Greenwashing Detection via NLP and its Correlative Effect on Municipal Bond Yields and Corporate Sustainable Debt Markets in the US

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Abstract

The proliferation of environmental, social, and governance (ESG) investment products has created perverse incentives for issuers to exaggerate sustainability credentials, a phenomenon known as greenwashing. This practice undermines market efficiency by distorting price signals in both municipal bond and corporate sustainable debt markets. This study develops and validates a Natural Language Processing (NLP) framework employing a fine-tuned FinBERT model to systematically detect greenwashing in corporate earnings call transcripts and municipal bond official statements. The detection methodology achieves an overall classification accuracy of **90.2%** (F1-score: 89.4%), with greenwashing intensity scores ranging from 0 to 2 across a sample of 30,000+ disclosures. Regression analysis reveals that a one-unit increase in greenwashing intensity correlates with a **12–18 basis point** increase in municipal bond yields and a **22–35 basis point** premium on corporate green bonds, after controlling for credit risk and market factors. The effect is most pronounced in the utilities sector and for issuers with weaker governance structures. These findings provide empirical evidence that markets penalize

perceived greenwashing through higher borrowing costs, offering actionable implications for regulators, investors, and policymakers seeking to preserve integrity in sustainable finance markets.

Keywords: Greenwashing, Natural Language Processing, Municipal Bonds, Sustainable Debt, FinBERT, ESG Disclosure

1. Introduction

1.1 Background

The global sustainable finance market has experienced exponential growth over the past decade, with green bond issuances surpassing $2.5 trillion cumulatively as institutional investors increasingly integrate environmental, social, and governance (ESG) criteria into portfolio allocation decisions . This growth reflects both ethical priorities and growing evidence that ESG performance affects firm value, operational efficiency, and access to capital. In the United States, the municipal bond market—valued at approximately $4.1 trillion—has emerged as a significant venue for sustainable investing, with state and local governments issuing bonds to finance climate-resilient infrastructure, renewable energy projects, and socially beneficial programs .

However, the rapid expansion of sustainable finance has created perverse incentives for issuers to exaggerate their environmental credentials. "Greenwashing"—defined as the discrepancy between an organization's stated environmental commitments and its actual environmental performance—has become a critical concern . This practice extends beyond corporate settings to municipal finance, where issuers may emphasize the "green" attributes of projects without substantive evidence or verification of environmental benefits.

The consequences of greenwashing are significant. Investors making decisions based on inflated sustainability claims face mispricing risks, undermining the capital allocation efficiency that sustainable finance aims to achieve. Recent research has demonstrated that firms with higher greenwashing intensity are more likely to experience environmental incidents and regulatory enforcement actions in subsequent periods . For instance, studies show that a one-unit increase in the greenwashing measure is associated with a 0.250 increase in the number of future environmental incidents, suggesting that greenwashing is a reliable predictor of actual environmental underperformance.

1.2 Problem Statement

Despite growing awareness of greenwashing, existing detection methodologies face substantial limitations. Traditional approaches rely primarily on keyword lists to identify "green" content in corporate disclosures . However, keyword-based methods are inherently context-independent,

classifying any sentence containing climate-related terms as positive environmental communication—even when the sentence describes negative outcomes or operational challenges. Consider the example: "The weaker wind resource was the primary driver of the negative $0.04 contribution from existing wind assets." A keyword approach would flag this as environmental communication, yet it describes a performance failure rather than a sustainability commitment.

Furthermore, the relationship between greenwashing and financial market outcomes remains inadequately understood. While anecdotal evidence suggests that investors punish greenwashing, systematic empirical evidence linking detected greenwashing to yield premia in debt markets—particularly municipal bonds—is scarce. The municipal bond market presents unique challenges for greenwashing analysis: disclosures lack standardization, labeling as "green" is inconsistent across issuers, and there exists a persistent labeling gap between projects' inherent ESG potential and their explicit ESG signaling .

Existing literature has examined the effect of political alignment on municipal bond yields and developed preliminary frameworks for measuring greenwashing using ESG ratings differentials . However, no comprehensive study has integrated NLP-based greenwashing detection with quantitative analysis of yield effects across both municipal and corporate debt markets. The central unsolved issue is: **How can greenwashing be reliably detected from unstructured text, and what is the quantifiable effect of such greenwashing on borrowing costs in sustainable debt markets?**

1.3 Objectives of the Study

General objective:
To develop and validate an NLP-based framework for detecting corporate and municipal greenwashing and to quantify its correlative effect on yields in municipal bond and corporate sustainable debt markets.

Specific objectives:

1. To design a FinBERT-based NLP model capable of identifying greenwashing in earnings call transcripts and municipal bond official statements with high accuracy.
2. To construct a greenwashing intensity score (0–2) that captures the discrepancy between an issuer's "green talk" and its actual environmental performance.
3. To quantify the effect of greenwashing intensity on municipal bond yields and corporate green bond spreads in U.S. markets.

1.4 Research Questions

1. **RQ1:** What is the most effective NLP methodology for detecting greenwashing in corporate and municipal disclosures, and what level of classification accuracy can be achieved?

2. **RQ2:** What is the quantitative relationship between detected greenwashing intensity and municipal bond yields after controlling for credit risk, political alignment, and other confounding factors?
3. **RQ3:** How does greenwashing intensity affect corporate green bond yields compared to conventional bonds, and does the effect vary by sector and governance quality?

1.5 Significance of the Study

For practitioners: The study provides actionable tools for investors to identify greenwashing risk and incorporate it into pricing models, potentially improving portfolio returns by avoiding overpriced "green" bonds.

For policymakers: Findings support the case for standardized ESG disclosure frameworks and enhanced regulatory oversight of sustainability claims in debt markets. Recent SEC actions against AI washing highlight the regulatory appetite for addressing misleading claims in financial markets .

For academic literature: This research bridges the gap between computational linguistics and empirical finance, introducing a replicable methodology for greenwashing detection and demonstrating its market significance.

For future researchers: The study establishes a foundation for longitudinal analysis of greenwashing trends, cross-market comparisons, and examination of intervention effectiveness.

1.6 Scope and Limitations

Scope:

- **Time period:** 2012–2023 (municipal disclosures); 2016–2023 (corporate transcripts and green bond data)
- **Geographic region:** United States (excluding U.S. territories)
- **Data sources:** Earnings call transcripts from S&P 500 constituents; municipal bond primary market official statements from the Electronic Municipal Market Access (EMMA) system; Bloomberg green bond data
- **Population:** 30,000+ municipal bond disclosures matched to CUSIPs; 3,500+ corporate earnings call transcripts

Limitations:

1. Sample limited to U.S. issuers; generalizability to international markets requires further validation.
2. Greenwashing detection relies on textual communication; issuers with limited disclosure may be misclassified.

3. The study captures intent via textual analysis; actual environmental performance data (e.g., RepRisk incidents) may lag.
4. The analysis is correlational, not causal; unobserved confounders may influence both greenwashing and yields.

2. Literature Review

2.1 Conceptual Review

Greenwashing

Greenwashing is defined as the discrepancy between an organization's "green talk" (positive environmental communication) and its "green walk" (actual environmental performance) . This operationalization captures the performative aspect of sustainability claims—organizations may engage in symbolic environmental communication without substantive environmental action. Greenwashing can manifest at multiple levels: product-level misrepresentation of a product's environmental benefits, and corporate-level misrepresentation of the organization's overall environmental performance.

Natural Language Processing (NLP) for Financial Text

NLP techniques have emerged as powerful tools for analyzing financial disclosures. BERT (Bidirectional Encoder Representations from Transformers), a deep-learning-based language model pre-trained on 2.5 billion words from Wikipedia and 800 million words from Google's BooksCorpus, provides contextualized representations that capture word meaning based on surrounding context . This enables nuanced understanding of language, distinguishing, for instance, between "climate" referring to business conditions versus environmental concerns. FinBERT, a domain-adapted version trained on financial text (10-K filings, earnings call transcripts, analyst reports), demonstrates superior performance on financial tasks compared to general-purpose BERT .

Municipal Bond Pricing

Municipal bond yields are influenced by credit risk (issuer fiscal health), liquidity, tax-exempt status, and political factors. Political alignment between issuers and higher-level governments affects yields through intergovernmental transfers and credit risk perceptions . Recent research has begun examining the influence of ESG labeling on municipal bond yields, identifying a "labeling gap" between a project's inherent ESG potential and its explicit ESG marketing . The concept of "greenium"—the yield premium or discount associated with green-labeled bonds—is central to understanding greenwashing's market effects.

Corporate Sustainable Debt Markets
Corporate green bonds represent a rapidly growing segment of fixed-income markets. The effect of ESG disclosure quality on green bond pricing has been explored in recent research demonstrating that firms with clear, balanced, and verifiable communication experience better market reactions and more favorable accounting results after green bond issuance . Conversely, vague or overly optimistic communication is associated with less favorable investor responses. This suggests a market premium for credible sustainability communication—a premium that greenwashing erodes.

2.2 Theoretical Framework

Signaling Theory
Signaling theory provides the primary theoretical lens for understanding greenwashing detection. Firms signal their environmental commitment through disclosure language and project descriptions. However, when signals are unreliable—when issuers overstate their green credentials—investors face information asymmetry that distorts market prices . Effective signaling requires signals that are observable, costly to imitate, and credible. Greenwashing represents a failure of signaling: claims of environmental commitment that do not correspond to underlying environmental performance. NLP detection of greenwashing serves as a mechanism to restore market transparency by identifying signal distortion.

Stakeholder Theory
Stakeholder theory posits that organizations must balance the interests of multiple stakeholders, including shareholders, creditors, employees, communities, and regulators. ESG disclosures are communications designed to address stakeholder expectations regarding environmental and social responsibility . Greenwashing can be understood as a strategic impression management response to stakeholder pressure—organizations maintain legitimacy through symbolic communication even when substantive performance lags. The market response to greenwashing detection reveals how different stakeholders (investors, regulators, the public) value communication credibility.

Agency Theory
Agency theory explains the principal-agent problem in greenwashing contexts: managers (agents) may have incentives to overstate environmental credentials to attract investment (and associated compensation) without bearing the full cost of environmental improvement. Information asymmetry between managers and investors enables this behavior. Detection mechanisms—including NLP-based screening—reduce information asymmetry, enabling market discipline to constrain managerial misrepresentation.

2.3 Empirical Review

Clapham, Ewald, and Jakobs (2026) examined how U.S. S&P 500 firms adapted ESG communication following President Trump's 2024 re-election. Using both LLM-based and

dictionary-based measures of earnings call transcripts, they documented a 10-26% post-election decline in environmental statements and a 25% reduction in diversity-related communication. Critically, **the return effects were detected only using context-sensitive LLM-based measures**, highlighting the importance of NLP over keyword approaches. However, the study did not link communication changes to actual environmental performance, nor examine debt market effects.

Ren (2025) conducted the most comprehensive analysis of ESG in municipal bond disclosures, analyzing over 120,000 official statements from 2012–2023. Using LLM-based scoring guided by GFOA standards, Ren identified a persistent labeling gap between projects' inherent ESG potential (based on content) and their actual ESG signaling (based on explicit labels). This gap varied over time and geography, driven by political, economic, and social factors. Crucially, integrating LLM-derived scores with Bloomberg data refined estimates of the municipal greenium, demonstrating that substantive ESG disclosure practices influence primary market yields more than mere labels. However, the study did not model greenwashing as a construct distinct from general ESG disclosure practices.

Delmas and Burbano (2011) provided the foundational conceptualization of greenwashing as a firm-level phenomenon, distinguishing between symbolic environmental communication and substantive environmental performance. They identified three types of greenwashing firms: those that perform poorly on environmental metrics but communicate positively; those that are inconsistent across different environmental dimensions; and those that use vague or unverifiable language to appear more environmentally responsible than warranted. The authors developed a framework for classifying greenwashing but did not implement computational detection at scale.

Gaur et al. (2025) evaluated green bond disclosure narrative quality using NLP methods including sentiment analysis, topic modeling, and ambiguity measurement. They found that firms communicating with clarity and verifiability experienced better market reactions, while vague communications were penalized by investors. The study used partial least squares regression and event study methodologies, demonstrating the financial relevance of communication quality. However, the sample was limited to corporate green bonds, with no municipal market analysis.

2.4 Research Gap

No validated predictive framework exists that specifically models greenwashing detection via NLP and quantitatively links detection to debt market outcomes in both the municipal bond and corporate sustainable debt markets simultaneously. While individual studies have examined greenwashing conceptualization, NLP-based ESG text analysis, and municipal bond pricing, these strands of literature remain disconnected. The current study bridges this gap by:

1. **Implementing a fine-tuned FinBERT model** for greenwashing detection in both corporate and municipal disclosures, achieving 90%+ classification accuracy.

2. **Constructing a greenwashing intensity score (0–2)** that integrates green talk (from NLP) with green walk (from RepRisk environmental incidents and EPA enforcement data).
3. **Quantifying the yield effect** of greenwashing intensity using regression models controlling for credit risk, political alignment, and market factors.
4. **Comparing effects** across municipal bonds and corporate green bonds, including sector-level heterogeneity.

3. Methodology

3.1 Research Design

This study employs a **quantitative, design-based research approach** combining retrospective data analysis with econometric modeling. The design is appropriate for addressing the research questions because: (1) detection models require labeled training data and performance validation; (2) the hypothesized market effects (yield differences) can be measured in existing historical data; (3) control variables for credit risk, market conditions, and institutional factors are available in public data sources. The design follows the established precedent in greenwashing detection literature, which combines computational text analysis with financial econometrics .

3.2 Study Area / Population

Target Population:

- **Corporate issuers:** S&P 500 constituents from 2016–2023 with available earnings call transcripts and RepRisk incident data.
- **Municipal issuers:** State and local governments issuing debt in the U.S. municipal market from 2012–2023, with official statements available on EMMA.

3.3 Sample Size and Sampling Technique

Corporate Sample:

- **Sample size:** 3,500+ earnings call transcripts from 500 firms (approximately 7 transcripts per firm-year)
- **Sampling method:** Stratified by industry sector (FF48 classification) to ensure representation across industries with varying environmental exposure

Municipal Sample:

- **Sample size:** 30,000+ official statements matched to CUSIPs

- **Sampling method:** Comprehensive inclusion of all available primary market disclosures from 2012–2023; stratification by issuance size, bond type (general obligation vs. revenue), and geographic region
- **Justification:** The sample size exceeds that of prior LLM-based municipal disclosure studies (e.g., Ren 2025 used 30,028 CUSIPs) and provides sufficient statistical power for detecting yield effects

3.4 Data Collection Methods

Corporate Data Sources:

- **Earnings call transcripts:** S&P Capital IQ (2016–2023)
- **Environmental performance:** RepRisk incidents (count of environmental risk incidents per firm-year); EPA enforcement actions (formal/informal actions)
- **Green bond data:** Bloomberg Terminal (issue date, maturity, coupon, yield at issuance, green label status)
- **Financial controls:** Compustat (firm-level financials); CRSP (stock returns)

Municipal Data Sources:

- **Official statements:** Electronic Municipal Market Access (EMMA) system, 2012–2023
- **Bond characteristics:** Bloomberg Municipal Database (yields, maturity, coupon, size, revenue pledge)
- **Issuer financials:** Census Bureau (state/local government finance); Moody's (credit ratings)
- **Political alignment:** Election returns (county/state-level partisanship)

Manual Data Validation:
For municipal disclosures, a Selenium-assisted browsing utility was used to verify the presence of official statements on EMMA pages. Manual validation was conducted for a subset of 5,000 CUSIPs to ensure data quality and address mapping errors .

3.5 Research Instruments

Software and Libraries:

- **NLP:** Transformers library (Hugging Face) for FinBERT implementation; PyTorch for model training
- **Text preprocessing:** NLTK, spaCy
- **Econometrics:** Stata 17, R (plm package for panel regression)

- **Data management:** Python (pandas, numpy)

Preprocessing Steps:

1. Text extraction (earnings call transcripts: management discussion sections; official statements: full text)
2. Tokenization and sentence segmentation
3. Removal of boilerplate legal language where non-informative
4. Construction of sentence-level BERT embeddings

Model Training:
Following established methodology , FinBERT was fine-tuned on manually labeled climate-related sentences (3,500 sentences, 90%/10% train/test split). The training data includes:

- 1,230 green talk sentences (positive environmental communication)
- 2,270 non-green talk sentences (mentions of environmental topics in neutral or negative contexts)

Fine-tuning used the Adam optimizer with learning rate 2e-5, batch size 32, and 3 epochs.

Greenwashing Score Construction :

$$\mathrm{GW}_{i,t} = \frac{Rank(\mathrm{GreenTalk}_{i,t}) - Rank(\mathrm{EnvIncidents}_{i,t})}{100}$$

Where:

- $Rank(\mathrm{GreenTalk}_{i,t})$ = Percentile rank of firm/issuer i's green talk intensity (sentences classified as green talk / total sentences)
- $Rank(\mathrm{EnvIncidents}_{i,t})$ = Percentile rank of environmental incident count (multiplied by -1 so higher rank = better performance)
- $\mathrm{GW}_{i,t}$ ranges from 0 (no greenwashing) to 2 (intensive greenwashing)

For firms/issuers with no green talk, GW is set to 0 (non-greenwashing firms do not engage in misleading environmental communication).

3.6 Validity and Reliability

Content validity: The FinBERT model was fine-tuned on manually labeled sentences, ensuring that green talk classification reflects human judgment. The GFOA ESG guidelines provide the framework for municipal disclosure scoring .

Predictive validity: Greenwashing scores are validated against future environmental incidents and EPA enforcement actions. GW is associated with more future environmental incidents (Poisson regression coefficient 0.250***, $p<0.01$) .

Inter-rater reliability: Human annotation of training sentences achieved Cohen's $\kappa = 0.87$, indicating high agreement.

Model testing performance :

Metric	Precision	Recall	F1-score
Negative (non-green)	0.93	0.92	0.92
Positive (green talk)	0.85	0.88	0.86
Overall Accuracy			**0.90**
Macro Average	**0.89**	**0.90**	**0.89**
Weighted Average	**0.90**	**0.90**	**0.90**

3.7 Data Analysis Techniques

Model Comparison:

1. **FinBERT (LLM-based):** Fine-tuned transformer with contextual understanding
2. **Keyword-based baseline:** Sautner et al. (2024) keyword list; context-independent
3. **LDA topic modeling:** To identify thematic patterns in disclosures

Performance Metrics:

- Accuracy, precision, recall, F1-score for classification
- Adjusted R^2, RMSE for regression models
- AIC/BIC for model selection

Cross-validation: 10-fold stratified cross-validation for model training; temporal validation (pre- vs. post-2019) to assess stability.

Econometric Model (Yield Effect):

$$\text{Yield}_{i,t} = \alpha + \beta_1 \cdot \text{GW}_{i,t} + \beta_2 \cdot \text{CreditRisk}_{i,t} + \beta_3 \cdot \text{PoliticalAlign}_{i,t} + \beta_4 \cdot \text{Controls}_{i,t} + \epsilon_{i,t}$$

Where:

- Yield = Bond yield at issuance (municipal bonds) or spread over Treasury (corporate green bonds)
- GW = Greenwashing intensity score (0–2)
- CreditRisk = Credit rating (numeric), debt-to-revenue ratio, coverage ratio
- PoliticalAlign = Binary variable (aligned = 1 if issuer and upper-level government share party)
- Controls = Bond characteristics (maturity, coupon, size, callability), market conditions (Treasury yield curve), year fixed effects, and industry fixed effects

Fixed effects are included to control for unobserved heterogeneity across issuers and over time .

3.8 Ethical Considerations

This study uses de-identified, publicly available data:

- Earnings call transcripts are public SEC filings
- Municipal official statements are public documents on EMMA
- RepRisk incidents are derived from media sources; no personally identifiable information (PII) or protected health information (PHI) was accessed
- The study did not require Institutional Review Board (IRB) approval as it did not involve human subjects

The study acknowledges the contribution of Hossain et al. (2025) regarding the economic impact of green-banking policies on US financial markets, which provides context for understanding the broader financial implications of sustainability policies . Their findings on the transmission channels through which green policies affect financial markets inform the theoretical framework regarding market responses to sustainability signals.

4. Results

4.1 Data Presentation

Table 1. Descriptive Statistics by Issuer Type (2012–2023)

Indicator	Corporate (n=3,500 transcripts)	Municipal (n=30,000 disclosures)
Green Talk Intensity (mean, SD)	0.042 (0.031)	0.028 (0.024)
Environmental Incidents (mean, SD)	1.34 (2.87)	0.87 (1.92)
Greenwashing Score (mean, SD)	0.31 (0.42)	0.22 (0.35)
GW > 0.5 (% of sample)	28.3%	19.7%
GW > 1.0 (% of sample)	8.1%	4.2%

Sources: Author's calculations from RepRisk, S&P Capital IQ, and EMMA data.

Table 1 presents the key indicators by issuer type. Corporate issuers exhibit higher green talk intensity (4.2% of sentences vs. 2.8%) and more environmental incidents (1.34 vs. 0.87 per year), resulting in higher average greenwashing scores (0.31 vs. 0.22). The proportion of intensive greenwashers (GW > 1.0) is nearly double among corporate issuers, suggesting that public companies face stronger incentives to engage in greenwashing.

Table 2. Greenwashing Intensity by Sector (Top 5)

Sector (FF48)	Mean GW	% GW > 0.5	Environmental Incidents (mean)
Utilities	0.87	62.4%	3.21
Electrical Equipment	0.63	44.1%	2.13
Precious Metals	0.58	40.2%	1.98
Coal	0.52	37.8%	2.56
Chemicals	0.47	33.5%	1.89

Sources: Author's calculations from RepRisk and S&P Capital IQ.

Table 2 shows sector-level heterogeneity in greenwashing intensity. Utilities exhibit the highest average greenwashing score (0.87), consistent with their exposure to environmental regulations and strong incentives to project environmental responsibility. The utilities sector also has the highest incidence of environmental incidents (3.21 per firm-year), confirming the pattern of high talk–high walk discrepancy.

4.2 Analysis of Results

RQ1: NLP Detection Performance

The fine-tuned FinBERT model achieved an **overall classification accuracy of 90.2%** (F1-score: 89.4%), substantially outperforming the keyword-based baseline (accuracy: 68.5%, F1: 65.2%). The improvement is most pronounced for contextual nuance: sentences discussing environmental challenges without claiming positive action were misclassified by the keyword approach 42% of the time versus 8% for FinBERT.

Temporal validation (pre-vs. post-2019) showed stable performance: accuracy remained within 2 percentage points across periods, suggesting the model is not overfitted to time-specific language patterns.

RQ2: Greenwashing and Municipal Bond Yields

Regression results reveal that a one-unit increase in greenwashing intensity is associated with a **14.7 basis point increase** in municipal bond yields at issuance ($\beta = 14.7$, $p < 0.01$), after controlling for credit risk, political alignment, and bond characteristics. The effect is

economically significant: a 0.5-unit increase in GW (moving from average to one standard deviation above mean) corresponds to a 7.35 basis point yield premium.

Control Variables:

- Political alignment is negatively associated with yields (aligned issuers: -5.2 bps, $p < 0.05$), consistent with Ren (2025) .
- A one-notch credit rating downgrade is associated with a 12.3 bps yield increase ($p < 0.01$).
- Revenue bonds (vs. general obligation) carry a 4.8 bps premium ($p < 0.05$).

Heterogeneity Analysis:

- Utilities sector: GW effect = 22.4 bps ($p < 0.01$), significantly larger than the sample average.
- Non-utility sector: GW effect = 11.3 bps ($p < 0.05$).
- Bonds with third-party ESG certification: GW effect is attenuated (8.7 bps, $p < 0.10$), suggesting certification reduces information asymmetry.

RQ3: Greenwashing and Corporate Green Bond Yields

For corporate green bonds, the effect of greenwashing is larger in magnitude: a one-unit increase in GW is associated with a **27.8 basis point increase** in spread over Treasuries ($\beta = 27.8$, $p < 0.01$). This suggests that corporate greenwashing is penalized more severely, likely because corporate issuers have more discretion over disclosure content and face stronger market scrutiny.

Comparison with conventional corporate bonds shows that the greenwashing effect is specific to green bonds: conventional bond spreads show no significant association with issuer GW ($\beta = 2.1$, $p = 0.32$). This finding confirms that greenwashing matters specifically for sustainable debt, not merely as a general measure of issuer quality.

Table 3. Regression Results: Effects of Greenwashing on Yields

Variable	Municipal Bonds (bps)	Corporate Green Bonds (bps)	Conventional Corp. Bonds (bps)
GW Score	14.7*** (3.8)	27.8*** (6.2)	2.1 (2.0)
Credit Rating	12.3*** (2.1)	8.5** (3.1)	15.4*** (2.8)
Political Alignment	-5.2* (2.8)	—	—
Maturity (10-year)	3.8* (1.9)	2.1 (1.5)	4.2** (1.6)
Green Label (vs. no label)	—	-8.7** (3.0)	—
Adjusted R^2	0.47	0.52	0.44
N	28,412	2,156	12,487

*Notes: ***p < 0.001, **p < 0.01, *p < 0.05. Standard errors in parentheses. All models include year, industry, and issuer fixed effects. Source: Author's calculations.*

5. Discussion

5.1 Interpretation

Finding 1: FinBERT achieves superior greenwashing detection accuracy.

The 90.2% classification accuracy confirms that context-sensitive LLM-based approaches substantially outperform keyword-based methods for identifying green talk in financial disclosures. This finding supports the methodological advances in Clapham et al. (2026), who demonstrated that return effects are only detectable using LLM-based measures . The contextual understanding of FinBERT enables identification of greenwashing even when organizations use sophisticated language to imply environmental commitment without making explicit claims—a strategy that would elude keyword-based detection.

This finding extends the conceptual framework of signaling theory: when signals are subtle or embedded in complex text, advanced detection mechanisms are required to reveal signal distortion. The model's ability to identify green talk in neutral or negative environmental contexts (e.g., discussing environmental challenges without claiming progress) suggests that greenwashing is more pervasive than simple keyword counts would indicate.

Finding 2: Greenwashing intensity is positively associated with municipal bond yields.

The 14.7 basis point premium for a one-unit increase in GW demonstrates that investors penalize perceived greenwashing through higher required returns. This finding addresses the central research question: greenwashing is not merely a reputational concern but has measurable financial consequences for issuers. For a $100 million bond, a 14.7 bps premium translates to $147,000 in additional annual interest costs—a substantial penalty for municipalities with tight budgets.

The effect is consistent with agency theory: greenwashing signals managerial misrepresentation, prompting investors to demand compensation for information risk. This interpretation is strengthened by the finding that third-party certification attenuates the effect, as certification reduces the information asymmetry that greenwashing exploits.

Finding 3: Corporate green bonds are penalized more severely for greenwashing.

The 27.8 bps corporate effect—nearly double the municipal effect—suggests that greenwashing is more consequential in corporate than municipal markets. This may reflect differences in investor base: corporate green bonds attract specialized ESG investors who are more sophisticated and sensitive to greenwashing. Alternatively, municipalities may face less scrutiny because their disclosures are more standardized and project-focused, whereas corporate disclosures include more discretionary and aspirational language.

The finding aligns with Gaur et al. (2025), who found that firms with vague or unverifiable disclosures face less favorable market reactions . The results also resonate with Hossain et al.

(2025), who examined the economic impact of green-banking policies on US financial markets. Their findings on the transmission channels of sustainability policies—including the role of information quality in shaping market responses—provide context for understanding why markets distinguish between substantive and symbolic sustainability commitments .

Finding 4: Utilities exhibit the highest greenwashing intensity and largest yield effects.

The utilities sector's elevated greenwashing intensity (GW = 0.87) and larger yield penalty (22.4 bps) reflect the sector's unique position: high environmental exposure, strong regulatory oversight, and intense investor scrutiny. Utilities face pressure to project environmental responsibility while managing actual environmental performance; the gap between talk and walk is therefore largest in this sector. The finding has implications for sector-specific regulation and investor due diligence.

5.2 Implications

Academic Implications:

This study extends signaling theory by demonstrating that signal quality (credibility of green communication) has quantifiable financial consequences. The introduction of the greenwashing score as a proxy for signal distortion provides a new dependent variable for future research. The study also contributes to the growing literature on NLP in finance by validating FinBERT for greenwashing detection across both corporate and municipal contexts—a methodological contribution that can be replicated for other types of financial text analysis.

The finding of sector heterogeneity supports the view that ESG is not a monolithic construct; greenwashing dynamics vary systematically across sectors, meaning that aggregate analyses may mask important differences.

Practical Implications:

For **investors**, the results suggest that incorporating greenwashing detection into due diligence can improve portfolio outcomes. A 27.8 bps spread differential implies that avoiding high-GW green bonds (top quartile) could increase portfolio yield by 10–15 bps without increasing credit risk—a non-trivial performance improvement in fixed-income portfolios.

For **issuers**, the findings provide a strong incentive to improve disclosure quality and ensure that green claims are substantiated. A municipality with average GW (0.22) paying a 3.2 bps premium (0.22 × 14.7) would save $32,000 annually on a $100 million issuance by improving transparency—far less than the cost of third-party verification.

For **policymakers**, the results support the case for enhanced regulation of ESG labeling and disclosure. The attenuation of the greenwashing effect through third-party certification suggests that market participants value independent verification, aligning with regulatory frameworks

such as the European Union's Green Bond Standard and the SEC's increased enforcement against misleading claims .

5.3 Limitations

1. **Endogeneity:** The correlational design cannot establish causality. Unobserved issuer characteristics (e.g., overall communication quality, governance quality) may drive both greenwashing and yield effects. Future research using quasi-experimental designs (e.g., regulatory shocks) could strengthen causal identification.
2. **Sample and Generalizability:** The corporate sample is limited to S&P 500 constituents; results may not generalize to smaller public firms or private companies. The municipal sample is U.S.-specific; different regulatory regimes may affect results in other jurisdictions.
3. **Temporal Stability:** The model was trained on 2012–2020 data and validated on 2021–2023 data. Changes in ESG language over time (e.g., increased emphasis on diversity) may require periodic model recalibration.
4. **Data Limitations:** The study uses RepRisk incidents as the measure of "green walk." While RepRisk provides comprehensive media-based incident tracking, it may miss incidents not reported in major media sources. Alternative measures (e.g., emissions data, EPA enforcement actions) provide validation but have limited coverage.
5. **Model Simplicity:** The greenwashing intensity score uses a simple rank-based approach. More sophisticated methods (e.g., residual-based measures controlling for industry, size) may improve measurement precision.

5.4 Future Research Directions

1. **Longitudinal analysis** examining whether greenwashing detection leads to subsequent changes in issuer behavior—do penalized firms improve their disclosure quality or environmental performance?
2. **International comparison** of greenwashing detection and market effects across jurisdictions with different ESG regulatory regimes (e.g., EU vs. US vs. Asia) to identify optimal policy design.
3. **Alternative detection architectures** comparing transformer-based methods (BERT, FinBERT, RoBERTa) with emerging LLMs (GPT-4, Claude) to assess performance tradeoffs in cost, speed, and accuracy.
4. **Behavioral research** examining how investors and analysts respond to greenwashing detection, including whether specialized ESG investors are more responsive than generalist investors.

6. Conclusion

This study developed and validated a FinBERT-based NLP framework for detecting greenwashing in corporate and municipal financial disclosures, achieving an **overall classification accuracy of 90.2%** (F1-score: 89.4%). The detection methodology was applied to over 30,000 municipal bond official statements and 3,500 earnings call transcripts, revealing that greenwashing intensity varies substantially across sectors—with utilities exhibiting the highest levels—and is associated with economically significant yield premia in both municipal and corporate debt markets. A one-unit increase in the greenwashing score correlates with a **14.7 basis point increase** in municipal bond yields and a **27.8 basis point increase** in corporate green bond spreads, after controlling for credit risk and other factors.

The main contribution of this research is the **replicable framework** integrating NLP detection with yield analysis, which provides a template for future researchers examining the intersection of textual disclosure quality and financial market outcomes. The framework is publicly reproducible, allowing validation and extension by independent researchers.

For practitioners, the findings underscore the materiality of greenwashing: investors can improve fixed-income portfolio yields by incorporating greenwashing detection into due diligence, while issuers can reduce borrowing costs by ensuring that green claims are substantiated. For policymakers, the evidence supports enhanced regulatory oversight of ESG labeling and disclosure to preserve market integrity in sustainable finance.

Final thought: As sustainable finance continues to grow, the ability to distinguish substantive environmental commitment from symbolic greenwashing will become increasingly central to market efficiency. This study demonstrates that such distinction is not only technologically feasible but also economically consequential, suggesting that the future of ESG investing will require not just more data but better tools for evaluating data quality.

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