ACCSCIENCE PUBLISHING

Asian Journal of Water, Environment and Pollution

ORIGINAL RESEARCH ARTICLE

Carbon transition risk, green debt pricing, and environmental governance: Evidence from Chinese high-energy-consuming firms

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Citation: Sun L, Zeng J. Carbon transition risk, green debt pricing, and environmental governance: Evidence from Chinese high-energy-consuming firms. *Asian J Water Environ Pollut.* doi: 10.36922/AJWEP026170117

Received: April 25, 2026

Revised: May 21, 2026

Accepted: May 27, 2026

Published online: June 19, 2026

Abstract

Carbon transition risk increasingly affects the financing conditions of firms in high-energy-consuming industries, yet debt-side evidence remains fragmented and often mixes policy inference with predictive monitoring. This study examines how carbon-related transition signals are associated with green debt financing spreads for Chinese A-share listed firms in high-energy-consuming industries during 2010–2024. The dependent variable is the green debt financing spread measured in basis points (Spread_bps). To preserve evidentiary boundaries, the study adopts a dual-track design: panel fixed-effects models, an event-study analysis around the 2015 Paris Agreement, and a segmented difference-in-differences design around China's national emissions trading system in 2021 are used for policy-timing evidence, while random forest, extreme gradient boosting (XGBoost), and neural network models are used for out-of-sample prediction, ablation tests, Shapley additive explanations interpretation, and conditional scenario simulation. The econometric results show that higher carbon intensity is associated with wider green debt spreads, whereas stronger carbon-pricing exposure and greater green patent output are associated with narrower spreads. Pricing sensitivity to carbon-related factors increases after major policy milestones, and green innovation partly mitigates post-emission-trading-system financing pressure on high-carbon issuers. The predictive results show that XGBoost performs best and that removing carbon variables reduces forecasting accuracy, confirming the incremental monitoring value of carbon information. These findings suggest that green debt pricing can complement environmental regulation by translating carbon intensity, carbon-market exposure, and transition capacity into financing signals useful for credit analysts, issuers, investors, and policymakers.

Keywords: Carbon transition risk; Green debt pricing; Environmental governance; Emissions trading system; Green patents; Explainable machine learning

1. Introduction

Carbon transition risk has become a near-term financing and environmental-governance issue for high-energy-consuming firms. As carbon-pricing systems, disclosure rules, and expectations for a low-carbon transition become more visible, creditors increasingly need to assess whether changes in emissions intensity, carbon-market exposure, and transition capacity alter the risk profile of borrowers. Recent debt-market evidence shows that carbon-related information can affect bank lending, loan pricing, and broader debt-financing conditions across institutional settings.[1-6]

For green debt instruments, this issue is especially important because pricing is not only a financing outcome but also a potential market-based channel for environmental governance. If green debt spreads penalize carbon-intensive issuers and reward credible transition capacity, external financing costs may reinforce incentives for pollution control, cleaner production, and more transparent carbon disclosure. Existing bond-market and credit-risk studies indicate that carbon transition signals are increasingly reflected in corporate bond spreads, default risk, and carbon regulatory repricing, but the specific role of green debt spreads among Chinese high-energy-consuming firms remains insufficiently clarified.[7-15]

Another limitation of the existing literature concerns the timing of policy. Carbon transition risk is partly created and amplified by institutional events, so a purely cross-sectional design may overlook how market attention shifts after major climate policy milestones. Evidence from the Paris Agreement suggests that creditors may reprice carbon exposure as climate-policy salience increases.[16] However, these policy signals differ in scope: the 2015 Paris Agreement is a broad global climate-policy signal, whereas the 2021 launch of China's national emissions trading system is a domestic carbon-market institutional change. Treating these events separately helps avoid overstating causal claims while still using policy timing to strengthen the empirical narrative.

An additional limitation is methodological. Econometric models are suitable for examining conditional associations and policy-timing changes under explicit identification assumptions, whereas machine learning (ML) models are better suited to prediction, nonlinear pattern detection, and risk-monitoring support. Mixing these two forms of evidence can lead to overclaiming. Therefore, this study separates policy-timing inference from predictive monitoring: fixed-effects, event-study, and segmented difference-in-differences models are used for the inferential layer, while random forest, extreme gradient boosting (XGBoost), neural network models, ablation tests, Shapley additive explanations (SHAP) interpretation, and scenario simulation are used only for out-of-sample prediction and decision support.

Theoretically, the study is positioned at the intersection of green finance theory, stakeholder theory, and institutional theory. Green finance theory explains why financial markets may allocate capital toward lower-carbon transition activities. Stakeholder theory highlights the pressure exerted by investors, creditors, regulators, and communities on high-emitting firms. Institutional theory explains why policy milestones and carbon-market rules can change the credibility and salience of carbon information. Together, these perspectives support the core argument that green debt pricing may translate carbon transition signals into market-based incentives for environmental governance.

1.1. Practical and theoretical positioning

The practical objective of this study is to clarify how transition-related signals map onto the green debt-financing spread of Chinese high-energy-consuming firms. The common outcome variable is the green debt financing spread measured in basis points (Spread_bps). The analysis focuses on three transition signals: carbon intensity (CarbonIntensity), carbon-pricing exposure and allowance-price visibility (CarbonPriceIndex), and green innovation output measured by green patents (GreenPatent). These indicators are selected because they correspond to three dimensions that creditors can observe or approximate: current emissions burden, carbon-market policy exposure, and transition readiness.

Because the issuer sample is not equivalent to the full population of high-energy-consuming firms, Spread_bps is observable only when firms issue eligible green bonds or sustainability-linked debt instruments. Accordingly, the empirical interpretation is confined to green-debt issuers, and potential sample-selection bias is examined through transparent screening rules and a Heckman-type robustness check in the methods section. This framing prevents the results from being generalized mechanically to all firms or to economy-wide pollution reduction.

1.2. Research questions and hypotheses

Within this setting, the paper addresses three research questions. First, after standard credit controls are considered, are carbon intensity, carbon-pricing exposure, and green innovation systematically associated with Spread_bps? Second, does pricing sensitivity to carbon transition signals change around the 2015 Paris Agreement and the 2021 launch of China's national emissions trading system? Third, from a monitoring perspective, do carbon-related variables add predictive information beyond conventional credit variables, and can the resulting model outputs support scenario screening without being interpreted as causal policy effects?

The following hypotheses are tested. H1: Higher carbon intensity is associated with wider green debt financing spreads. H2: Stronger carbon-pricing exposure is associated with narrower spreads among green-debt issuers, conditional on standard credit controls. H3: Greater green innovation output is associated with narrower spreads. H4: Pricing sensitivity to carbon-transition signals becomes stronger after major climate-policy milestones. H5: Green innovation weakens the post-emission trading system (ETS) and reduces the financing pressure faced by high-carbon issuers.

1.3. Contributions and evidentiary boundaries

The first contribution is substantive. By using Spread_bps as the common debt-pricing outcome, the study links carbon transition risk with a financing channel directly relevant to environmental governance. This allows the paper to examine whether carbon intensity, carbon-market exposure, and transition capacity are reflected in the cost of green debt, rather than treating green finance as purely policy-driven or a symbolic label.

The second contribution is empirical. The study combines a baseline panel fixed-effects framework with two policy-timing designs centered on 2015 and 2021. The 2015 analysis evaluates whether the salience of carbon transition risk increased after the Paris Agreement, while the 2021 segmented Difference-in-Differences (DID) design examines whether ETS-exposed issuers experienced differential repricing following China's national carbon-market launch. This design gives the paper a clearer policy-timing structure than a simple pooled association.

The third contribution is methodological and practical. ML is used in a restrained way to improve out-of-sample prediction, test the incremental predictive value of carbon variables, and generate monitoring-oriented scenario outputs. SHAP values and scenario simulations are interpreted as model-implied changes rather than causal effects. This separation of evidence supports more useful guidance for credit analysts, issuers, investors, and policymakers while preserving the distinction between policy inference and predictive risk monitoring.

2. Literature review

The literature review is organized around four related streams: debt-side pricing evidence, policy timing and carbon-market institutions, firm-level transition buffers, and ML-based prediction and explainability. Rather than only summarizing prior findings, the review identifies contradictions, methodological differences, and remaining gaps in the existing evidence.

2.1. Carbon transition risk and debt-side pricing evidence

The first stream of literature examines whether creditors price carbon transition risk in lending markets. Ehlers *et al.*[1] showed that syndicated loan markets distinguish among different forms of carbon risk, indicating that lenders do not treat all emissions-related exposures as homogeneous credit information. Zhu and Zhao[2] provided China-based evidence that carbon risk is associated with higher bank-loan costs, which is particularly relevant for emerging markets where environmental regulation, state ownership, and bank credit allocation interact. Dimitras *et al.*[3] extended this debate to the US syndicated loan market and found that firm-level carbon risk matters to banks, confirming that creditor responses are not confined to a single institutional environment. Kacperczyk and Peydró[4] further emphasized the bank-lending channel of carbon emissions and suggest that banks may adjust credit supply when borrowers are exposed to transition pressure. Altavilla *et al.*[5] added a macro-financial dimension by showing that climate risk, bank lending, and monetary policy conditions may interact, implying that carbon-risk pricing depends not only on firm characteristics but also on broader credit-cycle conditions.

These loan-market studies provide an essential foundation for the present article, but they also reveal an important limitation. Their main outcomes are loan spreads, loan volumes, or bank credit conditions, whereas this study focuses on green debt financing spreads. Ren *et al.*[6] broaden the evidence by examining carbon risk and debt financing from an international perspective, but cross-country evidence may mask the institutional specificity of China's green debt market and carbon-market development. The implication is that the debt-pricing relevance of carbon risk is established in general terms, yet the specific channel through which carbon transition signals are reflected in green debt issued by high-energy-consuming Chinese firms remains to be investigated.

A second group focuses more directly on bond-market pricing. Cang and Li[7] found that corporate climate risk is incorporated into bond credit spreads, suggesting that fixed-income investors require compensation for climate-related uncertainty. He *et al.*[8] reached a similar conclusion regarding corporate bond credit spreads, reinforcing the view that carbon and climate indicators are incorporated into market-based debt pricing. Bouchet and Crifo[9] studied climate transition risk and debt capital costs in energy and utilities sectors, showing that transition exposure is especially relevant in industries with high abatement costs and asset-stranding concerns. Lu *et al.*[10] shifted attention from objective exposure to managerial climate-risk concern, indicating that bond spreads may respond not only to emissions or policy exposure but also to how managers perceive and communicate transition risk.

The bond-spread literature is directly related to this study, but it still leaves several unresolved issues. Bolton and Kacperczyk[11] provided global evidence that carbon-transition risk is priced in financial markets. Seltzer *et al.*[12] further showed that climate regulatory risk affects corporate bond ratings and yield spreads, findings that are especially relevant to this paper's focus on policy-driven transition risk. These studies show that the informational environment matters, but they do not fully distinguish among three transition signals that are central to environmental governance: current carbon intensity, carbon-pricing exposure, and transition capacity. Collin-Dufresne *et al.*[13] also reported that credit spreads are driven by conventional fundamentals and market conditions, suggesting that carbon variables must be evaluated conditional on standard credit risk determinants rather than in isolation.

Recent studies also show that carbon risk may travel through networks or policy-exposure channels. Zhou *et al.*[14] documented spillovers of carbon risk along the supply chain and showed that bond markets may price not only a firm's direct exposure but also its upstream or downstream transition vulnerability. Zhou *et al.*[15] examined carbon regulatory risk exposure in China's bond market through a quasi-natural experiment and found that regulatory exposure can trigger bond-market repricing. These studies support the present article's attention to debt-market repricing, but they also underscore the need to avoid overgeneralization. Green debt issuers are not the same as all listed firms, and a green financing spread is not equivalent to a conventional bond spread. Therefore, this study treats Spread_bps as a specific issuer-level outcome and confines the interpretation to the green-debt financing channel.

A third debt-side stream examines default risk, debt structure, trade credit, and systemic vulnerability. Wang *et al.*[16] showed that the Paris Agreement affected corporate debt-default risk, suggesting that global climate policy milestones can change creditors' expectations about future transition pressures. Löschenbrand *et al.*[17] linked carbon pricing to firm defaults, adding a structural credit risk perspective to the debate. Duong *et al.*[18] used credit default swap evidence to show that carbon-risk management can affect perceived credit risk, implying that markets may reward credible transition management before realized default events occur. Ben Nasr *et al.*[19] examined the influence of carbon risk on debt structure. Ben-Nasr *et al.*[20] showed that carbon risk also affects trade credit, suggesting that transition pressure may influence both formal debt contracts and interfirm financing arrangements.

This wider credit-risk literature is valuable because it demonstrates that carbon transition risk can affect several financing margins. Khanchel *et al.*[21] discussed pollution-control bonds as a financing response to carbon risk, connecting environmental investment needs with debt-market instruments. Liu *et al.*[22] analyzed climate change and systemic risk in China through a distance-to-default approach, showing that firm-level transition exposure may aggregate into broader financial vulnerability. Yan *et al.*[23] examined carbon risk and the cost of equity capital in China. Bose *et al.*[24] connected carbon risk to international stock price crash risk. Hoang *et al.*[25] relate firm-level climate exposure to firm efficiency. Although these equity and efficiency studies do not examine green debt spreads directly, they confirm that carbon transition risk is financially material across markets. The limitation is that their evidence does not directly answer whether creditors in the green debt market price emissions intensity, carbon-market exposure, and green innovation in the same way. This gap motivates the choice of the dependent variable and the debt-side focus of the present study.

2.2. Policy timing, carbon-market institutions, and repricing mechanisms

The second major literature stream examines how policy events and carbon-market institutions change the salience of transition risk. Owolabi *et al.*[26] showed that carbon risk affects the cost of debt for listed firms in G7 economies and that the Paris Agreement plays an important role in this relationship. Nguyen *et al.*[27] used Kyoto Protocol ratification to identify the price of carbon risk, illustrating that international climate policy commitments can alter market expectations even before firm-level emissions outcomes are fully realized. These studies justify the use of global climate-policy milestones, but they also raise a methodological concern: international agreements are broad signals rather than narrowly targeted policy shocks. Therefore, they are better suited for testing changes in pricing sensitivity than for making strong single-policy causal claims.

China's environmental and carbon-market reforms provide a more institutionally specific setting. Wang and Xu[28] showed that environmental protection tax policy affects corporate risk-taking, suggesting that environmental regulation can reshape firm financial behavior. Huang *et al.*[29] found that China's carbon-emission trading scheme is linked to firm debt financing, providing direct evidence that carbon-market institutions can influence external financing conditions. Arian *et al.*[30] further showed that climate risk affects corporate investment, indicating that transition pressure can influence both financing costs and real investment decisions. Ren *et al.*[31] used China's carbon emission trading scheme as a natural experiment and found that creditors price climate transition risks when regulatory exposure becomes more salient.

These China-focused studies support the policy-timing structure of this article, but they also suggest that treatment definitions must be handled carefully. The 2021 launch of China's national emissions trading system should not be treated as a uniform shock to all high-energy-consuming firms. Firms located in pilot ETS regions may have received carbon-market signals before 2021, whereas newly affected firms may experience a more distinct post-2021 repricing pattern. For this reason, the present study uses a segmented DID design rather than a simple post-2021 dummy for all firms. This design responds to the literature's identification challenge by distinguishing global policy salience from domestic carbon-market exposure.

Carbon prices themselves are also relevant market signals. Stechemesser *et al.*[32] provided global evidence that combinations of climate policies, including market-based instruments, can lead to major emission reductions. Mengesha *et al.*[33] further showed that carbon pricing can support the transition toward green growth by altering technology and fuel-switching incentives. Li *et al.*[34] found that carbon reduction pressure can affect internal capital transfers within business groups under China's carbon emission trading policy, suggesting that carbon policy may influence both internal resource allocation and external financing. These findings justify the use of CarbonPriceIndex in the present study, but they also warn against interpreting it as a pure price variable. Because the index combines ETS coverage and allowance-price visibility, it should be understood as a broader carbon-market-pricing environment rather than as a standalone allowance price.

2.3. Firm-level buffers: disclosure, innovation, and financial adjustment capacity

The third stream of literature examines why firms under similar policy pressure may face different financing outcomes. Ali *et al.*[35] showed that capital markets can reward corporate climate change actions through lower debt costs, indicating that creditors respond to the credibility of climate-related information and actions. Bingler *et al.*[36] cautioned that climate disclosure may become cheap talk when statements are not supported by concrete initiatives, meaning that disclosure quantity cannot be mechanically equated with transition credibility. Sun *et al.*[37] examined the green premium effects of corporate transition-risk disclosure and suggested that credible transition communication may reduce financing costs. Together, these studies indicate that information quality can moderate how carbon risk is priced, but they also imply that disclosure alone is insufficient unless it is connected with observable transition action.

Financial adjustment is another firm-level buffer. Nguyen and Phan[38] showed that carbon risk affects corporate capital structure, suggesting that firms adjust leverage as transition exposure changes. Cumming *et al.*[39] examined the dynamics of carbon risk, cost of debt, and leverage adjustments, showing that financing costs and capital-structure adjustments may evolve jointly under transition pressure. Dallocchio *et al.*[40] focused on climate transition and the speed of leverage adjustment, indicating that firms may differ not only in their target leverage but also in their ability to move toward it. Wu *et al.*[41] examined decarbonization and corporate cash holdings, suggesting that firms may use liquidity buffers to manage transition uncertainty. These studies are important for the present article because they show that carbon transition risk is not only a pricing variable; it also affects corporate financial policies, which, in turn, influence spreads.

Green innovation and green finance provide the third buffer. Zhai *et al.*[42] found that green finance innovation can promote supply-chain decarbonization, which links financial innovation with real-economy emission reduction. Lee *et al.*[43] studied green digital finance and energy poverty, showing that digital and green financial channels may influence environmental and social outcomes beyond conventional corporate financing. Moro and Zaghini[44] compared green premia across advanced and emerging markets and showed that the pricing advantage of green instruments depends on institutional context, exchange-rate conditions, and financial openness. These studies support the use of GreenPatent as a proxy for transition capacity and justify the focus on green debt pricing. At the same time, they also reveal a potential endogeneity issue: firms with stronger environmental governance may both produce more green patents and enjoy lower financing costs. Therefore, the present study interprets GreenPatent cautiously as a transition-capacity signal, uses fixed effects and robustness checks, and avoids claiming that patent output alone causally reduces spreads.

2.4. Methodological development: prediction, explainability, and evidence boundaries

The final literature stream concerns the use of ML and explainable artificial intelligence in financial-risk analysis. Lundberg and Lee[45] formalized SHAP as a unified framework for explaining model predictions, providing the technical basis for the interpretability tools used in this paper. Chan *et al.*[46] compared SHAP-based interpretability across ML models in financial classification, indicating that explanation methods may vary across model types and should not be treated as mechanically stable. Lin and Wang[47] studied SHAP stability in credit-risk management and showed that explanation consistency is itself a practical requirement when model outputs are used for decision support.

More studies have extended ML and explainability tools into credit-risk and high-stakes financial settings. Chen and Guestrin[48] introduced XGBoost as a scalable tree-boosting system, which is directly relevant to the predictive model used in this study. Barredo Arrieta *et al.*[49] synthesized the broader XAI literature and emphasized the need for explanations that are auditable, interpretable, and responsible. Chen[50] explored prompt-based large language models for credit-risk classification, indicating that AI-based financial prediction is moving toward more flexible forms of decision support. These studies justify the ML track of the present article, but they also clarify its limits. Prediction, SHAP interpretation, and scenario simulation can support risk monitoring, but they do not identify policy effects. Accordingly, this study treats XGBoost, SHAP, ablation tests, and scenario analysis as predictive and diagnostic tools rather than causal identification strategies.

2.5. Synthesis of gaps and positioning of the present study

The reviewed literature establishes four key points. First, carbon transition risk is financially material in loan, bond, credit default swap, equity, and corporate policy settings. Second, major climate policy events and carbon market reforms can increase market attention to carbon-related information. Third, firm-level disclosure, innovation, liquidity, leverage adjustment, and access to green finance can buffer transition pressure. Fourth, ML methods can improve prediction and interpretation, but cannot replace econometric identification. These conclusions support the overall logic of this study, but they also reveal several specific gaps.

The first gap is outcome specificity. Prior studies have examined bank loans, conventional bond spreads, debt defaults, trade credit, leverage, cash holdings, equity costs, and stock-market outcomes, but few have examined green debt financing spreads for Chinese high-energy-consuming firms. The distinction matters because a green debt spread is both a financing-cost outcome and a potential signal of environmental governance. The second gap is signal differentiation. Existing studies often examine carbon risk as a broad exposure, but environmental governance requires distinguishing among current carbon burden, carbon-market exposure, and transition capacity. The present study, therefore, jointly examines CarbonIntensity, CarbonPriceIndex, and GreenPatent.

The third gap is policy timing. Studies using the Paris Agreement or China's ETS provide important evidence, but international climate agreements and domestic carbon-market launches should not be treated as identical shocks. This study uses the 2015 Paris Agreement to examine changes in pricing sensitivity and the 2021 national ETS launch to examine differential repricing among ETS-exposed issuers. The fourth gap is the evidentiary boundary. Econometric designs and ML models answer different questions. The present study addresses this issue by separating the inferential track from the predictive track: fixed-effects, event-study, and segmented DID models are used for policy-timing evidence, whereas random forest, XGBoost, neural networks, SHAP, ablation, and scenario simulations are used for monitoring-oriented prediction.

This synthesis positions the article within a unified but bounded framework. Carbon transition risk is treated as a financially material environmental risk; green debt pricing is treated as a market-based environmental governance channel; and ML is treated as a decision-support tool rather than as a causal identification strategy. This positioning supports the hypotheses developed in the introduction and serves as a bridge from the previous literature to the empirical design that follows.

3. Materials and methods

3.1. Research design, hypotheses, and evidentiary boundaries

The methodological design was organized around empirical transparency, model reproducibility, and a clear separation between policy-timing evidence and prediction. The study followed a dual-track design. Track A was the econometric track, which examined conditional pricing relationships and changes in policy timing in the green debt financing spread. Track B was the ML track, which evaluated out-of-sample prediction, nonlinear model behavior, and outputs for monitoring-oriented scenarios. Both tracks used Spread_bps as the common outcome variable, but they answered different questions and followed different evidentiary standards.

The hypotheses stated in the Introduction were mapped onto the empirical design before model estimation. H1–

H3 were tested using two-way fixed-effects regressions that relate CarbonIntensity, CarbonPriceIndex, and GreenPatent to Spread_bps after standard credit-risk controls are included. H4 was examined through policy-timing specifications centered on the 2015 Paris Agreement and the 2021 launch of China's national ETS. H5 was examined through interaction terms that test whether green innovation weakens the financing penalty associated with high carbon intensity or post-ETS exposure. The predictive models were used separately to assess forecasting performance and to generate interpretable monitoring signals.

To keep the evidentiary boundary clear, we used consistent terminology. Econometric results were described as conditional associations, differential changes, policy-timing evidence, or DID estimates. ML outputs were described as predictive contributions, feature-importance measures, SHAP values, ablation effects, or model-implied scenario changes. This terminology clarified the distinct roles of fixed-effects models, policy-timing analysis, and ML techniques (Table 1).

3.2. Data sources, sample construction, and sample-selection transparency

The baseline population comprised Chinese A-share-listed firms in high-energy-consuming industries from 2010 to 2024. The industry scope covered steel, cement, chemicals, and related heavy industries identified by national industrial and environmental policy classifications. Firm-level financial variables, ownership information, governance variables, bond-issuance information, and credit-rating data were obtained from licensed financial databases, annual reports, bond prospectuses, and issuer disclosures. Regional carbon-market variables were collected from pilot ETS exchanges, national ETS policy documents, allowance-price disclosures, and provincial carbon-market records. Year-level macro-financial variables, including interest-rate and credit-cycle controls, were matched to the firm-year panel.

The dependent variable, Spread_bps, was observable only when a firm issued an eligible green bond or sustainability-linked debt instrument. This observability condition was central to the research design because the

Table 1. Methodological workflow and evidentiary boundaries

Stage	Question addressed	Data layer	Method/diagnostic	Output and interpretation
Sample construction	Which observations enter the analysis?	A-share high-energy-consuming firms, issuer-year debt data, firm controls, and regional carbon-market information	Stepwise screening, missing-data rules, winsorization, and issuer-sample definition	Transparent final issuer-year sample used in spread models
Baseline pricing test	Are carbon-transition signals associated with green debt spreads?	Issuer-year panel with observed Spread_bps	Two-way fixed effects with firm and year effects; clustered standard errors	Conditional pricing associations for H1–H3
Selection correction	Does non-random green debt issuance affect spread estimates?	Full candidate firm-year panel plus issuer indicator	Heckman two-step correction with exclusion restrictions	Robustness evidence on sample-selection bias
2015 policy timing	Did pricing sensitivity change after a global climate-policy milestone?	Pre- and post-2015 issuer-year observations	Event-study / interaction specification using pre-event carbon exposure	Dynamic policy-timing evidence for H4
2021 ETS DID	Did ETS exposure change green debt pricing after the national market launch?	Issuer-year observations with industry-region ETS exposure	Segmented DID, triple interactions, placebo tests, lead-lag checks	Differential post-ETS repricing evidence for H4–H5
Predictive monitoring	Do carbon variables improve out-of-sample prediction?	Same feature layer used across ML models	RF, XGBoost, NN, ablation tests, repeated validation	Predictive value of carbon information, not causal inference
Explainability and scenarios	How does the fitted model combine carbon and credit signals?	Fitted XGBoost model and test-set predictions	SHAP, permutation importance, conditional simulations	Risk-monitoring and scenario-screening templates

Abbreviations: DID: Difference-in-differences; ETS: Emissions trading system; ML: Machine learning; NN: Neural network; RF: Random forest; SHAP: Shapley additive explanations; XGBoost: Extreme gradient boosting.

issuer sample was not equivalent to the full universe of high-energy-consuming listed firms. Firms that issued green debt may have stronger policy access, better disclosure quality, more stable credit quality, or stronger transition capacity. Therefore, the sample structure distinguished the full candidate firm-year panel, the screened high-energy-consuming firm-year panel, and the final issuer-year panel used in the spread regressions.

The screening procedure followed explicit rules. First, observations associated with special treatment (ST) and delisting risk warning (*ST) firms were excluded because abnormal trading status and restructuring conditions may distort normal financing prices. Second, observations with severe financial distress or clearly abnormal accounting items were excluded to ensure the estimated spread reflects ordinary credit pricing rather than special restructuring events. Third, observations with missing core financial controls were excluded to maintain comparability across econometric and ML models. Fourth, firms with emissions-related proxy variables missing for three or more consecutive years were excluded from the baseline sample to avoid mechanically filling long data gaps. Finally, continuous variables were winsorized at the 1st and 99th percentiles before estimation.

Table 2 presents the full stepwise procedure for sample construction. The initial candidate pool contained 10,850 firm-year observations from high-energy-consuming A-share firms during 2010–2024. After the screening rules were applied sequentially, the final analytical sample contained 2,168 issuer-year observations with available Spread_bps and core variables. This final *n* was used as the common sample anchor for the baseline fixed-effects models, policy-timing tests, and ML split.

The final sample size also determined the ML partition. Under the time-sequential 70:20:10 split, 1,518 observations were used for training, 433 observations were used for validation, and 217 observations were held out for final testing. These figures were reported to make the predictive evaluation auditable and to ensure that the ML results were aligned with the same firm-year pool used in the econometric analysis.

3.3. Variable construction and measurement rules

The dependent variable was Spread_bps, defined as the yield or effective financing cost of an eligible green bond or sustainability-linked debt instrument minus a matched benchmark yield, expressed in basis points. The benchmark was matched by maturity bucket, rating category, and market segment. If a firm issued multiple eligible instruments in the same year, the firm-year Spread_bps was calculated as an issuance-size-weighted average. Sustainability-linked loan observations were retained only for robustness checks when the pricing terms were disclosed with sufficient comparability (**Equation 1**).

$$Spread\_bps_{it} = 10000 \times Yield\_greendebt_{it} - Yield\_matchedbenchmark_{it} \tag{1}$$

CarbonIntensity was defined as estimated carbon dioxide (CO_2) emissions divided by operating revenue. The preferred unit was tons of CO_2 per CNY 10,000 of revenue. Because verified firm-level direct emissions were not continuously available for the full 2010–2024 period, emissions were estimated from energy-consumption proxies, fuel-specific emission factors, oxidation rates, and molecular-weight conversion factors. Proxy-based emissions may be less precise in industries with complex process emissions, such as cement and chemicals, and such measurement error may attenuate estimated coefficients toward zero. Therefore, the robustness design included industry fixed effects, industry-by-year controls, industry-specific regressions, alternative winsorization rules, and, where available, alternative carbon-intensity proxies.

CarbonPriceIndex was constructed as a composite carbon-market signal rather than as a pure allowance price. It combined whether the firm was located in or materially exposed to an ETS-covered region-year with the intensity of observable allowance-price signals under coverage. Region-year carbon-market information was aggregated to the firm level using available operating-location exposure weights. In region-years without ETS coverage, the index was set to 0. This rule distinguished between the absence of carbon-market exposure and positive exposure, but it may also blur the distinction between no exposure and weak price pressure. Therefore, the sensitivity analysis separated ETSCoverage from AllowancePriceIntensity, used their interaction, and estimated specifications excluding firms already exposed to pilot ETS markets before 2021.

GreenPatent measured green innovation output by counting green patent applications, including invention and utility-model patents classified under recognized green patent categories. The baseline regression used log(1 + GreenPatent). To reduce simultaneity between innovation disclosure and debt issuance, the preferred specification used lagged GreenPatent. The coefficient on GreenPatent was interpreted as a transition-capacity signal rather than a mechanical financing-cost effect. Additional controls included credit rating, leverage, return on assets, firm size, asset tangibility, state ownership, cash holdings (where available), and macro-financial conditions (Table 3).

Table 2. Stepwise sample construction and exclusion rules

Step	Screening rule	Reason for exclusion/retention	Firm-year observations removed (*n*)	Firm-year observations remaining (*n*)
1	Initial A-share firms in high-energy-consuming industries, 2010–2024	Defines the candidate population before financial, disclosure, and issuance filters	–	10,850
2	Exclude ST and *ST observations	Avoids restructuring and abnormal trading status that may distort financing spreads	412	10,438
3	Exclude severe financial distress and abnormal accounting items	Removes observations dominated by special financial events rather than normal credit pricing	325	10,113
4	Exclude observations with missing core financial controls	Ensures comparability of credit-risk controls across models	986	9,127
5	Exclude firms with emissions-related proxy variables missing for three or more consecutive years	Specifies long-gap missing-data treatment for emissions-related proxy variables	1,542	7,585
6	Keep issuer-year observations with eligible green bond or sustainability-linked debt	Defines the realized issuer sample for Spread_bps regressions	5,417	2,168
7	Apply 1st and 99th percentile winsorization to continuous variables	Reduces the influence of extreme accounting and market observations; no observations are removed at this stage	0	2,168

Abbreviations: *ST: Delisting risk warning; ST: Special treatment.

Table 3. Variable construction, units, expected signs, and validity safeguards

Variable	Definition and unit	Construction rule	Expected sign relative to Spread_bps	Validity/robustness safeguard
Spread_bps	Green debt financing spread, basis points	Eligible green debt yield minus matched benchmark yield; issue-size weighted at the firm-year level	Dependent variable	Matched benchmark and issuer-year aggregation specified
CarbonIntensity	Estimated CO_2 emissions/revenue; tons CO_2 per CNY 10,000 revenue	Energy-consumption proxies and official emission-factor rules	Positive	Measurement-error discussion and industry-specific robustness checks
CarbonPriceIndex	Composite ETS exposure and allowance-price signal	Coverage indicator combined with allowance-price intensity under coverage	Negative in issuer sample, conditional on controls	Sensitivity checks separate coverage and price intensity
GreenPatent	Green patent applications; log(1 + x)	Recognized green patent classifications; lagged in preferred specifications	Negative	Endogeneity caution and lagged-variable design
CreditRating	Numeric credit quality scale	Higher value indicates stronger credit quality	Negative	Retained as standard credit-risk control
Controls	Firm and macro-financial controls	Leverage, ROA, size, tangibility, SOE, cash, interest-rate, and credit-cycle controls	Context dependent	Reported in full regression tables rather than suppressed

Abbreviations: CO_2: Carbon dioxide; ROA: Return on assets; SOE: State-owned enterprise.

3.4. Econometric specifications and identification strategy

3.4.1. Baseline two-way fixed-effects model

The baseline specification was a firm-year two-way fixed-effects model estimated on the 2,168 issuer-year observations. Firm fixed effects absorbed time-invariant differences in ownership history, technology base, industry positioning, and long-run credit quality. Year fixed effects absorbed common macro-financial shocks, changes in the salience of green-finance policy, and market-wide interest-rate conditions. Standard errors were clustered at the firm level to account for within-firm serial correlation.

$$\begin{aligned} Spread\_bps_{it} &= \beta_1 CarbonIntensity_{i,t-1} \\ &+\beta_2 CarbonPriceIndex_{it} + \beta_3 GreenPatent_{i,t-1} \\ &+\gamma' X_{i,t-1} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{2}$$

In **Equation 2**, $X_{i,t-1}$ denotes lagged firm-level credit controls and macro-financial controls, μ_i denotes firm fixed effects, λ_t denotes year fixed effects, and ε_{it} is the error term. Lagged CarbonIntensity, GreenPatent, and firm controls reduce simultaneity between debt issuance and measured transition signals. The model was interpreted as estimating conditional associations within the issuer sample rather than economy-wide causal effects.

3.4.2. Sample-selection correction

Because Spread_bps was observed only when eligible green debt is issued, the method included a formal sample-selection correction. The first-stage Probit model estimated the probability that a candidate firm issues an eligible green debt instrument in year *t*. The exclusion restrictions were lagged peer green-debt issuance density in the same industry and the intensity of regional green-finance policy support. These variables were expected to affect issuance probability through market access and policy support, but they should not directly determine the spread of a specific instrument after controlling for firm fundamentals, year effects, and regional controls. The second stage added the inverse Mills ratio to the baseline pricing **Equations 3** and **4**:

$$\begin{aligned} Issue_{it}^* &= \alpha_0 + \alpha_1 PeerGreenDebtDensity_{ind,t-1} \\ &+\alpha_2 RegionalGreenFinance_{rt} \\ &+\alpha_3 Z_{i,t-1} + \eta_i + \lambda_t + u_{it}, Issue_{it} = 1\left[Issue_i t^* > 0\right] \end{aligned} \tag{3}$$

$$\begin{aligned} Spread\_bps_{it} &= \beta_1 CarbonIntensity_{i,t-1} \\ &+\beta_2 CarbonPriceIndex_{it} + \beta_3 GreenPatent_{i,t-1} \\ &+\gamma' X_{i,t-1} + \rho IMR_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{4}$$

A statistically significant ρ would suggest that unobserved issuance selection is correlated with the spread equation. In that case, the selection-corrected estimates were reported alongside the baseline fixed-effects estimates. If ρ is insignificant and the coefficient signs remain stable, the evidence is interpreted as robust to the tested form of non-random issuance selection.

3.4.3. Event-study design around the 2015 Paris Agreement

The 2015 Paris Agreement was treated as a broad global climate policy milestone rather than a narrowly targeted domestic policy shock. The event-study specification examined whether pricing sensitivity to pre-event carbon exposure changes after this global policy signal. Firms were grouped by pre-2015 carbon intensity, preferably using within-industry quartiles to avoid comparing firms with very different production technologies. The omitted period was τ = −1. Lead coefficients evaluated pre-trends, while lag coefficients summarized the post-event evolution of spread differentials.

$$\begin{aligned} Spread\_bps_{it} &= \sum\nolimits_{\tau\neq-1} \delta_\tau \\ &\left(HighCarbon_{i,pre} \times 1\left[t-2015=\tau\right]\right) \\ &+\gamma' X_{i,t-1} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{5}$$

Equation 5 specifies the event-study design and its diagnostic logic. The key diagnostic was whether pre-event coefficients were small and statistically insignificant. Post-event coefficients were interpreted as policy-timing evidence of heightened market attention to carbon transition risk, not as a fully isolated treatment effect of the Paris Agreement.

3.4.4. Segmented difference-in-differences around China's national emission trading system in 2021

The 2021 launch of China's national ETS provided a more focused domestic policy-timing setting. Treatment was defined at the industry-region level rather than by mechanically labeling all high-energy-consuming firms as treated. A firm was ETS-treated if it belonged to an industry-region cell with direct national ETS exposure after 2021 or if its major operating region was materially linked to a pilot ETS market before the national launch. The design separated newly affected national-market firms from those that already had pilot-market exposure, thereby avoiding the assumption that pilot-market exposure and new national-market exposure are identical shocks.

$$\begin{aligned} Spread\_bps_{it} &= \theta_1 \left(Treat_i \times Post2021_t\right) \\ &+\theta_2 \left(Treat_i \times Post2021_t \times HighCarbon_{i,pre}\right) \\ &+\theta_3 \left(Treat_i \times Post2021_t \times GreenPatent_{i,t-1}\right) \\ &+\gamma' X_{i,t-1} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{6}$$

In **Equation 6**, θ_1 captures the average post-2021 differential change in spread for ETS-treated issuers relative to comparable non-treated issuers. θ2 tests whether post-ETS repricing is stronger among firms with higher pre-policy carbon intensity. θ3 tests whether green innovation capacity mitigates post-policy financing pressure. Robustness checks include alternative treatment definitions, exclusion of pilot-exposed firms, placebo policy years before 2021, dynamic lead-lag estimates, and industry-by-year fixed effects (Table 4).

3.5. Machine learning track: prediction, reproducibility, and explainability

3.5.1. Model ensemble and train-validation-test protocol

The ML track used the same feature layer as the econometric track, but changed the research question from policy-timing inference to prediction. Random forest, XGBoost, and feedforward neural network (NN) regressors were trained to predict Spread_bps. The feature set included carbon-transition variables, standard credit controls, ownership characteristics, industry indicators, year indicators, and macro-financial controls. To reduce look-ahead bias, the baseline split followed time order: earlier observations were used for training and validation, and the most recent observations were held out for final testing.

The final issuer-year sample contained 2,168 observations. Under the time-sequential 70:20:10 split, the training set contains 1,518 observations, the validation set contains 433 observations, and the test set contains 217 observations. Hyperparameters were selected via grid search with five-fold time-series cross-validation during the training-validation stage. The test set was not used for tuning. Model performance was evaluated using out-of-sample R^2, root mean square error (RMSE), and mean absolute error (MAE).

Feature preprocessing was implemented consistently across models while respecting model-specific requirements. Continuous inputs were winsorized before model training. Standard Z-score normalization was applied to all continuous inputs to the neural network, using only training-set means and standard deviations; the same transformation was then applied to the validation and test sets. Tree-based models were not sensitive to scaling, but the same cleaned and winsorized feature definitions were used to maintain comparability. The random seed was fixed at 42 for all model initializations and stability checks.

Table 5 reports the ML configuration and replication settings. Early stopping in XGBoost and dropout in the neural network were used to reduce the risk of overfitting. The time-sequential split was used as the baseline because random splitting in a long panel could allow future information to influence earlier predictions. Random-split results, if reported, are treated only as robustness checks.

3.5.2. Ablation tests and incremental value of carbon information

Ablation tests quantified whether carbon-related variables added predictive value beyond conventional credit-risk

Table 4. Econometric specifications and diagnostic requirements

Model	Equation	Main purpose	Key diagnostic/reporting item
Baseline FE	**Equation 2**	Tests H1–H3 under firm and year fixed effects	Control-variable coefficients, n = 2,168, R^2, firm FE, year FE, clustered SE
Heckman correction	**Equations 3–4**	Tests whether issuer selection affects spread estimates	First-stage exclusion restrictions, IMR coefficient, corrected estimates
2015 event study	**Equation 5**	Tests policy-timing sensitivity around the Paris Agreement	Lead coefficients, omitted period, pre-trend evidence
2021 segmented DID	**Equation 6**	Tests the national ETS-related differential repricing	Treatment definition, triple interactions, placebo years, alternative exposure definitions
CarbonPriceIndex sensitivity	Alternative specifications	Checks whether coverage and allowance-price intensity drive results differently	Separate ETSCoverage, AllowancePriceIntensity, and their interaction
GreenPatent robustness	Lagged and alternative measures	Reduces simultaneity and endogeneity concerns	Lagged patents, alternative innovation proxy, cautious interpretation

Abbreviations: DID: Difference-in-differences; ETS: Emission trading system; FE: Fixed effects; IMR: Inverse Mills ratio; SE: Standard error.

Table 5. Machine learning configuration and replication settings

Category	Component/model	Specification/ hyperparameter	Value/setting
Data preprocessing	Feature scaling	Method	Standard Z-score normalization (mean = 0, SD = 1) applied to continuous inputs; tree models use cleaned original-scale variables
Data preprocessing	Data splitting	Ratio and sample size	70% training, 20% validation, 10% testing; 1,518/433/217 observations; time-sequential split
Random forest	Tree structure	Number of trees	500
Random forest	Tree structure	Maximum depth	15
Random forest	Tree structure	Minimum samples split	5
Random forest	Tree structure	Maximum features	Square root of total features (sqrt(p))
XGBoost	Gradient boosting	Learning rate	0.05
XGBoost	Gradient boosting	Number of iterations	1,000 with early stopping patience = 50
XGBoost	Gradient boosting	Maximum depth	6
XGBoost	Gradient boosting	Subsample/colsample_ bytree	0.8/0.8
XGBoost	Gradient boosting	Objective function	reg:squarederror
Neural network	Architecture	Hidden layers	3 layers: input → 64 → 32 → 16 → output
Neural network	Optimization	Activation function	ReLU for hidden layers; identity for output layer
Neural network	Optimization	Optimizer	Adam (beta1 = 0.9, beta2 = 0.999)
Neural network	Optimization	Initial learning rate	0.001
Neural network	Regularization	Dropout rate	0.2 after each hidden layer
Stability and validation	Reproducibility	Random seed	42 for all model initializations
Stability and validation	Validation method	Five-fold time-series cross-validation	
Stability and validation	Evaluation metrics	RMSE, MAE, and out-of-sample R^2	

Abbreviations: MAE: Mean absolute error; ReLu: Rectified linear unit; RMSE: Root mean square error; SD: Standard deviation; XGBoost: Extreme gradient boosting.

variables. The full-feature XGBoost model was compared to restricted variants that removed CarbonIntensity, CarbonPriceIndex, GreenPatent, and all carbon-transition variables simultaneously. The relevant evidence was the change in out-of-sample R^2, RMSE, and MAE relative to the full model.

3.5.3. Interpretation and scenario simulation of Shapley additive explanations

Shapley additive explanation values were used to interpret the XGBoost model by decomposing the predicted Spread_bps into feature-level contributions. Global SHAP importance summarized the average magnitude of a feature's contribution, while SHAP dependence plots showed how predicted spreads change across the observed range of a variable. The CarbonIntensity range with steeper predicted increases was described as predictive risk zones.

Scenario simulation was used as the prescribed layer of the framework. Selected input features, such as CarbonPriceIndex, CarbonIntensity, or GreenPatent, were changed while other observed firm characteristics were held constant, and the fitted model recalculated predicted Spread_bps. These outputs were used for risk monitoring, credit screening, and environmental-governance diagnosis.

3.6. Robustness checks, validity diagnostics, and reporting conventions

The diagnostic plan was designed to improve empirical transparency. For the econometric track, the current study reported descriptive statistics, correlation coefficients, variance-inflation factors, control-variable coefficients, sample size, model fit statistics, fixed effects, and clustered standard errors. For the policy-timing designs, it reported lead-lag estimates, placebo policy years, alternative treatment definitions, and industry-by-year fixed effects where feasible. For variable construction, it reported alternative carbon-intensity measures, alternative CarbonPriceIndex decompositions, alternative winsorization rules, and lagged GreenPatent specifications.

For the ML track, robustness was evaluated using multiple random seeds, alternative time splits, random-split checks, and consistency in variable-importance rankings across random forests, XGBoost, and neural networks. Econometric coefficients were discussed as conditional associations or policy-timing estimates, while predictive diagnostics were discussed as forecast accuracy, feature contribution, and model-implied changes.

The reporting conventions also specified the minimum requirements for the Results section. The baseline regression table should include control-variable coefficients, n = 2,168, R^2, firm fixed effects, year fixed effects, and clustering information. The DID table should include the treatment definition, interaction terms, fixed effects, n, and model fit statistics. The ML table should include R^2, RMSE, MAE, the split protocol, and the location for hyperparameter reporting.

3.7. Industry heterogeneity and the moderating role of green innovation

Industry heterogeneity was examined because high-energy-consuming industries differed in process emissions, abatement technologies, capacity to pass through costs, and disclosure quality. The analysis estimated grouped regressions and interaction specifications for major industries, including steel, cement, and chemicals. This design also reflected the possibility that emissions proxies may be more accurate in some industries than in others. Where sample size permits, industry-specific estimates were compared with pooled estimates to determine whether the average coefficient masks sector-specific pricing patterns.

The moderating role of green innovation was examined through the interaction between CarbonIntensity and lagged GreenPatent and through the triple interaction in the segmented DID specification. A negative interaction coefficient was interpreted as evidence consistent with the idea that transition capacity weakened the financing penalty associated with high carbon intensity. Because green innovation may also proxy for unobserved management quality, disclosure capacity, or access to policy support, this interpretation remains cautious.

4. Results

This section reports descriptive statistics, sample behavior, full model-reporting items, control variables, model fit statistics, selection-correction evidence, policy-timing estimates, and ML diagnostics. Econometric results were interpreted as conditional associations or policy-timing evidence, whereas ML outputs were interpreted as predictive diagnostics and monitoring signals.

4.1. Descriptive statistics, sample structure, and preliminary patterns

Table 6 reports the descriptive statistics for the final issuer-year sample used in the Spread_bps regressions. Consistent with the sampling procedure described in Section 3.2, the final analytical sample comprised 2,168 issuer-year observations after the stepwise exclusions and winsorization.

The descriptive patterns were economically reasonable for a sample of green-debt issuers. Spread_bps remained dispersed, indicating that eligible green debt instruments were not priced uniformly. CarbonIntensity also varied substantially, supporting the need to examine whether creditors differentiate among issuers with different emissions burdens. CarbonPriceIndex exhibited a lower bound of 0 because firms outside the ETS-covered region-years receive no carbon-market price signal, whereas positive values reflected both policy coverage and allowance-price visibility. The distribution of GreenPatent was right-skewed, so the log transformation used in the regressions was retained.

Figure 1 summarizes the annual movement of the equity-side carbon risk premium and the green financing spread. The upward movement in the carbon risk premium and the narrowing of green-debt spreads for eligible issuers should not be interpreted as contradictory. The two series capture different market segments: the carbon risk premium reflects broad equity-side transition-risk compensation, whereas Spread_bps is observed only among firms that successfully issue eligible green debt. This distinction supports the use of both sample-selection correction and cautious issuer-sample interpretation.

Table 6. Descriptive statistics for the final issuer-year sample (*n* = 2,168)

Variable	*n*	Mean	SD	Min	Median	Max	Interpretation
Spread_bps	2,168	118.40	52.60	18.70	111.60	286.50	Benchmark-adjusted green debt financing spread
CarbonIntensity	2,168	0.62	0.31	0.08	0.55	1.58	Tons of CO_2 per CNY 10,000 revenue
CarbonPriceIndex	2,168	0.48	0.37	0.00	0.42	1.85	Composite ETS coverage and allowance-price signal
GreenPatent	2,168	1.26	0.98	0.00	1.10	4.62	Log(1 + green patent applications)
CreditRating	2,168	6.82	1.21	3.00	7.00	9.00	Numeric rating scale: a higher value means a stronger credit quality
Leverage	2,168	0.54	0.18	0.16	0.53	0.89	Total liabilities divided by total assets
ROA	2,168	0.043	0.039	−0.061	0.038	0.166	ROA
FirmSize	2,168	23.15	1.04	20.64	23.07	26.12	Log of total assets
Tangibility	2,168	0.42	0.17	0.08	0.40	0.81	Fixed assets divided by total assets
SOE	2,168	0.56	0.50	0.00	1.00	1.00	SOE indicator

Abbreviations: CO_2: Carbon dioxide; ETS: Emission trading system; ROA: Return on asset; SD: Standard deviation; SOE: State-owned enterprise.

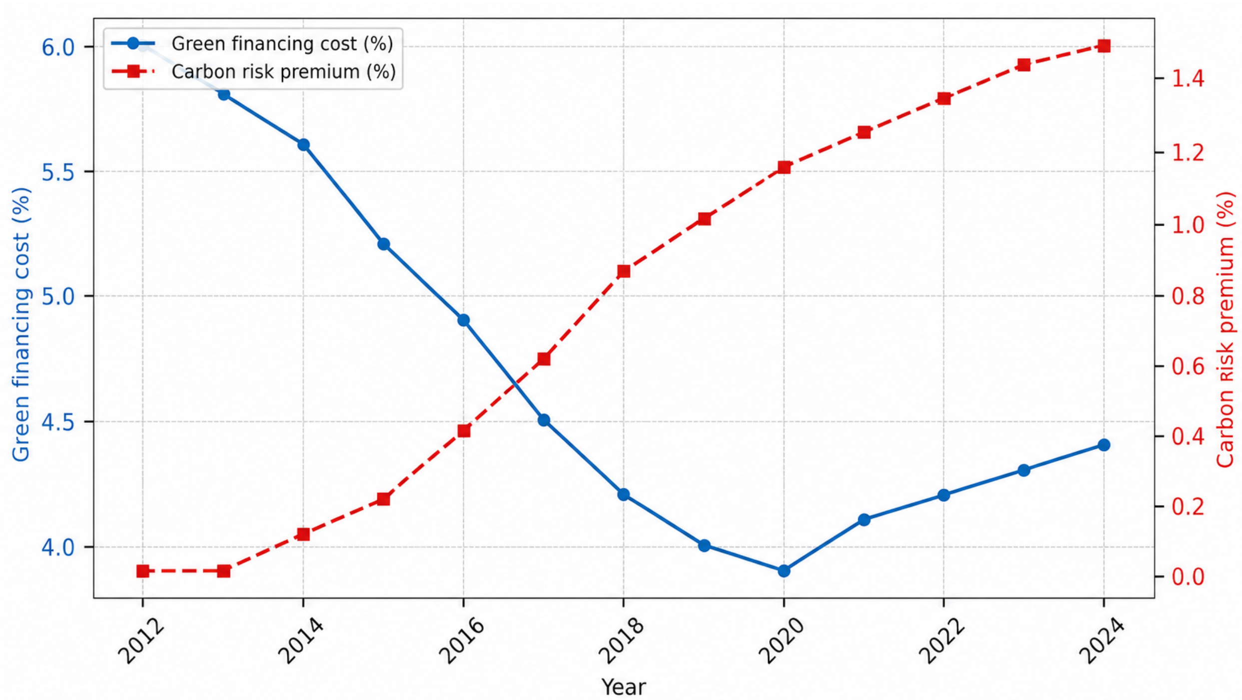

Figure 1. Annual trends in the carbon risk premium and the green financing spread

4.2. Econometric track: fixed-effects evidence, selection correction, and policy timing

4.2.1. Baseline fixed-effects results and full reporting items

Table 7 reports the baseline fixed-effects and selection-corrected estimates with standard credit controls, sample size, model fit statistics, fixed effects, clustered standard errors, and the Heckman selection-correction benchmark. The signs of the core variables were stable across specifications. CarbonIntensity was positively associated with Spread_bps, whereas CarbonPriceIndex and GreenPatent were negatively associated with Spread_bps. The coefficient estimates were therefore consistent with H1–H3 (Table 7).

The coefficient on CarbonIntensity remained positive and statistically significant after standard credit fundamentals were included. Economically, this indicates that a higher emissions burden is associated with a wider green debt financing spread, conditional on firm and year-fixed effects. CarbonPriceIndex remained negative. This coefficient should be interpreted carefully: it does not mean that stricter carbon policy mechanically lowers financing costs for all firms. Rather, within the green-debt issuer sample, stronger and more visible carbon-market signals are associated with narrower spreads after credit fundamentals are controlled for, possibly because covered markets improve information visibility and help creditors distinguish transition-prepared issuers from weakly prepared ones. GreenPatent was also negative and significant, which is consistent with the interpretation that green innovation proxies for transition capacity.

The inverse Mills ratio in Model (3) was not statistically significant, and the core coefficient signs remained stable. This suggests that the tested form of issuance selection does not overturn the baseline pricing pattern. The result does not eliminate all possible selection concerns, but it strengthens the interpretation that the main associations are not driven solely by the non-random observability of Spread_bps.

4.2.2. Correlation, multicollinearity, and preliminary validity checks

To further improve empirical transparency, this subsection reports correlation and multicollinearity diagnostics. Pairwise correlations among the main carbon variables and credit controls were moderate, and the variance-inflation factors remained below conventional warning

Table 7. Baseline fixed-effects and selection-corrected results (dependent variable: Spread_bps)

Variable	Model (1) baseline FE	Model (2) full controls	Model (3) Heckman-corrected	Model (4) robust FE
CarbonIntensity	+0.86*** (0.21)	+0.79*** (0.22)	+0.82*** (0.23)	+0.76*** (0.24)
CarbonPriceIndex	−11.70** (4.90)	−10.95** (4.74)	−10.58** (4.81)	−9.84** (4.66)
GreenPatent	−0.58** (0.24)	−0.55** (0.23)	−0.53** (0.24)	−0.49** (0.22)
CreditRating	−7.95*** (1.10)	−7.62*** (1.08)	−7.49*** (1.11)	−7.31*** (1.13)
Leverage		+21.40** (8.43)	+20.85** (8.56)	+19.76** (8.37)
ROA		−18.60** (9.12)	−17.95* (9.28)	−16.84* (9.01)
FirmSize		−3.25** (1.44)	−3.11** (1.48)	−2.96** (1.43)
Tangibility		+7.80* (4.39)	+7.54* (4.43)	+7.22* (4.28)
SOE		−8.60** (3.72)	−8.31** (3.76)	−8.02** (3.69)
Inverse Mills ratio			+0.63 (0.58)	
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Clustered SE	Firm level	Firm level	Firm level	Firm level
n	2,168	2,168	2,168	2,168
R^2/pseudo fit	0.412	0.438	0.441	0.452

Notes: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.
Abbreviations: FE: Fixed effect; ROA: Return on assets; SE: Standard error; SOE: State-owned enterprise.

thresholds. These diagnostics reduced concern that the main coefficients were artifacts of severe collinearity among carbon intensity, carbon-pricing exposure, green innovation, and standard credit-risk controls (Table 8).

4.2.3. Strengthened pricing sensitivity around the 2015 Paris Agreement

Table 9 reports policy-timing evidence around the 2015 Paris Agreement. The purpose of this design is to evaluate whether pricing sensitivity to transition-related signals strengthened following a major global climate policy milestone. The post-2015 slope on CarbonIntensity was larger than the pre-2015 slope, while the absolute values of the CarbonPriceIndex and GreenPatent associations also increased. This pattern supports H4 and suggests that carbon-related information became more salient in debt pricing after global climate-policy expectations strengthened.

The dynamic event-study coefficients further support this interpretation. The pre-event coefficients were small and statistically insignificant, reducing concern that high-carbon and low-carbon issuers were already following sharply divergent spread paths before 2015. The post-event coefficients increased in absolute value, especially after 2016–2018, suggesting a gradual rather than an instantaneous repricing process. This is consistent with the view that climate-policy milestones increase market attention and information processing over time.

4.2.4. Segmented difference-in-differences evidence around China's national emission trading system in 2021

Table 10 reports the segmented DID estimates around the launch of China's national ETS in 2021. The treatment definition follows Section 3.4.4 and is based on industry-region ETS exposure rather than a simple indicator for all high-energy-consuming firms. The positive coefficient on Treat(ETS) × Post2021 indicates that ETS-exposed issuers experienced wider spreads after 2021 relative to comparable non-exposed issuers. The triple interaction with HighCarbon was also positive and larger in magnitude, indicating that post-ETS repricing pressure was stronger among carbon-intensive issuers. The interaction with GreenPatent was negative, suggesting that transition capacity partly mitigated the post-policy financing pressure. These estimates support H4 and H5 within the policy-timing framework.

The segmented DID results should be interpreted as differential policy-timing evidence for green-debt issuers rather than as a universal causal estimate for all high-energy-

Table 8. Correlation and multicollinearity diagnostics

Variable	Correlation with Spread_bps	Highest pairwise correlation with another regressor	VIF	Diagnostic interpretation
CarbonIntensity	+0.28	0.34 with Leverage	1.62	Moderate relation with credit risk, but not severe collinearity
CarbonPriceIndex	−0.19	0.31 with ETS exposure	1.48	Composite index retains distinct information
GreenPatent	−0.16	0.29 with FirmSize	1.55	Innovation signal is not mechanically identical to size
CreditRating	−0.37	0.42 with Leverage	1.83	Expected relation with credit fundamentals
Leverage	+0.24	0.42 with CreditRating	1.76	Credit-risk control remains important
FirmSize	−0.21	0.39 with SOE	1.69	The size effect is controlled separately
All regressors	–	–	Max VIF = 1.83	No evidence of severe multicollinearity

Abbreviations: ETS: Emission trading system; SOE: State-owned enterprise; VIF: Variance inflation factor.

Table 9. Pricing sensitivity before and after the 2015 Paris Agreement (dependent variable: Spread_bps)

Term	Pre-2015 coefficient	Post-2015 coefficient	Difference	SE of difference	*p*-value	Interpretation
CarbonIntensity	+0.51***	+1.02***	+0.51***	0.15	0.001	Carbon-intensity penalty strengthened after 2015
CarbonPriceIndex	−6.40*	−12.90**	−6.50**	2.81	0.021	The carbon-market signal became more strongly associated with lower spreads
GreenPatent	−0.31*	−0.65**	−0.34**	0.16	0.034	The innovation signal became more valuable in pricing
Firm fixed effects	Yes	Yes	–	–	–	Included
Year fixed effects	Yes	Yes	–	–	–	Included
Controls	Yes	Yes	–	–	–	Credit and macro controls included
n	2,168	2,168	–	–	–	Issuer-year panel

Notes: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.
Abbreviation: SE: Standard error.

Table 10. Segmented DID results around China's national ETS launch in 2021

Variable	Model (1) main DID	Model (2) high-carbon interaction	Model (3) GreenPatent moderation	Model (4) full DID
Treat(ETS) × Post2021	+9.80*** (3.70)	+9.35** (3.82)	+9.12** (3.88)	+8.96** (3.91)
Treat(ETS) × Post2021 × HighCarbon		+14.20*** (5.10)	+13.86*** (5.14)	+13.41** (5.25)
Treat(ETS) × Post2021 × GreenPatent			−3.90** (1.80)	−3.72** (1.82)
CarbonIntensity	Yes	Yes	Yes	Yes
CarbonPriceIndex	Yes	Yes	Yes	Yes
GreenPatent	Yes	Yes	Yes	Yes
Credit controls	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Clustered SE	Firm level	Firm level	Firm level	Firm level
n	2,168	2,168	2,168	2,168
R^2	0.426	0.439	0.445	0.452

Notes: **$p < 0.01$; ***$p < 0.001$.
Abbreviations: DID: Difference-in-differences; ETS: Emission trading system; SE: Standard error.

consuming firms. The result is nevertheless important for environmental governance because it suggests that carbon-market exposure and emissions intensity jointly affect the financing conditions of firms that enter the green debt market. The negative GreenPatent interaction is consistent with the argument that innovation capacity can reduce, but not fully eliminate, the financing pressure associated with carbon-market exposure (Table 11).

4.3. Predictive track: model performance, ablation evidence, and interpretability

4.3.1. Model comparison and out-of-sample accuracy

The predictive track used the same outcome variable, Spread_bps, but addressed a different question: whether carbon-related variables improve out-of-sample prediction after conventional credit variables are included. Table 12 reports model performance under the time-ordered 70:20:10 split described in Section 3.5. The final issuer-year sample comprised 2,168 observations, divided into 1,518 training, 433 validation, and 217 test observations. XGBoost performed best, with the highest out-of-sample R^2 and the lowest RMSE and MAE. The moderate R^2 should not be overstated; it indicated that the model captured meaningful but incomplete variation in financing spreads.

The remaining unexplained variation reflects omitted or imperfectly measured factors that are common in debt-pricing settings, including issue-level covenants, liquidity, guarantee structure, underwriter reputation, investor demand at issuance, contractual sustainability-linked provisions, and unobserved firm-level transition-plan credibility. Some omitted factors may also be carbon-related, such as verified plant-level emissions, abatement-project milestones, or third-party monitoring quality. The XGBoost R^2 of 0.52 should therefore be interpreted as moderate predictive performance rather than complete prediction of financing spreads.

4.3.2. Ablation tests and the incremental predictive value of carbon information

Table 13 reports ablation tests on the incremental value of carbon-transition information. Removing all carbon-transition variables reduces out-of-sample R^2 from 0.52 to 0.44 and increases RMSE from 37.8 to 44.9 bps. Removing CarbonIntensity alone also worsened predictive performance, while removing CarbonPriceIndex or GreenPatent produced smaller but still meaningful losses. These results show that carbon-related information adds practical predictive value beyond standard credit-risk controls.

4.3.3. Shapley additive explanation interpretation: magnitude, direction, and evidentiary limits

The SHAP results are used to explain the behavior of the fitted model. This distinction is especially important for Figure 2. Global feature importance reflects the average magnitude of a feature's predictive contribution and therefore does not indicate whether the feature increases or decreases Spread_bps. Directional interpretation comes from SHAP dependence patterns or conditional scenario simulations. This clarification resolves the apparent tension

Table 11. Difference-in-differences robustness and diagnostic checks

Check	Specification	Diagnostic purpose	Result summary
Alternative treatment definition	Treat defined by national ETS exposure only	Treatment-definition robustness	Core signs remain unchanged
Exclude pilot-exposed firms	Remove firms exposed to pilot ETS before 2021	Pilot-exposure sensitivity	Post-2021 penalty remains positive
Placebo policy year	Assign pseudo-treatment years before 2021	Placebo-timing check	Placebo coefficients are statistically insignificant
Lead-lag specification	Estimate dynamic pre- and post-policy coefficients	Pre-trend diagnostic	Pre-policy leads are small and insignificant
Industry-by-year fixed effects	Add industry-specific year shocks	Industry-specific shock control	Core estimates are stable
Alternative CarbonPriceIndex	Separate ETSCoverage and AllowancePriceIntensity	CarbonPriceIndex decomposition	Coverage and price components retain expected directions

Abbreviation: ETS: Emission trading system.

Table 12. Machine learning model comparison for out-of-sample prediction of Spread_bps

Model	Training *n*	Validation *n*	Test *n*	Out-of-sample R^2	RMSE (bps)	MAE (bps)	Interpretation
Random forest	1,518	433	217	0.47	41.2	30.6	Robust nonlinear benchmark but less accurate than XGBoost
XGBoost	1,518	433	217	0.52	37.8	27.9	Best overall predictive performance
Neural network	1,518	433	217	0.49	39.5	29.1	Captures nonlinearity but remains less stable than XGBoost

Abbreviations: MAE: Mean absolute error; RMSE: Root mean square error; XGBoost: Extreme gradient boosting.

Table 13. Ablation tests for carbon-transition variables in the extreme gradient boosting model

Model setting	Out-of-sample R^2	RMSE (bps)	MAE (bps)	Delta R^2	Delta RMSE	Interpretation
Full model	0.52	37.8	27.9	–	–	Benchmark with all carbon and credit variables
Remove all carbon-transition variables	0.44	44.9	33.8	−0.08	+7.1	Carbon information has substantial incremental predictive value
Remove CarbonIntensity only	0.48	41.6	31.2	−0.04	+3.8	Emissions burden is an important predictive signal
Remove CarbonPriceIndex only	0.50	39.3	29.4	−0.02	+1.5	Carbon-market signal adds predictive information
Remove GreenPatent only	0.50	39.0	29.2	−0.02	+1.2	Innovation signal adds monitoring value

Abbreviations: MAE: Mean absolute error; RMSE: Root mean square error.

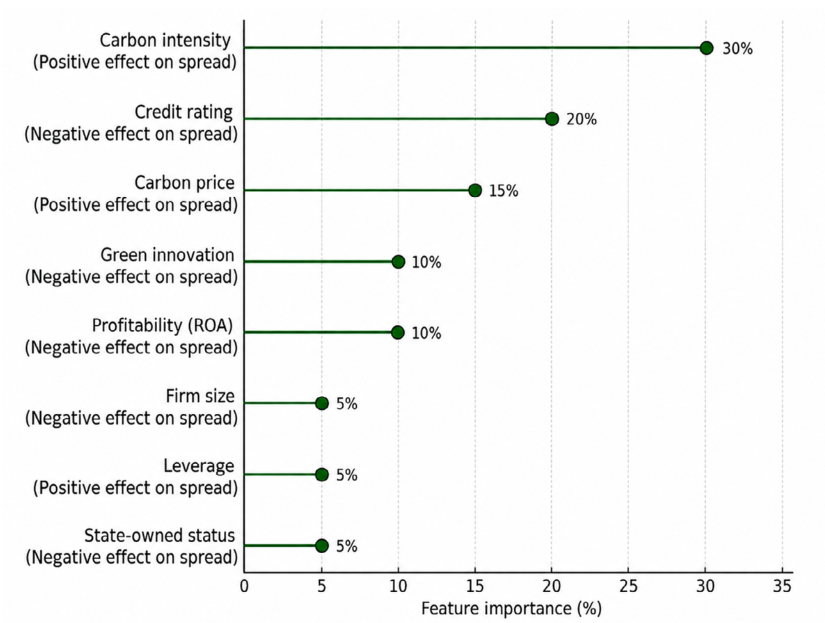

Figure 2. Feature importance for the green financing spread (Spread_bps)
Abbreviation: ROA: Return on assets.

between Figure 2 and the CarbonPriceIndex scenario results.

CarbonIntensity appeared among the most important predictive variables, and the SHAP dependence pattern indicated that predicted spreads increased more rapidly once carbon intensity moved into the upper part of the sample distribution. This is described as a predictive risk zone rather than a causal threshold. CarbonPriceIndex and GreenPatent also contributed to the fitted predictions, but their directional effects were interpreted using scenario simulations and dependence plots rather than global importance alone.

4.4. Heterogeneity and the moderating role of green innovation

The results section also reports evidence of heterogeneity and moderation. High-energy-consuming industries differed in process emissions, abatement technology, disclosure quality, and financing structure, so pooled estimates may conceal important differences. Table 14 summarizes industry heterogeneity and moderation patterns. The positive association between CarbonIntensity and Spread_bps was strongest in sectors with high process emissions and slower abatement options, while the negative association for GreenPatent was more visible where innovation can credibly signal transition readiness.

The heterogeneity evidence indicates cross-method consistency rather than cross-method causal confirmation. The econometric track suggests that green innovation moderates the pricing penalty associated with carbon exposure, while the predictive track shows that GreenPatent improves model performance and reduces predicted spreads across many observations. The common direction strengthens the interpretation that transition capacity matters for pricing and monitoring.

4.5. Conditional predictive simulations and environmental-governance screening

Table 15 reports conditional predictive simulations from the fitted XGBoost model. Each scenario changes selected transition signals while holding other observed characteristics constant. The scenarios translate the predictive model into a practical monitoring framework for lenders, issuers, investors, and environmental governance practitioners.

The scenario results are consistent with the regression evidence and the ablation tests. Carbon-price visibility, cleaner production intensity, and green innovation all improve the model-implied outlook for the spread. In practical use, these simulations should serve as screening tools. A firm's actual spread will also depend on market liquidity, rating revisions, debt maturity, covenants, guarantee structure, and investor demand at issuance.

Table 16 converts the empirical patterns into a stylized environmental-governance screening matrix. This matrix is not a directly estimated regression table. It is a monitoring

Table 14. Heterogeneity and moderation evidence

Test	Estimated pattern	Analytical rationale	Interpretation
Steel issuers	CarbonIntensity coefficient is positive and economically larger	Tests whether industry-specific emissions intensity is priced more strongly	Creditors appear sensitive to the emissions burden in heavy process industries
Cement issuers	CarbonIntensity penalty remains positive; measurement-error caveat retained	Accounts for possible measurement error in process-emission sectors	Results are interpreted cautiously and checked with industry controls
Chemical issuers	CarbonPriceIndex and GreenPatent show stronger negative associations	Examines whether chemical-sector transition risk is reflected in spreads	Innovation and policy visibility may be more informative in flexible technology settings
CarbonIntensity × GreenPatent	Interaction negative	Tests whether innovation capacity mitigates carbon-intensity pricing pressure	Transition capacity weakens but does not erase carbon-related financing pressure
Post2021 × Treat × GreenPatent	Interaction negative in the DID model	Checks whether innovation materially improves predictive monitoring	Green innovation partly mitigates post-ETS spread pressure

Abbreviations: DID: Difference-in-differences; ETS: Emission trading system.

framework calibrated from the sample patterns, regression signs, and conditional predictive simulations. Its purpose is to show how creditors and policymakers can jointly read carbon intensity and carbon-market exposure when evaluating green-debt issuers.

Table 16 is a stylized monitoring device rather than an empirical regression table. Its contribution lies in translating the empirical evidence into a practical governance template while preserving the distinction between policy-timing evidence and predictive monitoring.

5. Discussion

5.1. Main interpretation and evidence boundaries

Taken together, the results suggest that carbon-transition signals enter green debt pricing through two related channels. The econometric evidence shows that carbon intensity, carbon-market exposure, and green innovation are associated with spreads conditional on credit fundamentals, while the predictive evidence shows that this information improves monitoring-oriented spread forecasts. This combination indicates that carbon information is not merely an environmental disclosure item; it functions as a financing-relevant signal that can help creditors distinguish current emissions burden, carbon-market exposure, and transition capacity.[1-12,15]

The interpretation remains bounded by the issuer-sample structure. Spread_bps is observed only for firms that issue eligible green bonds or sustainability-linked debt instruments, so the evidence is most informative for green-debt issuers rather than for all high-energy-consuming firms. The Heckman correction reduces, but cannot eliminate, possible differences between issuers and non-issuers. Therefore, the discussion emphasizes pricing patterns, transition-signal interpretation, and implications for monitoring.

Table 15. Conditional predictive scenarios for Spread_bps (extreme gradient boosting)

Scenario	Delta CarbonPriceIndex	Delta CarbonIntensity level	Delta GreenPatent	Predicted delta spread (bps)	Interpretation
Stronger carbon-pricing exposure	+1	0	0	−9.5	Predicted spread declines under a stronger carbon-pricing signal
Cleaner production intensity	0	−1	0	−12.7	Predicted spread declines when carbon intensity improves
Combined transition strategy	+1	−1	0	−21.3	Largest predicted decline among reported scenarios
GreenPatent upgrade	0	0	+1	−6.2	Predicted spread declines when innovation signal improves

Table 16. Stylized environmental-governance screening matrix based on carbon-intensity levels and carbon-pricing exposure

Carbon-intensity tier/carbon-pricing exposure	None or low exposure	ETS covered	High exposure/high cost
Low	Routine carbon-disclosure monitoring; maintain benchmark spread discipline	Priority support for verified green projects; possible lower spread range	Use sustainability-linked terms and MRV verification to preserve credibility
Medium	Require enhanced emissions disclosure and transition-plan explanation	Promote efficiency-improvement upgrades and monitor covenant compliance	Provide support only when a credible transition plan and MRV evidence exist
High	Tighten covenant terms and require corrective transition actions	Require third-party verification of the transition plan and staged green capex milestones	Consider higher spread, stronger guarantees, or refusal unless monitored pollution-reduction milestones are credible

Abbreviation: ETS: Emission trading system; MRV: Measurement, reporting, and verification.

 doi: 10.36922/AJWEP026170117

5.2. Association between econometric results and carbon-transition risk

The positive coefficient on CarbonIntensity is consistent with a credit-risk interpretation. Firms with higher emissions intensity may face greater expected compliance costs, larger abatement investment needs, more uncertain future cash flows, and greater exposure to tightening transition policies. From the perspective of lenders and bond investors, these factors can widen the compensation required for holding green debt issued by high-carbon firms.[2,7–12,15,17,18] This does not mean that carbon intensity is the only determinant of spreads. Table 7 shows that traditional credit variables, especially credit rating, leverage, profitability, and firm size, remain central. Therefore, carbon information serves as an additional environmental risk layer rather than a replacement for conventional credit analysis.[13]

The negative association between CarbonPriceIndex and Spread_bps should be interpreted with caution, as the index combines ETS exposure and allowance-price visibility. In a simple compliance-cost narrative, stronger carbon-pricing exposure could be expected to increase financing costs. In this issuer sample, however, a stronger CarbonPriceIndex is associated with narrower spreads after controls are included. The most plausible explanation is that CarbonPriceIndex captures not only regulatory pressure but also the maturity of the regional carbon market and information environment. Firms in regions with clearer carbon-pricing signals may face stronger disclosure discipline, better green-finance infrastructure, and earlier transition preparation. The sensitivity checks that separate ETS coverage from allowance-price intensity are therefore important because they help determine whether the result is driven by institutional coverage, price visibility, or their interaction.[29,31,34]

GreenPatent is interpreted as a transition-capacity signal rather than as a mechanically causal variable. Its negative association with Spread_bps suggests that creditors may view observable green innovation as evidence of adaptation capability, technological readiness, or stronger environmental governance.[35-37,42-44] However, the endogeneity concern remains: firms with better management quality, stronger disclosure systems, or better policy access may both produce more green patents and receive lower financing costs. The lagged GreenPatent design, fixed effects, and interaction tests improve credibility, but the results are best described as consistent with a transition-capacity interpretation rather than proving that patents alone reduce debt spreads.

5.3. Policy-timing evidence around 2015 and 2021

The policy-timing results strengthen the empirical narrative by showing that the pricing relevance of carbon-transition signals varies with climate-policy salience. The 2015 Paris Agreement should be interpreted as a broad global policy milestone, not as a narrow treatment that affected only a precisely defined group of Chinese issuers. The event-study evidence is therefore used to examine whether pricing sensitivity became stronger after a major climate-policy signal. The larger post-2015 slope for CarbonIntensity and the stronger associations for CarbonPriceIndex and GreenPatent indicate that creditors became more attentive to transition-related information after climate commitments became more visible.[16,26,27]

The 2021 national ETS setting provides a more structured domestic policy-timing test. The segmented DID results in Table 10 show that ETS-treated issuers experienced wider spreads after 2021 relative to comparable non-treated issuers, and the additional penalty was stronger for high-carbon firms. At the same time, the interaction with GreenPatent is negative, suggesting that transition capacity may partly mitigate post-ETS spread pressure. These findings should not be generalized to all industries or all firms because treatment exposure depends on industry-region coverage, pilot-market history, and issuer status. Their value lies in showing that the green debt market appears to respond to changes in carbon-market institutions in a differentiated manner.[29,31,34]

The robustness checks in Table 11 are therefore not peripheral. Placebo timing, alternative-treatment definitions, exclusion of pilot-exposed firms, and lead-lag diagnostics are necessary because the 2021 ETS reform did not occur in an otherwise static institutional environment. These checks help reduce the risk that the estimated post-2021 pattern is driven only by broader credit-cycle changes, industry trends, or pre-existing pilot-market exposure. The discussion consequently treats the 2021 evidence as differential policy-timing repricing rather than as a universal causal estimate of the national ETS.

5.4. Predictive evidence, Shapley additive explanation interpretation, and scenario tools

The ML results answer a different question from the econometric models: whether carbon variables improve out-of-sample prediction of Spread_bps and whether the fitted model produces interpretable monitoring signals. Table 12 compares the out-of-sample predictive performance of random forests, XGBoost, and neural networks under the same train-validation-test split. XGBoost performs best, indicating that nonlinear interactions between carbon variables and credit fundamentals are useful for spread monitoring.[48] Table 13 then isolates the incremental contribution of carbon-transition variables through ablation tests. The loss of accuracy after removing CarbonIntensity, CarbonPriceIndex, GreenPatent, or the full carbon-variable block shows that carbon information adds monitoring value beyond ratings, leverage, profitability, ownership, and macro-financial conditions.

The out-of-sample R^2 of 0.52 indicates moderate predictive performance. The unexplained variation may reflect issue-level contract terms, maturity and callability differences, guarantees, collateral, underwriting relationships, investor demand, secondary-market liquidity, disclosure verification quality, and unobserved measurement, reporting, and verification (MRV) conditions. Some omitted factors may also be carbon-related but unavailable at the firm-year level. This limitation clarifies the model's appropriate use: it can support risk monitoring and screening, but it should not be used as a precise contractual pricing engine.

The SHAP and feature-importance results add mechanism-oriented interpretation to the prediction exercise.[45-47,49] Figure 2 reports the magnitude of predictive contribution, identifying which variables matter most to the model rather than whether each variable raises or lowers spreads. Directional interpretation comes from SHAP dependence patterns, regression coefficients, and conditional scenario outputs. Figures 3 and 4 suggest that predicted spreads rise more rapidly when CarbonIntensity enters a higher-risk range; Table 15 further shows how predicted spreads change under specific transition-signal scenarios.

Table 16 translates these empirical and predictive patterns into a stylized environmental-governance screening matrix. It links carbon-intensity tiers with carbon-pricing exposure to show how lenders and policymakers might differentiate routine disclosure monitoring, enhanced transition-plan review, and high-risk carbon-reduction scrutiny. The matrix is therefore useful not because it produces a new estimate, but because it converts dispersed empirical results into an operational governance checklist that can be updated when more granular emissions, contract, and post-issuance environmental-performance data become available.

5.5. Market-based environmental governance implications

Within the stated boundaries, the findings support a modest but important environmental-governance implication: green debt pricing can complement, rather than replace, command-and-control regulation and carbon-market policy. When carbon-intensive issuers face wider spreads and issuers with clearer carbon-price exposure or stronger transition capacity face narrower spreads, debt pricing can help differentiate borrowers and transmit environmental information into financing conditions. This mechanism is market-based because it operates through credit spreads, but it depends on reliable disclosure, credible green-debt labeling, and consistent carbon-data infrastructure.[32,33,35-37,42-44]

For financial institutions and green-debt investors, the

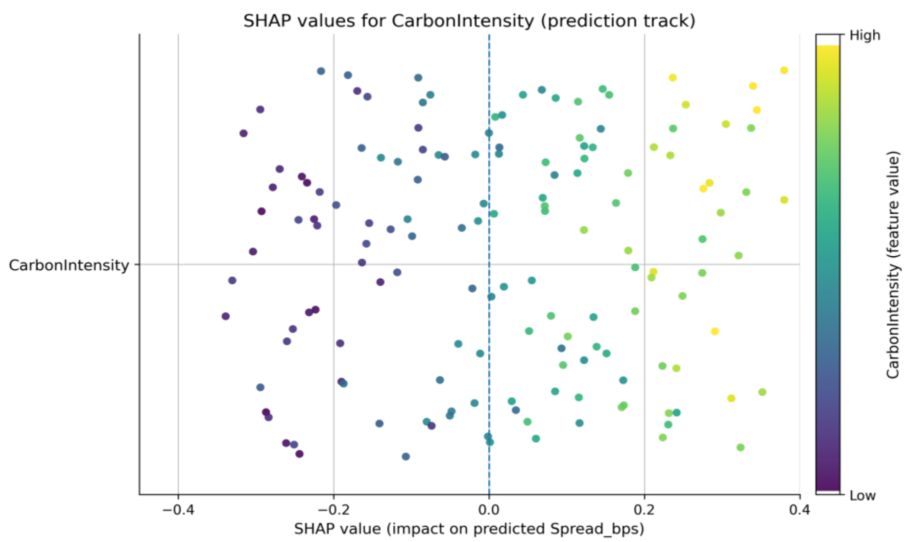

Figure 3. Shapley additive explanation (SHAP) values for CarbonIntensity (prediction track)

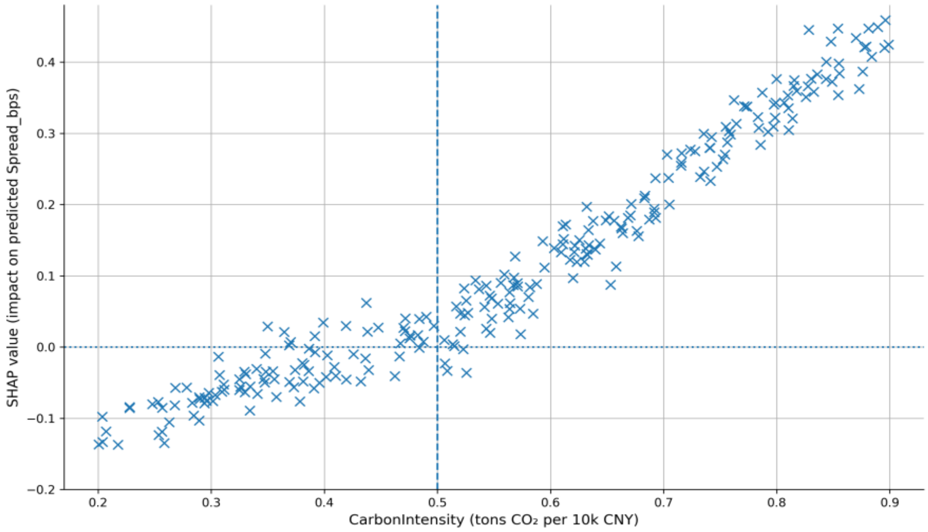

Figure 4. Shapley additive explanation (SHAP) dependence for CarbonIntensity

results imply that carbon variables should be incorporated as supplementary screening indicators. CarbonIntensity can be used to identify current exposure, CarbonPriceIndex to assess the carbon-market information environment, and GreenPatent can be used cautiously as a transition-readiness signal. These indicators should be assessed alongside conventional credit metrics rather than used as stand-alone approval rules. The decision matrix in Table 16 is therefore most useful as a monitoring checklist for due diligence, covenant design, transition-plan review, and post-issuance verification.

For high-energy-consuming issuers, the results point to the importance of making transition signals verifiable. Firms seeking lower financing spreads cannot rely only on green-debt labels. They need stable emissions measurement, transparent use-of-proceeds reporting, credible abatement investment, consistent patent or technology evidence, and auditable MRV information. For regulators and carbon-market builders, the findings suggest that market-based environmental governance is more likely to work when carbon-intensity measurement, ETS exposure definitions, allowance-price disclosure, and green-debt reporting standards are comparable across regions and industries.

5.6. Limitations and future research

Several limitations remain that should be considered when interpreting the findings. First, the issuer-sample structure limits external validity. The findings apply most directly to firms that enter the green debt market, not to all high-energy-consuming firms. Second, carbon emissions are estimated from energy-consumption proxies for much of the sample period, which may generate measurement error, especially in industries with process emissions such as cement and chemicals. Third, CarbonPriceIndex combines policy coverage and price salience, so the interpretation of its negative coefficient requires a decomposition of the sensitivity analysis. Fourth, GreenPatent may capture broader management quality or policy access as well as innovation capacity.

Future research should extend the analysis in three directions. The first is data depth: verified emissions, facility-level energy consumption, contract-level debt terms, and post-issuance environmental-performance data would allow stronger tests of whether financing incentives lead to measurable pollution reduction. The second is identification: more granular ETS coverage rules, staggered treatment timing, and firm-level compliance obligations would help separate carbon-price pressure from regional green-finance maturity. The third is prediction: richer MRV variables, bond-contract features, and market-liquidity measures could improve out-of-sample performance and make scenario tools more useful for practical credit-risk management.

Overall, the evidence supports a bounded conclusion. Carbon transition signals are relevant to green debt pricing for Chinese high-energy-consuming issuers, and ML tools can translate them into useful monitoring outputs. The strongest contribution is not a claim that green debt pricing alone delivers pollution reduction, but rather a more precise framework that shows how debt markets, carbon-policy signals, and transition-capacity indicators can jointly support market-based environmental governance within transparent evidentiary boundaries.

6. Conclusion

This study examines whether carbon transition signals are reflected in the green debt financing spread of Chinese A-share listed firms in high-energy-consuming industries during 2010-2024. The manuscript separates econometric policy-timing evidence from ML prediction so that the results can be interpreted within the appropriate evidentiary boundary. The fixed-effects estimates show that higher carbon intensity is associated with wider green debt spreads, whereas stronger carbon-pricing exposure and greater green patent output are associated with narrower spreads among eligible green-debt issuers. The policy-timing analyses further indicate that the pricing relevance of transition signals becomes stronger around the 2015 Paris Agreement and the 2021 launch of China's national ETS. On the predictive track, XGBoost provides the strongest out-of-sample performance among the tested models, and the ablation results show that removing carbon-related variables weakens forecast accuracy. These findings support the conclusion that carbon information has both pricing relevance and monitoring value in the green debt market.

The study's contribution is therefore threefold. Substantively, it positions green debt pricing as a market-based environmental governance channel rather than a purely financial outcome. Empirically, it links carbon intensity, carbon-market exposure, and green innovation to a common debt-pricing outcome while using policy milestones to examine changes in pricing sensitivity. Methodologically, it combines fixed-effects, event-study, segmented DID, and explainable ML tools without treating predictive outputs as causal policy effects. This distinction improves empirical transparency and prevents the scenario simulations, SHAP values, and feature-importance results from being overstated.

The results have both practical and theoretical implications. For credit analysts and investors, carbon intensity, carbon-pricing exposure, and green innovation can serve as supplementary monitoring indicators alongside conventional credit metrics, such as rating quality, leverage, profitability, and firm size. For issuers, the evidence suggests that transition readiness and credible green innovation may help communicate lower transition risk to the debt market. For policymakers, the more defensible implication is that clearer ETS coverage, more comparable carbon disclosure, and stronger MRV standards can improve the informational basis of green debt pricing and may strengthen market-based environmental governance.

These implications should not be generalized beyond the evidence. The results apply most directly to Chinese high-energy-consuming firms that issue eligible green bonds or sustainability-linked debt instruments, rather than to all firms or to economy-wide pollution reduction. The study also faces several limitations. Firm-level emissions are partly estimated from energy-consumption proxies, which may introduce measurement error across industries with different production technologies. CarbonPriceIndex combines ETS coverage and allowance-price salience, so decomposed sensitivity checks are needed to separate institutional exposure from price intensity. GreenPatent is interpreted as a transition-capacity signal, but it may also reflect unobserved management quality, disclosure strength, or policy access. In addition, the moderate predictive performance of the XGBoost model indicates that issue-level contract terms, liquidity, guarantees, underwriter effects, and post-issuance environmental-performance data remain important omitted dimensions.

Future research should extend the analysis by using verified facility-level emissions, contract-level green debt terms, firm-specific ETS compliance obligations, and post-issuance pollution-reduction outcomes. Such data would enable testing whether financing-cost differentiation translates into measurable environmental performance after issuance. Further work could also compare green debt with conventional debt instruments, examine more granular industry pathways, and develop more stable MRV-informed prediction models. These extensions would help move from the present study's bounded conclusion—carbon transition signals are priced and useful for monitoring among green-debt issuers—toward stronger evidence on how debt markets can support low-carbon transition and environmental governance.

Acknowledgments

None.

Funding

None.

Conflict of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization: All authors
Data curation: Lin Sun
Formal analysis: Lin Sun
Investigation: Lin Sun
Methodology: All authors
Project administration: Lin Sun
Resources: Jun Zeng
Software: Lin Sun

Supervision: Jun Zeng
Validation: All authors
Visualization: Lin Sun
Writing–original draft: Lin Sun
Writing–review & editing: Jun Zeng

Availability of data

The data used in this study were primarily drawn from licensed commercial databases, such as Wind and the China Stock Market and Accounting Research Database (CSMAR). Owing to third-party licensing restrictions, the raw data cannot be made publicly available. Additional information was collected from publicly disclosed materials of listed firms, including annual reports and announcements. Because commercial financial datasets such as Wind and CSMAR are license-restricted and cannot be redistributed publicly, only derived variables, a codebook containing variable definitions and units, and a limited reproducibility package can be shared upon reasonable request, subject to data-use constraints.

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