly accessible ESG information to rating agencies and investors. Disclosure is a prerequisite for obtaining a higher ESG performance score, despite not directly yielding benefits. Major US corporations commonly practice ESG disclosure, indicating their recognition of associated ESG risks. However, companies aiming to reduce issuance costs should prioritize improving their actual ESG performance and increasing their ESG scores, rather than relying solely on disclosure.

From a policy perspective, ESG premia can be seen as a tool to promote sustainability and responsible corporate behavior. For example, policymakers may consider implementing regulations or incentives, such as subsidies for renewable energy and tax incentives for companies that meet certain ESG criteria, encourage companies to improve their ESG performance and limit greenwashing, as recent actions by the SEC indicate. While ESG disclosures alone may not effectively mitigate information asymmetry, as firms can strategically tailor their disclosures to optimize their economic decisions (Lindquist et al. 2022), regulation around ESG benchmarking and compliance will serve to reduce confusion.

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